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Artificial intelligence and hedge fund performance

An analysis of hedge fund trading styles

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ABSTRACT:

This study focuses on understanding the relationship between the level of automation employed by hedge funds on the level of performance that these funds are able to obtain. As technologies are constantly evolving and being used to further different fields, one could ask if the adaptation of the latest technological advancements in term of artificial intelligence could be used to further the trading performance of hedge funds. As hedge funds enjoy less restrictions for their trading processes, they are at a prime position to take advantage of every edge that can be obtained.

Using data from the Preqin hedge fund database we can to uncover this level of automation by sorting funds based on their trading styles. The term AIML hedge funds refers to hedge funds using both artificial intelligence and machine learning. These AIML funds are taken as their own trading style and their performance is compared against systematic, discretionary and combined funds which utilize both the systematic and the discretionary methodologies in their trading processes. Using both the efficient market hypothesis and the behavioral finance frameworks, we are able to conduct a detailed analysis of both the motivation for the need of automation and for the existence of hedge funds. Past literature relating to hedge fund performance, artificial intelligence and algorithmic trading, and hedge fund comparisons are also reviewed in detail. By only focusing on funds that trade U.S equities we are able to utilize common factor models used for pricing U.S. equities. Performance is analyzed both in terms of the full sample period and by employing subsample analysis to uncover underlying performance persistence.

Based on the results of our factor models we are able to see the statistically significant overperformance shown by AIML funds. Moreover, our subsample analysis supports these findings and shows that the performance obtained by AIML funds is persistent. When the effects of serial correlation between the fund types is taken into account the outperformance of AIML is further established. Lastly, when comparing the alphas of AIML funds against the other hedge fund trading style portfolios, AIML funds exhibit statistically significant outperformance even at a one percent level of significance. Thus, our results indicate that by using artificial intelligence hedge funds can improve their performance on a persistent basis and to stand out from their peers. Our results are not in breach of the efficient market hypothesis as the underlying reasons for AIML fund performance can be noted as their ability to adapt and their ability to take advantage of small market dislocations. Behavioral finance also shows how adaptability combined with an emotionless ability to execute strategies are key for AIML outperformance Our findings present interesting directions for future research and showcase the likely future trend of increased AI usage within the hedge fund industry.

KEYWORDS: Hedge fund, Artificial intelligence, AIML, Systematic, Discretionary

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TIIVISTELMÄ:
Tämä tutkimus keskittyy ymmärtämään suhdetta hedgerahastojen käyttämän automatisaation ja niiden saavuttaman suorituskyvyn välillä. Koska tekniikoita kehitetään jatkuvasti ja niitä käytetään eri aloilla, voidaan teorisoida, josko uusimpien teknisten kehitysten ottaminen osaksi hedgerahastojen strategioita johtaa tulosten paranemiseen. Koska hedgerahastoilla on vähemmän rajoituksia kaupankäyntiin käytettäville strategioille, ne ovat ensisijaisessa asemassa hyödyntämään kaikkia saatavia etuja.

Preqin-hedgerahastotietokannan avulla pystymme löytämään vastauksen tähän tutkimuskysymykseen, lajittelemalla rahastot niiden kaupankäyntityylien perusteella. Termillä AIML-hedgerahastot viitataan hedgerahastoihin, jotka hyödyntävät sekä tekoälyä että koneoppimista. Nämä AIML-hedgerahastot otetaan omaksi kaupankäyntityylikseen ja niiden tuottoa verrataan systemaattisiin, harkinnanvaraisiin ja yhdistettyihin hedgerahastoihin, jotka käyttävät kaupankäynnissä sekä systemaattista että harkinnanvaraista menetelmää. Käyttämällä sekä tehokkaiden markkinoiden hypoteesia että käyttäytymistaloustiedettä teoreettisina viitekehyksinä, voimme suorittaa yksityiskohtaisen analyysin sekä automatisaation tarpeen, että hedgerahastojen olemassaolon perusteista. Hedgerahastojen suorituskykyyn, tekoälyyn ja algoritmeihin sekä hedgerahastojen keskinäiseen vertailuun liittyvää aiempaa kirjallisuutta tarkastellaan myös yksityiskohtaisesti. Keskittymällä vain Yhdysvaltojen osakkeilla kauppaa käyviin hedgerahastoihin voimme hyödyntää Yhdysvaltojen osakkeiden hinnoittelussa käytettyjä yleisten riskifaktoreiden malleja. Suorituskykyä analysoidaan sekä koko otosjakson perusteella että käyttämällä osaotos analyysiä paljastamaan taustalla olevan suorituskyvyn jatkuvuus.

Riskifaktorimallien tulosten perusteella voimme nähdä AIML-rahastojen osoittaman tilastollisesti merkitsevän ylituoton. Lisäksi osaotos-analyysimme tukee näitä havaintoja ja osoittaa, että AIML-rahastojen näyttämä suorituskyky on jatkuvaa. Kun kaupankäyntityylien välisen sarjakorrelaation vaikutukset otetaan huomioon, AIML-rahastojen ylivertaisuus todetaan edelleen. Lopuksi, verrattaessa AIML-rahastojen alfa-arvoja muiden hedgerahastojen kaupankäyntityylien arvoihin, AIML-rahastot saavat tilastollisesti merkitsevän ylivertaisen tuloksen jopa prosentin merkitsevyystasolla. Tuloksemme osoittavat, että tekoälyn avulla hedgerahastot pystyvät parantamaan suorituskykyään jatkuvasti ja erottumaan muiden kaupankäyntityylien joukosta. Tuloksemme eivät ole ristiriidassa tehokkaiden markkinoiden hypoteesin kanssa, sillä AIML-rahastojen ylituoton taustalla olevina syinä voidaan mainita niiden kyky sopeutua ja kyky hyödyntää pieniä markkinahäiriöitä. Käyttäytymistaloustiede osoittaa myös, kuinka sopeutumiskyky yhdistettynä automatisoituun kykyyn toteuttaa strategioita ovat avainasemassa AIML- rahastojen tulosten saavuttamisessa. Tuloksemme esittävät mielenkiintoisia suuntaviivoja tulevia tutkimuksia varten ja näyttävät tekoälyn todennäköisen enenevissä määrin kasvavan merkityksen hedgerahastojen keskuudessa.

AVAINSANAT: Hedge fund, Artificial intelligence, AIML, Systematic, Discretionary

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Abbreviations

AI	Artificial intelligence
AIML	Artificial intelligence machine learning
AUM	Assets under management
BF	Behavioral finance
CAPM	Capital asset pricing model
CTA	Commodity trading advisor
EMH	Efficient market hypothesis
ETF	Exchange-traded fund
FSA	Financial supervisory authority
HFT	High-frequency trading
ML	Machine learning
SEC	Securities and Exchange Commission

1 Introduction

Hedge funds are often characterized by the different strategies they employ. Agarwal et al. (2018) for one note that with the reduced regulation that they face, they are often both more willing and capable to pursue alternative methods of investing and utilize strategies that are not available to most other major market participants. At the same time, continuous technological advances have created a lot of new possibilities when it comes to the implementation and creation of different trading strategies. Kooli and Stetsyuk (2020) detail the extremely competitive environment that hedge funds operate in and the growing pressure that this creates towards hedge fund fee structures in relation to recent performance. Thus, there is a clear incentive in exploring the viability of the latest technologies.

According to the Investment Company Fact Book (2021), the total net assets for passive exchange-traded funds (ETFs) have grown by a multiplier of four in just the U.S. in the past decade, surpassing 4 trillion dollars. Grégoire (2020) outlines that passive management represented 42% of all US equity mutual funds in the year 2016 and noted a similar compounding growth. As the importance of passive investing is continuing to grow and receive more capital inflows, this results in there also being capital outflows from some other types of investment vehicles.

The Preqin (2020, p. 12) report details this effect as record capital outflows as of late are seen for the wider hedge fund industry in 2019. Kooli and Stetsyuk (2020) show that there has been a full percentage point reduction in the capital managed by the industry in 2018, which in term makes it more apparent that the performance-to-fee relationship of many funds is not adequate for many of their investors.

Kooli and Stetsyuk (2020) uncover this relationship between fees and performance further by trying to uncover the real value added by hedge fund managers. In short, they note the same worrying trend where hedge funds do actually perform better than their passive counterparts, but the same cannot be said after taking into account the notably higher fees. Inversely, the Investment Company Fact Book (2021) data shows the clearly declining expense ratios of both index mutual funds and their ETF counterparts, noting that while increased competition plays a role for these continuously reduced fees, also the inherent nature of passive management is essential to take into account. As there is no need for costly active management and active analysis of the traded instruments, the expenses are also significantly reduced.

Hence, we see that the hedge fund industry is currently facing some very meaningful challenges. The competition is increasing, and it is also coming from players from outside the industry, mostly represented by passive management. Preqin (2020, p. 24-25) shows that this results in pressure to reduce fees especially during times where the performance figures are lackluster. As the complex active analysis of securities along with the development of related trading strategies represents both the differentiating factor for hedge funds compared to other fund types and the reasoning for the added fees, it begs the question whether this process of being active can benefit from the various technological advances that have been introduced, from trading algorithms all the way to artificial intelligence (AI).

The usage of computerized trading is nothing new as it dates back to the early 1970s and the creation of different types direct market access programs that enable the connection between an algorithm and a stock exchange. Kim (2010, p. 1-4) details that these automated trading systems have then gotten more complex over time, taking on an ever-bigger role in the trading process. Gerlein et al. (2016) show that AI on the other hand can be understood as an evolutionary step from simple automations to tasks where the responsibilities of the algorithm come close to, or even replace, the end-user.

Harvey et al. (2017) additionally note that while algorithms are already commonplace for many of the worlds hedge funds, their roles differ to a great extent. In their research paper hedge funds are divided into discretionary hedge funds which make the trading decisions manually and to systematic hedge funds in which the trading decisions are made almost or fully by using trading algorithms. Even with this clear split, the authors note that as technology advances, it may become ever harder to distinguish between the two. The technology is here to stay, but its advantages remain to be seen.

1.1 Purpose of the study

The purpose of the study is to research whether using the latest advances in terms of AI leads to meaningful advantages when it comes to the performance of hedge funds. In addition to the performance figures, some descriptive statistics on these funds will also be uncovered as they will reveal important information relating to these funds. One could for example hypothesize that using AI will not only lead to levels of increased returns, but also to possible reductions in costs. On the contrary one could also theorize that by using AI these hedge funds are able to provide higher returns that better justify these high costs. As such the general analysis of the data is also of importance.

Capocci and Hübner (2004) detail that there are almost 6000 funds managing around $400 billion in capital and as such hedge funds justify an increased attention in financial press as well as in the academic world. The Preqin (2021, p. 5) Global Hedge Fund Report allows us to glimpse the most current figures for the industry and the global assets under management (AUM) now stand at around 3,87 trillion dollars. Additionally, the report notes that there are 18 303 active hedge fund managers, meaning that the number of individual hedge funds is even greater. Also, of interest is the forecasted growth that these AUM figures are expected to reach. With a forecasted compounded annual growth rate of 3,6%, the total AUM is predicted to go as high as 4,28 trillion dollars by 2025. That is why if anything, the importance of researching hedge funds is even more justified than before.

The main purpose of this thesis can therefore be simplified as an analysis on the effect of the degree of automation on the degree of performance. In other words, whether having less direct interaction with the trading decisions and handing more control into the hands of differently advanced trading algorithms would yield better returns. This control would then revolve from automated and predictive analysis to fully automated decision making, where to role of the human manager would shift more into that of an observer, with continuously lesser involvement in the day-to-day trading decisions.

Therefore, this thesis aims to uncover whether advances in computing, spanning from simple trading algorithms all the way to extremely complex and completely self-sufficient systems are truly applicable when it comes to the quest of hedge funds aiming to outperform. The topic is especially current as AI is starting to impact a lot of different fields, from medicine to self-driving cars, and one could then make inferences that similar developments are bound to take place in the financial markets as well.

1.2 Research hypothesis

The research question for this thesis is whether the usage of AI is able to improve hedge fund performance. For this purpose, the following hypothesis pair will be used:

$$H_0: AIML\ hedge\ funds\ do\ not\ outperform\ funds\ of\ conventional\ trading\ styles$$
$$H_1: AIML\ hedge\ funds\ outperform\ funds\ of\ conventional\ trading\ styles$$

The funds of conventional trading styles are defined as funds that do not use AI, even if standard trading algorithms are in place. The outperformance is then measured by comparing the possible alphas obtained by these AI hedge funds against the alphas exhibited by their conventional counterparts. In addition to this, the performance in terms of excess returns by using factor models is evaluated and the persistence of this performance is also uncovered to make a strong case for both the outperformance against conventional style funds along with the persistence of said performance.

1.3 Contribution

This thesis aims to contribute to the growing literature on hedge funds and hedge fund performance in various ways. Firstly, it helps to understand a lot of general information on hedge funds and brings forth various up-to-date figures on the field. This in itself is already valuable as is noted by Capocci and Hübner (2004) as they detail the general difficulty in obtaining data on individual funds. They note both the prevailing secrecy within the field along with the fact that hedge funds are not legally required to reveal almost anything in regard to their trading, allowing them to operate out of the eye of the general public.

Fung and Hsieh (1999) detail this further by noting the sophisticated investors that hedge funds are only allowed to attract, meaning that regulators and financial supervisory authorities (FSAs) do not impose strict restrictions for the types of investments that these funds are able to pursue, or the types of disclosures that they are mandated to give. Treleaven et al. (2013) add to the theme but from the viewpoint of using trading algorithms of varying sophistication, noting the difficulty in finding the details on their usage.

Therefore, being able to bring to light a very comprehensive and current dataset on hedge funds which shows factors such as AI usage and additional specifics such as the average size of costs for investing in such funds can be thought as being a strong contribution for the research within the field. As for any research on hedge funds, data is the most valuable and precious asset.

The main contribution of this thesis will still naturally be on uncovering whether AI usage can improve the performance of hedge funds and help them obtain performance that sets them apart from their conventional peers. Certain publicized research papers have already researched the performance differences between systematic and discretionary funds and Harvey et al. (2017) for one come to the conclusion that combining both approaches is the best course of action. Our research paper categorizes funds into systematic, discretionary and combined funds which use both the before mentioned approaches which enables us to revisit the findings found in their study. The main contribution being of course the addition of a fourth category, AI funds which combine elements from all the other categories but using an advanced technological framework that sets them apart from the rest.

Therefore, research into hedge fund performance will be especially furthered as to the best of my knowledge no publicized studies carrying similar performance comparisons for hedge funds are available. The aim will be to give both a detailed outlook into the industry and a detailed analysis on the performance that can be obtained with the latest tools available to these funds.

1.4 Structure of the thesis

The structure of the thesis will be the following. Firstly, relevant theoretical frameworks for the topic at hand will be researched, with both the efficient market hypothesis (EMH) and the behavioral finance (BF) being the theories that best cater to our needs. This can be justified in short as the EMH allows us to distinguish the reasoning for the need for active trading hedge funds in the first place if the markets are fully efficient and BF helps us to understand some of the underlying reasons why one would want to automate their trading activities and remove behavioral factors from the investment process in the first place.

Secondly, we will focus on the relevant literature within the field, starting from research papers focused on comparing hedge fund performance. These studies will then be analyzed and compared in a detailed manner in terms of their main findings and conclusions. The second type of research papers will be ones dedicated to algorithmic trading and AI being used to improve trading performance in general, as this will help give an outlook into what the potential benefits of using such systems are and as such it will also help detail the motivations that hedge fund managers may generate towards employing them. Lastly, we will review literature on research papers comparing systematic and discretionary funds as this is the topic most related to our theme. This choice of literature review topics should help give a general overview of hedge fund performance, algorithm and AI performance, and the comparative performance studies done for the hedge funds so far.

The third step in our structure will be to uncover as much information as possible on hedge funds themselves and to help obtain a deeper level of understanding of both the individual funds and the industry that they operate in. Along with main characteristics, focus will naturally be on each of the categories of hedge fund trading styles that we have already outlined so that also the non-numerical side of these funds gets uncovered.

The fourth step will be the data and methodology stage of the thesis, where very recent figures going up to January 2021 will be shown relating to our sample of funds and a lot of additional metrics such as AUM and fees will be seen for each hedge fund type. Additionally, our methodology for the performance comparison will be discussed.

The fifth step is the actual empirical analysis of our data of hedge funds using various factor models. As was mentioned before in the hypothesis section, raw performance, performance persistence and performance comparison to peers will all be carried out to obtain robust results to either accept or reject our null hypothesis.

The sixth and final step will naturally be the conclusion where our results are reflected against the results based on the analysis of theory, the results found in the literature review and on the findings based on our general analysis of funds. Thus, the meaningfulness of our discoveries gets evaluated from a wider and more profound perspective.

2 Theoretical background

There are a lot of different theoretical frameworks that can be considered for studying both the hedge fund industry and the implications of using AI technologies for asset management. For the purpose of this thesis, the relation between AI usage and hedge fund performance will be explored through the viewpoints presented by the EMH and its somewhat competing counterpart, BF.

Fung and Hsieh (1999) note that hedge funds are in general characterized by their usage of dynamic and non-passive strategies. The authors also detail that hedge funds are active participants within the markets while on the other hand they also display very little correlation with the markets that they themselves operate in. Sun et al. (2012) remark the extreme secrecy among the entire hedge fund industry and the need for these funds to keep trading strategies secret, along with the fees they impose upon their clients that are very high when compared to other investment vehicles.

Thus, it can be theorized that if investors are willing to pay a notable premium for having a hedge fund actively manage a portion of their wealth, some market-beating returns are likely to be obtained. Therefore, one could pose a question on whether being active could lead to better returns as opposed to plain buy and hold passive investing. Barber and Odean (2000) on the other hand find an opposing view and note that increased active trading leads to lower returns. Hence, using efficient-market hypothesis as the first main frameworks for this thesis is more than justified.

For BF aspects, the most immediate reasoning for its inclusion can be deducted from the man versus machine setting that is ultimately being reviewed in this thesis. Humans are emotional beings and are affected by a wide variety of different behavioral biases, from overconfidence to loss aversion. Algorithms and machines on the other hand can be typically thought of as emotionless machines that follow their specific objectives no matter what. Ritter (2003) especially writes that most people suffer from overconfidence in their abilities and Statman et al. (2006) and Barber et al. (2005) are able to link overconfidence with a very active level of trading.

Again, it can be conceptualized that if we all suffer from behavioral biases that are detrimental to our performance as investors, using AI and algorithmic trading would in general lead to better returns. Here the question we pose is whether varying the degree of human involvement and therefore reducing the degree to which behavioral factors can interfere in the decision-making process is beneficial. Still it needs to be noted that algorithms and AI methodologies are still written and programmed by humans, making them at least theoretically susceptible to some low level of biases.

Dawes (1979) indicates that when it comes to the process of forecasting, algorithms display a clear edge over their human counterparts. Continuing on that notion Promberger and Baron (2006) note that humans favor the input of other humans more strongly than that of an algorithm. Lastly Kirilenko and Lo (2013) write that the effects of behavioral factors displayed by humans affect the world of finance to an ever-greater extent than before. Therefore, using the BF framework as the second main theoretical framework for this study is more than relevant.

2.1 Efficient-market hypothesis

The EMH is one of the foundational theories of finance that aims to describe how the financial markets operate. Fama (1970) explains market efficiency as simply a state in which the prices of securities fully reflect all of the information that is available for market participants. If this relation between market prices and information is constant, then they determine the market to display efficiency. The author also notes that there can be no transaction costs, the flow of information must be free and publicly available, and the market participants themselves must be in agreement of the significance of this information in relation to the market prices for such an efficient market to exist.

The EMH has its fair share of supporters and critics and one could easily argue that the necessary conditions for such efficiency described above are far from realism. Though it needs to be noted that even Fama (1970) states that it is enough for these conditions to be sufficiently met for one to be able to observe market efficiency. Wolff and Neugebauer (2019) are one of the many researchers to note the controversy surrounding the EMH and in their research paper especially the predictability of stock returns is seen as proof for the lack of market efficiency. In addition, in their analysis they are able to find some evidence of this predictability and as such cite a multitude of other studies that come to the same conclusion.

Timmermann and Granger (2004) take a different approach when studying the EMH. They note that while there may be predictability in stock returns this is not something that can be used as evidence against the EMH. They reason that EMH in its essence is only concerned with the absence of arbitrage opportunities and these stock price predictabilities can very rarely be profitably exploited. Thus, taking a viewpoint where the markets are actually inherently efficient as presumed inefficiencies are impossible to take advantage of.

As the debate for and against market efficiency can be observed from many different viewpoints, Fama (1970) devised different tests of market efficiency to provide evidence for his views. The first one being weak form tests that consider testing whether the historical and lagged prices of securities are able to provide an edge when it comes to the forecasting of future prices. He notes that these tests are also the ones most mentioned in the random walk literature as it would naturally imply that the stock prices follow a random and unpredictable path. Fama (1991) later notes that some predictability is still visible within the past prices of securities, but Sullivan et al. (1999) and Bossaerts and Hillion (1999) on the other hand display the inability to profit from using trading rules based on this finding.

Semi-form tests are concerned with testing whether the prices of securities adjust to publicly available information at a rapid rate. This on the other hand is something where one would assume great efficiencies due to the constant advances in technology. Gerlein et al. (2016) note the trading timeframes of high-frequency traders (HTFs) that go down to as far as nanoseconds. As such, one could assume that in today's markets the transmission of information to prices is highly efficient.

The strong-form tests are the strongest possible tests outlined by Fama (1970) to prove market efficiency and in these tests the levels of monopolistic and insider information that have affected past price changes are attempted to be measured. These tests are naturally the hardest to carry out due to the specification of insider information, but the author was still able to only observe limited evidence towards the rejection of the EMH. The weak- and semi-strong form tests against the EMH hypothesis are outright rejected in his study and he notes that prices adjust in an efficient manner when considering past price history and public fundamental information.

For the purpose of this thesis these specifications and tests of market efficiency are especially important as a lot of the trading strategies employed both by hedge funds and different algorithmic methods focus on these to generate returns. Caldwell (1995, p. 1-5) notes that the primary strategy used by the first ever hedge fund was the long-short equity position along with additional leverage and Kooli and Stetsyuk (2020) uncover that this is also the most common investment style that is being used by hedge funds today. Fung and Hsieh (1999) broaden this information by detailing the extensive use of mechanical trading rules by hedge funds and Treleaven et al. (2013) show how these same rulesets are mostly dependent on financial and economic data.

Returning to the thoughts presented at the beginning of the chapter, if hedge funds are able to charge fees that are substantially higher than for other investment types then their returns must be on par or otherwise as per logic no one would invest in such funds. Therefore, if these funds mainly function based on technical price data and fundamental economic data one could assume that their sheer existence is against the weak- and semi-strong forms of market efficiency.

Again, the EMH can theorize this further to maintain its relevance and it is especially well explained by Timmermann and Granger (2004). They note that while EMH can be quickly understood as a way to render all attempts at forecasting future prices to be a useless activity, in reality predictability can exist for short periods of time. They detail that this is due to the uniqueness of the investment ideas and as soon as they are discovered by a wider number of investors, the ability of these strategies to generate abnormal returns disappears. Sun et al. (2012) detail this same effect of the inverse economies of scale where they remark that only unique investment ideas can produce performance that can beat the market.

Therefore, it can be seen that actually the existence of hedge funds, the ability to make profits by active trading and the ability to forecast prices, all factors used to undermine the EMH in various research papers, are not against the EMH. It is merely the longer-term persistence of being able to do these actions that renders them to violate the EMH. Timmermann and Granger (2004) outline that even asset price bubbles are not against the EMH as long as the risk premiums are indicative of the inherent dangers.

As Hwang et al. (2017) note, hedge funds are absolute return vehicles designed to provide returns irrespective of market cycles and conditions, hence the term hedge. This inherent market neutrality means that strategies play an even more important role for the return characteristics of the funds. Sun et al. (2012) detail further that strategies known to market participants stop working due to increased competition for the same pool of returns.

The Preqin (2020, p. 20-21) Global Hedge Fund Report shows that asset inflows for the hedge fund industry are moving towards emerging managers and this strongly reflects the findings of Sun et al. (2012). They uncover that especially young and upcoming hedge fund managers introduce new and innovative ideas and this uniqueness also leads to higher returns which is in term shown by the Preqin (2020, p. 20-21) report where emerging managers have been able to beat their more established counterparts from at least 2012 to 2019.

All the findings discussed above lead us to the following reasoning. Price predictability is something that disappears over time and this is in line with the EMH. Hedge fund returns are not against the EMH weak- and semi-form tests but they cannot be persistent for this to hold true. Naturally one could argue that performance persistence cannot be achieved by continuously using the same trading strategy, but a fund manager that is always innovating and using different methods to find returns could arguably obtain persistent returns and still not violate the basic principles of EMH detailed by Timmermann and Granger (2004).

Hence, it could be further argued that forecasting is not a meaningless activity and on the contrary a lot more forecasts would be required if each truly valuable forecast is only valid at a certain point in time. The findings of Sun et al. (2012) mirror this thought process as they note that continuous success requires continuously developing ideas that are both unique on their own, but also different enough compared to the ones employed by the other market participants.

The main point of this thesis from the view of the EMH is therefore the following. Sun et al. (2012) point out that the development of new trading strategies is a very expensive process. Additionally, Timmermann and Granger (2004) note that most forecasters go through a multitude of different models to come up with their forecasts. If new and dynamic, seemingly adaptive strategies that would work for the specific period where market efficiency has yet to diminish returns are being required, it wouldn't be unreasonable to assume that AI can provide the answer.

Gerlein et al. (2016) especially go through the functionalities of machine learning (ML) which is marked, as the name suggests, by its ability to learn. They note the capabilities of such models for finding so called hidden forecasts that humans are unable to easily uncover and exploit. Therefore, one could imagine that a forecasting machine that is continuously adapting and changing similarly to the way efficient markets adapt and change as described by Timmermann and Granger (2004), it could theoretically be possible to always be on the on the bleeding edge of forecasting models that work for the time being and provide abnormal returns.

Algorithms and AI models themselves function mainly using financial and economic data as is shown by Treleaven et al. (2013). Therefore, a similar type of analysis can be carried out for these systems, especially as the above authors detail that algorithms mainly function based on technical analysis. Technical analysis on the other hand is in its basic forms fully reliant on historical price data, meaning that the weak-form tests of EMH risk being violated if such performance would remain persistent.

Wolff and Neugebauer (2019) detail further the difference between AI and ML as opposed to plain rule-based algorithms mainly by their ability to learn. They show that these new approaches are able to learn without being given an explicit model and the authors estimate that such a flexible and adaptive approach might prove superior to simple rule-based systems. Similarly, to what has been discussed before, AI and ML have at least inherent potential to adapt and vary between multiple different forecasts for multiple different periods. When taking the EMH into consideration, these possibilities become very interest when considering performance persistence.

2.1.1 Active investing

Active investing can be simply understood as the act of being an active participant within the markets and not simply following a passive buy and hold strategy where the underlying market index or ETF is bought. Sharpe (1991) defines an active investor as one holding a portfolio of stocks that differs from the market portfolio. He elaborates further by noting that an active investor is fundamentally acting based on presumed mispricing that they observe within the markets. As the thoughts and opinions on the true intrinsic value of securities might differ from day to day, active investors adjust their positions similarly by trading and hence being active.

Hedge funds are inherently active as they function as absolute return investments. As a hedge fund aims to produce returns irrespective of the current state of the market it can already been seen that the definitions of being active by Sharpe (1991) are quickly met. Ammann and Moerth (2005) point out that the low correlations between hedge funds and other asset classes caused by this underlying investment philosophy is one notable reason why investors choose to invest in hedge funds in the first place. They function as diversifiers of risk when taken as part of a wider portfolio.

Jensen (1978) on the other hand looks at active investing through the viewpoint of the EMH. He notes that if the markets are efficient as described by Fama (1970) then there are no possibilities for obtaining returns that are greater than the returns of the market. Rubinstein (2001) accordingly notes the inability of most fund managers in beating the market. The more recent findings by Timmermann and Granger (2004) that were discussed in the previous section show that these views by Jensen (1978) are often not the case, but once again especially then longer-term persistence of this performance is the deciding factor.

Sharpe (1991) continues by reasoning that an active investor cannot beat a passive manager after taking transaction costs into account. He argues that this is due to the many components that are needed for truly active investing, which involve expensive research and the development of costly trading strategies as was mentioned by Sun et al. (2012). He additionally details that a small and rare minority of outperforming managers does truly exist but to uncover the true advantage that active investing can give, the returns of these funds need to be benchmarked against a comparable passive alternative. Hence, active investing is meaningless unless its passive counterpart is beaten.

Timmermann and Granger (2004) add to the debate the potential short-term forecastability of asset prices that can be seen as favoring the approach of passive investing. Similar to what Sharpe (1991) discussed, only brief advantages can be obtained as on the whole, overperformance in one period will turn into underperformance on the next when comparing active strategies against their passive correspondents. The authors also propose an interesting viewpoint for the debate between active versus passive investing as they note that if truly profitable active strategies are discovered by researchers, they likely wouldn't be published in scientific journals.

This in term leads to interesting implications where one could theorize that only unsuccessful active strategies get shared to the wider public, causing a larger than actual skew in results towards favoring passive investing. As was previously shown by Sun et al. (2012) hedge funds are very secretive and Treleaven et al. (2013) documented the same for the usage of trading algorithms. Additionally, Sun et al. (2012) analyzed the strong effect of competition towards the expected returns of different strategies and when taking into account the limited time window during which these strategies are able to provide abnormal returns as was shown by Timmermann and Granger (2004), withholding profitable active strategies seems to be highly motivated.

Ammann and Moerth (2005) detail this effect of overcrowding on a particular trading setup further by analyzing the size limits in terms of AUM set forth by some funds. Even on a fund level, certain trading setups experience diminishing returns if they a scaled up, an event described by the researchers to show the effects of limited capacity. Timmermann and Granger (2004) come to the same conclusion, noting how increasing position sizes from the viewpoint of one fund would increase both the transaction costs along with the actual market impact of the trade, rendering the actual opportunity impossible to take advantage of. Thus, it can be seen that for active strategies there are inherent size limits and a common consensus amongst the researchers is this effect of diminishing returns of scale.

When it comes to algorithmic trading, similar findings that were uncovered for hedge funds can be put forth. Algorithms and AI methods rely largely on technical analysis as was shown by Treleaven et al. (2013). Dash and Dash (2016) confirm this reliance and detail the constant need for historical data required by these algorithms. Treleaven et al. (2013) also note that acquiring the input data for these algorithms is highly expensive and Sun et al. (2012) mention the expensiveness of developing trading strategies. Lastly, Gerlein et al. (2016) uncover in more detail the computational resources needed for deploying these trading systems.

If such a complex and costly system is put into place one can without a doubt assume that an asset manager would expect a return for this investment. An abnormal return to be more precise as the whole reason for carrying out costly research is to obtain market beating returns as was noted by Sharpe (1991). As such, algorithmic trading and various AI systems can be assumed to always represent active trading, and this can also be inferred from the literature surrounding these automated trading systems which revolve around testing the weak-form and semi-form hypotheses of the EMH. An observation that is also noted by Timmermann and Granger (2004).

2.1.2 Passive investing

Passive investing is naturally an essential part of the EMH. As is noted by Jensen (1978) if the market is fully efficient, it is impossible to obtain abnormal returns as all the available information is already incorporated within the prices of individual securities. Timmermann and Granger (2004) identify that in the strictest form of the EMH outlined by Fama (1970) all forecastability in asset prices would disappear and it would be impossible to beat the market.

This is easily something highly disputed as we have seen in the previous sections. The active versus passive debate has therefore become an essential part of the EMH related literature. Sharpe (1991) details that fund managers are unable to beat the market on average and investing through the means of active methods is counterproductive. For an individual investor such arguments would naturally sound concerning and for forecasters such inability to profitably predict asset prices becomes very concerning.

French (2008) argues that a typical investor would obtain notably higher returns if he or she would switch to passive investing. This mirrors the views of Sharpe (1991) and of Fama (1970). Indeed, it can easily be theorized that the average investor is unable to beat the market, but questions remain as to what the effect becomes when observing the not so average investors, out of which hedge funds and their highly liberated arsenal of trading tools is a great example.

French (2008) continues by aiming to uncover this relationship for hedge funds, coming to a conclusion that after taking into account the higher fees involved, on average these funds are unable to beat passive investing. He also notes that a passive investor enjoys the benefits of greater diversification by the sheer nature of holding the market portfolio. Lastly, he remarks that investors preference towards these active investment opportunities is likely due to behavioral factors and lack of knowledge of better alternatives.

The views expressed above show an interesting pattern where active investing is seen on the whole as driven by behavioral factors. Passive investing on the other hand is seen as the logical more profitable course of action, as after all the markets are presumed to follow the EMH. Kooli and Stetsyuk (2020) argue this view by uncovering that on average a hedge fund manager is actually able to beat the market, and this can be attributed to skill as opposed to luck. In their research they are also able to showcase that while some funds destroy investor value, the value added by the most profitable funds is more than enough to offset this balance. Most importantly the authors note that they find no evidence that this value that has been created is being shared to the investors.

Which leads us to the following analysis. For the context of the EMH, algorithmic trading systems and hedge funds can be grouped as one. They both represent active participants within the market and they both attempt to forecast and take advantage of different quickly disappearing opportunities, using a diverse set of strategies. Their performance is also against the EMH if it is persistent, but the same cannot be said if strategies are regularly changed. As we have shown forecastability does exist, but it is something that can evaporate quickly.

Therefore, whilst passive investing is a natural favorite of EMH literature, it can be seen that the success of hedge funds or algorithmic systems is nothing that the theory cannot cope with. French (2008) outlines the challenges of this active approach by noting the zero sum or even negative sum game, where the profits of one investor mean losses for someone else. Sun et al. (2012) expose this relation further by detailing the need of unique investment ideas that are needed to beat both the other market participants along with the passive market-indices.

Ultimately, it can be hypothesized that a limited number of hedge funds could be able to produce abnormal returns that favor active investing and their performance can be persistent as long as they remain continuously innovative. Which is a finding that brings us back to the topic of this thesis. AI can easily be seen as one of the most innovative and revolutionizing forces for a multitude of fields as is shown by Mullainathan and Spiess (2017). Employing it to remain innovative in regard to trading strategies for the markets seems like an obvious solution to the many issues related to active investing that are highlighted by the EMH.

2.2 Behavioral finance

The analysis of the EMH showcased the debate between active and passive investing that is naturally very relevant for a research paper analyzing active trading. If algorithmic trading systems and hedge funds could be thought of as representing the same type of investor in the viewpoint of the EMH, the BF framework provides the clear distinction between the two. This man versus machine setting is something where behavior undoubtedly plays a role and the difference between a human trader and its algorithmic counterpart are much more diverse than pure EMH literature would lead one to believe.

BF is seen by some researchers as an opposite view to the market efficiency hypothesis proposed by the EMH, whereas some other studies site it as an extension for the frameworks that are already in place. Ritter (2003) highlights the most notable differences between BF and EMH by noting the rejection of the rational investor as proposed in the EMH. He details the bounded rationality that influences the decision-making process of investors as one in which different patterns of behavior and characteristics are too meaningful to be ignored in the way of the EMH. Markowitz (1952) for one notes, that the perceived utility is often defined over current gains and losses instead of focusing on the cumulative gains, hence showcasing the process of bounded rationality.

Ritter (2003) especially highlights overconfidence which he sees as causing investors to weigh recent events to an exceeding extent. Gervais and Odean (2001) note that such traits can also be developed as an investor with a lot of recent success might feel very overconfident in their own abilities. Odean (1998) saw the link between overconfidence and excessive trading as was discussed before and Barber and Odean (2000) point out the reduced returns caused by this additional trading.

Thus, the above serves as an obvious and easily understandable train of events where behavioral factors lead to actual and quantifiably reduced returns for an investor. Naturally overconfidence serves as only one example of psychological factors affecting investors. Lord et al. (1979) for one note belief perseverance that leads to the inability of an investor to change his opinion once it is set. Buehler et al. (1994) and Weinstein (1980) add a systemic planning fallacy that showcases the over-optimism and wishful thinking of investors.

These various behavioral factors contribute to Barberis and Thaler (2003) remarking the need for change in the standard financial paradigm based on the EMH. They note that BF itself can be understood as a study on the limits to arbitrage and human psychology and Ritter (2003) comes to the same conclusion. Similarly, to the themes discussed for the EMH by Timmermann and Granger (2004), even if arbitrage opportunities would present themselves it would often be both risky and bring meaningless rewards if transaction costs are taken into account. Therefore, pricing inefficiencies might persist but Timmermann and Granger (2004) on the other hand do not consider this as violation EMH if no profits can be obtained. De Long et al. (1990) detail also the risks involved with arbitrage as noise trader risk, where the perceived pricing inefficiencies first become worse, creating notable risks for arbitrageurs.

As we are exploring the man versus machine aspect in our thesis, our attention turns solely to the human psychology aspects of BF. Mainly finding where both machines and humans prevail will help to uncover the primary motivation for the development for such trading systems. Barberis and Thaler (2003) are able to uncover interesting findings in their research paper that suit the analysis of hedge funds particularly well. They note that while there is a strong belief amongst people that experts make less mistakes, this added experience is something that might easily cause overconfidence for said individuals.

Continuing on the topic, the researchers also note that even if advanced quantitative models are being used, overconfidence might present itself if there aren’t enough means to evaluate the accuracy of these models. In other words, especially the testing and feedback environment for different types of trading algorithms is especially important. In regard to this, the authors also note that on their own people are in general not good at estimating probabilities and this on the other hand would put human managers at a disadvantage as an algorithm would naturally be able to give a figure value, instead of a ballpark estimate. Interestingly, while they note that human traders exhibit all of the before mentioned characteristics, the authors also detail that hedge funds are actually one of the main market participants trying to take advantage of these biases that other investors might show.

Ritter (2003) gives a good outline of the main biases that humans exhibit. Heuristics are of particular importance and these can be understood as easily available rules of thumb, but as factors which easily lead to erroneous assumptions. Conservatism on the other hand can be especially harmful in trading as this makes individuals anchor to their beliefs even when the fundamentals around which their original thoughts were based on change. Similarly, the disposition effect makes investors vary of realizing losses, hence letting losses grow to a disproportionate level. The author also notes that especially hedge funds aim to profit from these behavioral traits.

As hedge funds appear to seek returns by capitalizing on these psychological biases, one could also make the logical assumption that these funds themselves end up displaying some of the same factors. If for one a manager would be overconfident in their forecasts to take advantage of these types of investors and have a conservative stance towards changing opinions, a fund might rack up large losses in the process.

From the perspective of trading algorithms, Treleaven et al. (2013) note the rule-based approach utilized. Similarly, to the rule-based trading strategies employed by human traders, algorithms use a similar if-else system where proven strategies are programmed into step-by-step actions that the trading algorithm can then execute. Wolff and Neugebauer (2019) further this to the usage of AI and ML, noting the lesser need for distinct rules and models, and instead emphasizing the more free approach where the machines are themselves able to learn and improve based on a certain feedback loop where good actions are rewarded and negatives ones discouraged. The authors think that especially this flexibility to adapt will lead to the great potential of these models both now and in the future.

Therefore, in terms of BF, interesting thoughts can be made. Static rule-based algorithms are emotionless execution machines of trading strategies but still the effects of behavior cannot be fully ruled out as the human programmer might still have used erroneous assumptions or similar factors that make them impacted by human psychology. Still from the most part trading algorithms can be thought of as rather immune in terms of the effects of behavior.

AI on the other hand aims to mimic the human brain and the ability to learn will likely also make the machine learn different heuristics which are counterproductive. As opposed to this, an AI model would also learn from this experience and no longer repeat the errors of the past which is something that cannot be said for humans as shown by Ritter (2003).

Chincarini (2014) argues that trading algorithms and therefore additionally AI are able to fully eliminate behavioral errors and note that using these methods also enables funds to lower their trading costs. Dawes (1979) additionally writes that when it comes to the process of forecasting, algorithms prevail over their human counterparts. Ritter (2003) notes the hunt for misvaluations carried out by hedge funds, which implicitly details their use of forecasting models to find the correct asset prices. Promberger and Baron (2006) on the other hand note that people regard the opinions and input given by a human more strongly than that of an algorithm.

Hence, the following course of action can be seen. Algorithms and AI are to be considered practically immune from behavioral biases, with AI held a bit more highly in this regard as it doesn't have to follow any specific rules programmed by a human. These systems make better and less erroneous predictions in terms of the BF framework and they are therefore able to prevail over their human counterparts. The recipients of these forecasts are still humans and they evaluate these forecasts through their own emotional processes and hold it at a lower value.

As humans are skeptical and often resistant to change, superior systems might still not get taken into use even if their performance is proven. While from a BF point of view trading algorithms are naturally perfect, especially Dietvorst et al. (2015) describe this phenomenon as algorithm aversion where these algorithms and AI are mistrusted no matter the proof.

As we have seen, when observing the two opposite sides of the active trading spectrum, trading algorithms and human traders, it is especially the behavioral aspects that set them apart. Additionally, as advantages for algorithms one can also note the speed of execution, the capability to process information at a scale unimaginable for a human and the ability to work tirelessly day and night. Behavior sets us apart from machines and when it comes to trading this as we have seen can be considered a negative aspect.

2.2.1 Discretionary trading

Discretionary trading is a trading style, which mainly involves the use of mechanical trading rulesets as is shown by Fung and Hsieh (1999), but by the means of a human trader. In other words, a detailed trading strategy is constructed, and it is left up to the fund manager to ensure that this strategy gets executed correctly. Therefore, the discretionary approach to trading can be thought of as the early beginnings of hedge funds, where the possible assistance provided by computers was practically non-existent.

Currently, discretionary trading involves the usage of technology to a great extent as is shown by Harvey et al. (2017) but the actual decision-making process is still carried out by humans. Therefore, from the viewpoint of BF, discretionary trading represents the human side of the man versus machine comparison. While the usage of the discretionary trading style is fairly similar to the rule-based methodologies employed by their mostly fully automated counterparts, systematic traders, it is in the analytical process where differences can firstly be observed.

Preqin (2021, p. 106-109) notes especially the reduced usage of models, as discretionary trading is more focused on the individual skillset of the trader. Treleaven et al. (2013) also detail that sometimes different analytical methods are used in terms of fundamental analysis to forecast security prices, which involves using factors such as a firms' balance sheet data and macroeconomic variables to gain an understanding of underlying value. The authors also note the possible use of economic data and figures reported by central banks and government institutions with releases such as general unemployment and current interest rate, which can be considered natural as humans are more flexibly able to take advantage of a more various set of data.

While the data used by discretionary traders can be seen as sometimes being different to the one commonly used by algorithms and AI, the main difference when being compared against systematic traders is the before mentioned execution process of trading strategies. Discretionary traders are therefore subject to all of the potential behavioral biases we have seen in this chapter so far and this is naturally something that would render them at a disadvantage. Still compared to plain trading algorithms discretionary managers would especially benefit from their ability to adapt, but when being compared against AI the advantages are less clear.

Sun et al. (2012) note that funds using the discretionary trading style might benefit from the above flexibility as going after innovative ideas is easier. This is especially true in the case of small funds but something that can be seen as having some general implications for discretionary funds as a whole. Unique ideas for investing depend on the analysis process that has been done and the authors also note how time consuming this process is in terms of the potential profits. This is due to the findings discussed by Timmermann and Granger (2004) where the uniqueness of these ideas quickly disappears.

Therefore, discretionary trading can be seen as somewhat less capital intensive to begin with as less is needed in terms of the technological infrastructure and no capital needs to be spent on developing complex trading algorithms. Still in the long run discretionary traders continuously need to innovate and to do so with a much-reduced reliance on said technology.

As we have seen, the performance of discretionary trading is heavily focused on the skills of the actual trader. As the dependence on the individual is great, so are the risks that the trader is exposed to in terms of behavioral biases. A human manager tends to be highly affected by a number of different biases and these might make the following of a well thought out trading strategy different when being implemented in the real world. The physiological limits on humans would also set their own limits on the execution of these strategies as it would likely be impossible to always be present and to take advantage of every opportunity that would present itself.

2.2.2 Systematic trading

As opposed to discretionary trading, systematic trading involves the extensive use of technologies and different types of trading algorithms to execute a trading strategy. Treleaven et al. (2013) note that most systematic traders aim to replicate and copy the step-by-step processes of successful traders and then obtain rewards through the perfect execution of these rulesets.

While the difference between discretionary and systematic trading can be noted especially in the execution process of trading strategies, also the process of generating these strategies is different. As is detailed by Treleaven et al. (2013) systematic trading mainly comprises of utilizing technical analysis to obtain trading signals and this involves the use of price data to uncover patterns and different trends to help forecast future directions of this price.

While technical analysis plays an important role also for discretionary trading, systematic trading is additionally marked by the quantitative side of their investment processes, which involves the usage of different types of mathematical models to forecast and predict future prices. Treleaven et al. (2013) detail this as involving the usage of similar financial and economic data used by discretionary traders, but by the means of models and not individual discretion.

As such systematic trading involves potentially different types of data, different methods used to extract information from the data and different methods for the usage of this information to make actual trading decisions. Still it can be seen that the main difference between these two types of trading styles is the role of the human trader. In discretionary trading the human trader is very involved in the day-to-day processes, whereas in systematic trading the traders take more the role of an observer while the algorithms carry out the daily operations. Therefore, one can think of systematic trading as requiring more planning of long-term perspectives and less focus on the short-term fluctuations.

Consequently, discretionary trading can be seen as representing the side of trading styles subject to behavioral biases and systematic trading showcasing the more methodical model focused automated approach. Discretionary traders are thus more easily at risk of different behavioral biases while systematic traders are by the nature of their trading style almost fully immune to the effects detailed by BF. Additionally, we have been able to observe some initial findings in terms of the usage of AI which seem to enable the best practices of both the different styles of trading. The emotionless of the systematic side and the ability to adapt of the discretionary style.

In this chapter we have been able to divide the active traders outlined by EMH into two distinct categories separated using BF. While this framework allows us to maintain a clear distinction, still further analysis is needed into the more defined categories that exist between both the discretionary and systematic trading style. The utilization of both methodologies is completely possible and as we have seen AI is something that can from a behavioral point of view be seen as showcasing more human like traits, without human like biases.

3 Literature review

In the previous chapter we have seen how both the EMH and the BF frameworks help us in understanding the key categorical differences that serve as the base for our further performance comparison. The analysis of the EMH helps us to see how active trading hedge funds stand out from the rest on a top level and the themes of BF help in creating the categorical differences between the distinct trading styles employed by hedge funds.

Now our attention shifts to analyzing relevant literature within the field to further understand what has been done and uncovered relating to our topics so far. This analysis of literature is split into first reviewing research papers that analyze hedge fund performance using different methods and methodologies to give a more general overview of what is the consensus on the performance of these funds. Additionally, the focus will be to present some initial motivation into the choices made further along during the actual performance comparison between our sample of funds.

The second part of the literature review will be focused on reviewing studies relating to algorithmic trading and AI as this is a theme of special importance for the topic of this thesis and needs to be further reviewed in more detail. Here the focus will be especially on the types of advantages and disadvantages that these models are able to bring along with the type of performance that can be expected when they are being used in real live-market environments.

The final part of our literature review will focus on the research papers closest to the topic of this thesis, the past analyses between discretionary and systematic funds. While systematic funds can be seen as less advanced than pure AI funds in some respects, these studies help in showing what findings have been made so far when similar man versus machine setups have been utilized by other researchers.

3.1 Hedge fund performance

There are several studies relating to hedge fund performance and the research carried out by Capocci and Hübner (2004) serves as a good starting point for this review. In their research paper, the authors first detail several findings for the hedge fund industry as a whole noting the concentration of hedge funds within the U.S. along with the greatly varying fund sizes measured in terms of AUM. The key figures being that 90% of managers operate from the U.S. and that over 80% of hedge funds have AUM figures of under 100 million. The industry is marked by high fees and high minimum investment amounts and the access to funds is limited to only accredited investors.

In their analysis of hedge fund performance, the authors especially note that based on their factor models hedge fund returns show a positive coefficient towards the Fama and French three-factor model size factor, meaning that funds generally invest in small stocks. They also note that while performance persistence might be disputed, when measuring sheer performance, 27% of the funds in their sample display statistically significant excess returns.

The authors also detail the adjusted coefficient of determinations that they are able to obtain by using their factor models, noting values of 0,44 for the single factor capital asset pricing model (CAPM) and 0,60 for the Carhart four-factor model. Performance persistence is measured in part by employing a subperiod analysis which shows that hedge funds on the long-term are able to deliver great returns but the same cannot be said for the short term where returns are notably more varied.

Ammann and Moerth (2005) on the other hand investigate the impact of fund size to returns and note interesting findings in terms of the negative relation between increasing inflows and diminishing returns. This is then further detailed by Lim et al. (2016) who are able to display this effect of investors chasing past returns in terms of their asset allocation decisions. Hence, one could hypothesize that investors chasing returns make funds unable to take full advantage of their preferred strategic opportunities due to the impact that this increased size brings to the markets.

The authors are able to discover and prove the same causality by noting the reduced ability of larger funds in being able to take advantage of trading strategies that exhibit fundamental capacity constraints. In their findings they are able to discover that while small funds do not need to take these capacity constraints into account simply due to their size, they struggle as a result of the higher fees and expenses that they have to endure as they cannot take advantage of certain economies of scale that are available to larger funds.

Larger funds are also noted as being in a more dominant position as they are more easily able to control the assets that they manage by imposing various withdrawal conditions upon their investors. This in term creates possibilities according to the researchers as having a stable asset base also enables investing in less liquid types of financial assets in search of returns.

In their research paper they are also able to discover that while this is the case, smaller funds are able to have more flexibility in terms of their potential trading strategies, they are able to take on additional risks and they are able to focus more on specific ideas and innovations to further their returns. Larger funds are able to attract capital more easily due to their proven track record, but this size might also make these funds take on a more defensive stance towards investing. From a more systemic risk point of view an interesting finding is the fact that smaller funds are more quickly able to react to different types of events as their portfolios are in general more liquid due simply to the reduced size of their positions. Still in their final results the researchers are able to find a positive relationship between the size of the hedge fund in terms of AUM and the performance that the fund is able to obtain.

Lastly, the authors note that larger funds display lower volatilities and higher returns which in term allows them to have higher Sharpe ratios. One interesting dilemma noted is the agency problem related to the size of a fund. As the manager is compensated based on a proportion of the AUM, one might be inclined to grow their asset base uncontrollably to earn more for themselves while maintaining the same strategy. Therefore, the need for a balance between manager revenues and fund performance is noted.

Contrary to their findings Berk and Green (2004) note that as investor flows chase past returns, these opportunities disappear due to increased competition and fund growth and hence an opposite economies of scale effect is noted. Herzberg and Mozes (2003) are able to discover that small hedge funds obtain better performance in general but that especially their risk adjusted returns are of more relevant significance.

Edwards and Caglayan (2001) are able to find that as hedge funds grow, their performance also increases but this ratio declines rapidly. Gregoriou and Rouah (2002) on the other hand find no meaningful connection between the size of a fund and the returns that it is able to obtain. Sadka (2010) takes a different stand to comparing performance amongst hedge funds as he notes that most of the variation between the returns of individual funds are actually being driven by liquidity risk, where funds holding illiquid securities take on more risk but earn a premium over other funds.

When it comes to performance especially the persistence of this performance is of importance as can be reasoned from both the viewpoint of a fund manager and that of a prospective investor. In regard to this, the research paper by Capocci and Hübner (2004) also details its importance due to the dynamic nature of hedge fund investors. The attrition rates for the industry are notably more significant than those seen within mutual funds and as such persistence in performance takes on an even more important role. Agarwal and Naik (2000) for one are able to find such persistence in the performance figures of the hedge funds in their sample.

Liang (1999) also makes interesting findings in terms of performance, noting that hedge funds are on average able to outperform mutual funds but the same cannot be said when the performance is compared against the returns of appropriate market indices. Also, the characteristics of this performance are detailed as the author notes the higher volatility that hedge fund returns are subject to when being compared against either mutual funds or market indices. Lastly, the impact of fund characteristics upon the degree of performance are also detailed, with fund age and the degree of leverage employed being seen as meaningful.

As we saw in the analysis of EMH, overperformance is highly disputed and Carhart (1997) for one attributes most of it down to random factors as far as the average returns of funds are concerned. Opposed to this, Kosowski et al. (2006) find in their research paper that at least mutual funds are able to exhibit alphas net of fees that are both large and too persistent to be caused by luck.

Kooli and Stetsyuk (2020) continue on this topic from the view of the hedge funds as they measure the skill shown by hedge fund managers by researching the value that they are able to add. In their research paper they come to the conclusion that hedge fund managers are on average skilled but more interestingly, they note that it appears that the revenues attributable to this skill are not being shared to the investors of these funds due to the high fees involved.

They further conclude that after the returns are taken net of fees the amount of funds that are able to deliver abnormal performance is notably reduced. From an industry wide perspective an especially relevant finding is also that the most successful hedge fund managers are clearly able to offset the losses incurred by the worst performing funds, thus making the average of managers show clear skill in terms of overperformance.

Lastly, they note that size has an impact on the variation of returns amongst funds and hedge funds in particular seem to benefit from the reduced regulation that they face.

Also, in terms of managerial performance, the high fees and therefore high compensations that the managers are able to obtain are noted as important incentives behind this outperformance.

Agarwal et al. (2018) analyze performance by splitting returns into parts explained by traditional factors and parts unexplained which they describe as exotic risk. This is done to uncover the uniqueness of trading strategies that hedge funds are able to pursue with the lesser regulatory frameworks that they are under. They note the addition to the literature that they are able to bring by not only interpreting the portion of return unexplained by traditional factors as alpha but by also uncovering the factors that this excess return is attributable against.

In their research they note that while some investors do not pay specific attention to the risk factors a fund is exhibiting, certain investors are actively seeking them as they look for funds employing specific strategies. Conversely to the findings by other research papers noted before, the authors do not find performance persistence in their sample of funds. One main finding they are able to produce is the fact that investors seem to put more emphasis on these before mentioned exotic risk exposures of hedge funds as they note that these serve as the main reasons for an investor choosing to invest in hedge funds in the first place. Exposure to traditional factors is available through mutual funds and the high costs of investing in hedge funds do not justify investing purely based on returns attributable to these factors.

The authors are also able to uncover that investors use the alpha value obtained through the CAPM to evaluate and rank funds. Hence, investors seem to exhibit a preference towards market beating returns. As such especially the CAPM is noted as explaining fund asset flows and the authors also note evidence of abnormal returns being eliminated due to increased inflows of capital.

Kacperczyk et al. (2014) define skill as either an inherent ability to pick winners or to time the market and in their research the authors are able to show the hedge funds are able to obtain substantial outperformance compared to their mutual fund peers of passive benchmarks. Contrary to some of these findings Ackermann et al. (1999) on the other hand do not find evidence that hedge funds on average would outperform the S&P500 stock index and they also note some of the findings seen before where hedge fund returns are attributable to characteristics of individual funds. Bali et al. (2013) also find that hedge funds are unable to outperform the S&P500 and Stulz (2007) proposes an interesting hypothesis where he notes that the performance of hedge funds will converge towards the performance exhibited by mutual funds in the long run.

As the final paper on hedge fund performance used for the literature review part of this thesis, the research paper by Hwang et al. (2017) is focused on studying the relationship between systemic risk and hedge fund returns. When researching the risk profile displayed by hedge funds, the authors were able to find that there is a positive and statistically significant relationship between the level of systemic risk that a fund is exposed to and the level of returns that the fund is able to attain. In other words, funds investing in high beta stocks earn better rewards for this added risk-taking.

As such, they note negative returns during periods of market downturns, but this is to be expected as the high beta portfolios of these funds amplify the movements of the market. The authors similarly note that the added returns are due to the added exposure that these funds are risking in different negative systemic events. They are also able to show that the positive relation between this level of systemic risk and better performance also holds after taking into account different firm specific characteristics. Billio et al. (2012) add to this by detailing that when negative developments take place, small funds are more affected by the spillover effects of these systemic risks and Boyson et al. (2010) note the contagion experienced by hedge funds in times of crises. Acharya et al. (2017) interestingly note that large hedge funds can grow to sizes where they themselves serve as a source of systemic risk.

Lastly, the authors note that as hedge funds benefit from taking on added systemic risk in terms of risk premiums, these practices are likely to continue but they also detail the effects that various crises have had on hedge funds, both in terms of AUM, returns and number of funds. Thus, coming to a conclusion that while these practices entail clear risks, the profits are also distinctive and as such justify these risks for most funds.

As we have now seen, the performance analysis of hedge funds has been done using various different methods and comparisons in past literature. While the returns are compared against indices, with the S&P500 being the most popular, the performance of hedge funds is also often compared against that of mutual funds. The evaluation of different risk exposures is also present in various studies as is the analysis of performance persistence which is deemed as especially relevant. Finally, the analysis of hedge fund performance using different fund characteristics and styles remains the most common method of performance evaluation in the literature we have selected, and it seems that especially the comparisons amongst hedge funds are deemed relevant in the research within the field.

3.2 Algorithmic trading and AI

In the following section our attention turns to the literature analysis of research papers published on both algorithmic trading and the usage of AI for trading purposes. Starting with the research paper by Paiva et al. (2019) we are able to observe some findings relating to the forecasting ability of AI. The authors detail the inherent complexity of the process of price and return forecasting for the stock market which is caused by the nature of the market itself. It is especially the dynamics of market prices and the large amount of the so-called noise within those prices that makes it difficult to detect what factors are truly meaningful for the process of forecasting. Additionally, the market is impacted by various external factors on a continuous basis, making the stock market an incredibly complex playground for different types of models.

The authors detail this further by breaking down the process of forecasting as one involving only the linkage between the past and the present. Especially interesting is their discussion of the two main methods used both in the literature and on the field for this process. The first one being different econometric models based on statistics and implemented using trading algorithms and the second one being the usage of advanced ML models which are then implemented by the means of AI.

The trading algorithms are defined as ones using tools such as linear regression and GARCH-modelling. Whereas AI algorithms are noted as using artificial neural networks, random forests, support vector machines and other similar frameworks for their process of generating forecasts. Also, the level of flexibility of AI models is detailed as the authors describe the ability of these models to utilize both quantitative and qualitative sources of data. While trading algorithms need to rely mostly on financial time series data, AI models are able to function with a much more flexible and diverse dataset and work with data that is imperfect.

In their research paper, AI models are based on technical analysis, meaning that they are functioning based on return data for individual securities. The authors note that when working on the same data, AI models as opposed to trading algorithms are able to find complex patterns and so-called hidden meaning behind the data, which refers to complex relationships and causalities that would otherwise be impossible to detect. Also, the main reasoning behind using technical analysis is detailed as they note that this revolves around the belief that past patterns in prices repeat themselves and hence, that prices do not follow a random walk process.

In their final findings, the authors are able to show that their AI model is able to generate meaningful and significant returns, but the authors also note the great impact that transaction costs have on the profitability that their model is able to obtain. When more realistic assumptions are taken into play and transaction costs are accounted for, the model struggles to make a profit.

Dash and Dash (2016) on the other hand detail a lot of background information regarding the usage of algorithmic trading and AI. They especially note the increasing relevance of the topic as data is currently more available than ever before and this makes it possible to develop highly advanced models. Similarly, to the paper by Paiva et al. (2019), the authors describe the forecasting based on financial time series data as a very difficult process, noting the different trends, variations and irregularities within the data.

While the difficulty of understanding this data is being understood, they also deem AI models as best suited for this purpose due to their high level of automation, speed and flexibility for going through these very large datasets and finding hidden meaning. The process of data mining is therefore also mentioned, and this is described as simply involving the extraction of meaningful statistics from big data as detailed by Witten et al. (2011, p. 191-202).

AI models are seen as both tools for automating and as advantages for decision making. As more information is available to investors using AI, Dash and Dash (2016) note that this will likely also enable a reduction in the level of risk that the investor needs to take in order to obtain a profit. When it comes to literature in the field, the authors note the common trend of using technical analysis to create different types of indicators, which are then used to develop trading signals and strategies for or by the models to generate returns.

The authors also detail the use of supervised AI models, which entail the training of these models using a set of inputs along with a set of desired outputs. The process of trading is trained as a simple classification task, where the buy, sell and hold decisions simply represent a set of outputs based on some set of inputs. In their final conclusions, the authors do not deem the sole use of technical analysis as being sufficient as they note the need for the usage of different types of big data analysis to further the probability of their AI forecasts.

White (2000) discusses some pitfalls of the datamining approach as he notes that some perceived results are only caused by luck instead of real forecasting ability. Gerlein et al. (2016) on the other hand note the unbiasedness of AI model creation guaranteed by the splitting of the data into so called training sets and testing sets. With this approach the AI model is first trained on the training set and later the actual forecasting ability of the model is validated by applying it on the testing set that it has not been exposed to before.

Continuing on the research paper by Gerlein et al. (2016) focused on the creation of profitable ML algorithms, the authors similarly note that AI is well suited for the process of finding hidden relationships within data and consequently having a strong capability towards forecasting. It is also noted that most research papers and experts in the field train their AI models based on different types of variables, attributes and indicators that have been processed from the financial time series data, instead of using this raw data on its own.

The authors note that while the usage of AI models seem to imply better forecasts, this does not always translate to higher profits. In this regard, they note that different models must always be evaluated based on their actual performance and not solely based on the accuracy of their predictions, as this does not always reflect well when being applied to actual live markets. Especially higher volatility situations are seen as troublesome for AI models due to the fact that this renders the generalization of forecasts and finding causalities increasingly difficult. It is noted that traders should incorporate the results of multiple AI models as a weighted average to obtain meaningful results.

Matias and Reboredo (2012) further this discussion of AI models by noting their advantages in solving different types of problems by using nonlinear data. Ballings et al. (2015) additionally detail that various factors influence the stock market, and this results in highly nonlinear price data for the market as a whole. Hence, it can be seen that this nonlinearity an important aspect to consider as far as predictions are concerned and again the suitability of AI models for the purpose of price predictions is displayed.

Mullainathan and Spiess (2017) uncover more how AI models function and also discuss what types of developments have led to their creation. Firstly, they discuss both the contribution created by advances in computing and the findings made in the field of statistics. The way these models function is simply explained by means of comparison against standard algorithms which need distinct rulesets to carry out their tasks. AI models on the other hand are given an input and an output and the models are tasked with finding an underlying function that best predicts an output based on a set of inputs.

As such, AI and ML have a lot more freedom in finding different solutions and therefore also the results might bring additional findings that were not originally considered. The authors especially note that AI is not to be used only to solve old problems using new ways, but to solve completely new problems, before thought too difficult to tackle. Due to the noted ability of AI in finding hidden patterns, one can also hypothesize that it would be very well suited in the field of technical analysis where the uncovering of different patterns within the return data are used as trading signals.

The authors note this ability of AI as these models are able to discover patterns without the need for specifying them in advance. In regard to typical regressions, AI models are noted as finding optimal models of best fit especially in nonlinear datasets. Also, the before mentioned flexibility of AI is noted in the research paper and these models are explained simply as tools to extract substance from big data.

Finally, they note that AI models are allowed to choose the models and rules that work best for the data and no such rules are specifically programmed. Therefore, these models find meaning based on the data itself and not on the presumptions of the programmer, making them likely less to be biased and better suited for the task at hand.

Antweiler and Frank (2004) for one create a ML algorithm to go through online posts as a way to forecast and explain stock market volatility and they are able to obtain a statistically significant small positive performance. Hendry and Clements (2004) additionally make interesting findings noting that combining multiple forecasts from multiple different models creates more accurate results than simply relying on one model, a view which is shared by Bates and Granger (1969).

Wolff and Neugebauer (2019) set out to study how well different types of ML models are suited for stock return predictions, noting the wide use and acceptance of these models in other fields such as facial recognition. They also define AI models by their ability to learn as opposed to static rule-based algorithms and similarly to past studies they also note how well the models are suited for nonlinear datasets. Interestingly, the authors are still unable to find significant outperformance by these models as opposed to more advanced types of linear regressions. When it comes to the process of stock return predicting clear outperformance is still noted against a buy-and-hold strategy.

In the research paper the training of the model is seen as of particular importance along with the usage of new data to test the model on to obtain unbiased results. It is also seen that the models need a large amount of data during the training phase to obtain decent forecasts in live environments. One key observation is the ability of the programmer to control certain tuning parameters for an AI model which in term determine the degree of fit that the model will aim for. While a model can be almost perfectly fit to the training data, this in term results in poor performance when the same model is exposed to out-of-sample data due to overfitting. This is also noted to be of concern when dealing with stock market predictions, as there is such a large amount of noise within the data.

Also, different complexities of AI models are examined along with their pros and cons, and the problem noted with very complex models is the large amount of training data that they need. Conversely, these complex models are also described to be specially well suited to model complex relationship as they have inherent flexibility. The authors detail that this need for data becomes a problem when using solely financial time series data due to the noise and changing factors that drive returns over time. Therefore, older return data is significantly less relevant.

Lastly, it is noted that while ML and AI technologies are beginning to be more widely used within the asset management industry, the low signal-to-noise ratio of stock return data makes advanced linear models the preferred option. Still they note that AI models are better when the number of potential predictors for forecasting is very large within the dataset in question.

Treleaven et al. (2013) examine a lot of descriptive information on the usage of algorithmic trading and similarly to the hedge fund industry, the secretive nature of the field is uncovered. In their study algorithmic trading simply refers to the usage of algorithms to automate either any part or the entirety of the trading process. In terms of hedge funds using algorithmic trading the real-life implementation process of this trading style is also detailed, with pre-trade analysis, signal generation, trade execution, post-trade analysis, risk management and asset allocation noted as key steps by the authors.

For the process of both creating and improving models, especially backtesting and different simulations based on historical data are seen as relevant. Additionally, the risk of employing these systems is noted, with possible programming errors resulting in unexpected behaviors and great potential losses. Some of the main challenges for both the implementation and literature within the field are noted as being the lack of understanding of the interactions that these algorithms have amongst each other and the widely varying behaviors that these systems exhibit if certain variables are changed.

Khandani and Lo (2011) analyze situations where different trading algorithms used by systematic traders are seen as exhibiting a high degree of correlation amongst each other. The authors note that similar factors are used by fund managers as they try to take advantage of identical anomalies. This in term can lead to the unwind hypothesis during market downturns, where the commonality of these traders creates a race to the bottom where losses are seen across the trading style.

Dawes (1979) finds that algorithms are better forecasters than humans and Grove et al. (2000) mirror this view noting how algorithms are able to show outperformance against their human counterparts when it comes to forecasting. Arkes et al. (1986) interestingly note that while algorithms are better, as people obtain more experience within a field their usage of these systems is reduced, leading to worse performance.

Shaffer et al. (2013) also note that the reliance towards algorithms is seen as a negative in some fields and Promberger and Baron (2006), Önkal et al. (2009), Diab et al. (2011) and Eastwood et al. (2012) all show that people have an inherent preference towards predictions made by humans as opposed to those created by algorithms.

Dietvorst et al. (2015) continue on their findings, noting that some people showcase genuine algorithm aversion, which they deem as a mistrust of systems. While algorithms are noted as performing notably better than human forecasters, the forecasting output by humans is preferred. Interestingly, they are also able to show that an algorithm is judged more harshly if it makes an error as opposed to a human, even if the resulting financial consequences of the mistakes made by algorithms are notably smaller.

The authors detail that while there is a general consensus that algorithms are able to avoid small mistakes such as typos due to their automated processes, humans often deem algorithms and AI as unable to learn from experience and mistakes, hence ending up preferring human forecasters. Therefore, when making the same mistake, algorithms and humans are not evaluated equally. This is something that is noted to be counterproductive as algorithms are superior and can produce significant additional value.

Box et al. (2015, p. 2-16) and Engle (1982) on the other hand show that algorithmic trading has been carried out through the usage of statistical models in the past and Chen et al. (2006), Li and Kuo (2008) and Tenti (1996) show that while AI and ML models are superior in other fields, their performance in trading is disputed. Lastly, Kim (2003) shows that different types of models are required for different types of market conditions and more importantly that frequent retraining of these AI models is needed in order to maintain their forecasting accuracy. This in term is due to the dynamic and continuously changing nature of the stock market, where the factors driving returns evolve over time.

We can therefore see that algorithmic trading and trading done by the means of AI and ML are both widely researched topics. It is also to be noted that the results of these different research papers remain varied, and no general consensus amongst these models truly exists. Overall, AI models can be seen as being better when it comes to the process of forecasting as opposed to plain static algorithms, as they have an inherent ability to adapt which is especially important due to the nature of the market that they operate in. It is also noted that the usage of multiple AI models is the preferred approach as opposed to a single forecast and lastly and most importantly it can be seen that humans sometimes oppose to these systems, even if this does not make sense in terms of their overall performance.

3.3 Discretionary versus systematic approach

The final section of the literature analysis is focused on disclosing some of the findings revealed by research papers that have compared the performance obtained between the human driven discretionary approach and the machine-driven systematic style. Also, research papers carrying out similar comparative approaches are evaluated.

Firstly, the research paper by Sun et al. (2012) aims to uncover how the uniqueness of a trading strategy and trading style are related to the performance of hedge funds. The authors note that while hedge funds are generally seen as delivering overperformance in related literature, the persistence of said performance is often not in place. Common agreement can be seen in the fact that the more known a trading strategy is, the less profitable it will be. This in term serves as the motivation for the authors and they uncover that the more unique the strategy a fund is pursuing, the better the performance.

It is especially noted how the hedge funds with the most distinctive trading strategies show clear overperformance against funds with the most common strategies. Additionally, some funds are seen as simply appearing to be active, while mostly following the movements of a general index. Unique strategies are therefore seen as bringing better rewards and this is a finding that can be seen as favoring the usage of AI models. This is due to the fact that these models are able to produce a somewhat unlimited number of unique forecasts depending on individual specifications.

Cremers and Petäjistö (2009) conduct a similar analysis on the topic, but in terms of how active a fund is within the marketplace. In their conclusions the most active funds are seen as showcasing the greatest amount of outperformance, which is again something that can be seen as a result favoring a more automated approach towards trading.

The research paper by Chincarini (2014) carries out a direct comparison between systematic and discretionary funds and a lot of interesting differences and commonalities are noted between the two. Firstly, the discretionary trading style is noted as being more widely used, which is shown both in terms of the larger number of funds and the larger amount of capital that they manage. Though it is to be noted that this is also the trading style that hedge funds have been using throughout time, with a systematic approach represent more recent developments.

Second, the authors are able to discover that when management practices are reviewed the differences among the fund styles is reduced. Additionally, while discretionary funds are more in numbers, systematic funds tend to be bigger in terms of AUM per fund. Systematic funds are also seen as investing in more liquid securities and they are noted as being more secretive as they do not appear as often in registers maintained by the Securities and Exchange Commission (SEC).

The third main finding is the fact that systematic funds do indeed outperform their discretionary counterparts and the additional discovery that this outperformance is driven by their better market timing ability. A result which seems rational as they are able to quickly enter and exit positions due to their usage of algorithms. Lastly, it is noted that this outperformance is driven by systematic funds trading using a macro strategy instead of systematic funds only investing in equities.

In the paper the general growth of the hedge fund industry is also noted and the overall hedge fund overperformance is justified by the reduced regulatory frameworks, the high incentives within the industry and consequently the ability of funds to attract highly talented individuals. Li et al. (2011) concur with this view, discovering that both the education and experience of managers are important for the performance of funds.

The recent research paper by Harvey et al. (2017) can be seen as the one with the most commonalities with this thesis as it is especially focused on the man versus machine aspect when comparing hedge fund performance. While AI, ML and algorithmic trading are all grouped under systematic trading in their methodology, interesting findings are obtained when comparing against the discretionary trading style.

Firstly, they define discretionary funds as funds that are dependent on the skills of individuals in their daily investment decisions, whereas systematic funds are seen as funds in which rule-based trading strategies are executed by AI and algorithms and where humans themselves have very little intervention within the daily process. Additionally, the relevance of AI and ML usage for trading is noted as both the growth and interest within the field is growing rapidly.

Similarly, to the themes of algorithm aversion seen before with Dietvorst et al. (2015), some investors are detailed as being vary of investing in hedge funds using either AI or algorithmic trading. Reasons for such fears are noted as being the possible homogeneity of systematic funds along with the difficulty of understanding their investment processes. While possible homogeneity was additionally noted by Khandani and Lo (2011), it can also be seen that if AI models are fed a certain input and different types of trading signals are produced as outputs, the decision-making process becomes obscured. This the authors note as reduced transparency as also the specifics of strategies are not shared to investors. A common belief among investors is that systematic funds only use past price data and as such some investors do not think these funds have the ability to outperform.

The authors note that these beliefs by investors are not justified as systematic funds show good performance in general. Also, interesting is the finding that discretionary funds are noted as having more of their return attributed to the factors within multifactor models. One key finding of the paper is especially the commonality between systematic and discretionary funds, which is something that will be returned to later. Also, the performance of these funds is noted as being similar after controlling for factor exposures, as far as equity and macro funds are concerned.

AI and ML models are seen as trustworthy alternatives to automate the trading process and their strong performance in related fields is noted. Additionally, discretionary funds are considered to approach systematic funds especially due to their adoption of AI and ML technologies, as the authors note the big investments made by also discretionary hedge funds in the fields of big data and AI. As such systematic and discretionary funds using AI are considered to become just general AI funds as their differences are slowly disappearing.

In their final conclusions, systematic and discretionary trading styles are both noted as having their own market inefficiencies best suited for each style. Therefore, the authors propose that a combined approach using both trading styles is likely a path for the best performance. This seems to especially be the case as far as AI is concerned but this is not researched further. Consequently, the contribution by this thesis, as separating AI funds into their own trading style and comparing their returns against more traditional algorithmic and manual approaches, becomes established.

We have now seen that the comparison of hedge funds of systematic and discretionary trading styles is an ever more relevant topic, but one that has not been researched to a great extent. While the previous literature is able to find answers to the plain man versus machine setup, no real differentiation is taken between AI and algorithmic trading. These two approaches are very different as can be noted in the previous subchapter and as such requires a more detailed analysis.

Generally, as was the case with AI models, different types of combined approaches are the best course of action as far as past literature is concerned. Also, it can be seen that AI models are able to deliver somewhat unique forecasts on a rapid basis and especially the uniqueness of the trading strategy is a key factor for outperformance. Next our attention turns to the general analysis of hedge funds and a review of the main trading styles that they employ.

4 Hedge fund characteristics

Hedge funds are a rather unique type of investment vehicle and as such they contain a lot of different types of characteristics which are not shared by their mutual fund counterparts. With the first hedge fund established in the 1940s by Albert Winslow Jones as noted by Caldwell (1995, p. 1-5), the history of the industry goes back several decades. Additionally, the same research paper notes that this first hedge fund employed a long-short equity strategy, used leverage and operated with an incentive fee that was based on performance. As such, it can be seen that the main building blocks of hedge funds have remained the same throughout all of this time.

Commodity trading advisors (CTAs) which involve organizations advising on the buying and selling of mostly futures contracts and commodity options are sometimes also referred to as hedge funds. Fung and Hsieh (1999) note this as being caused by the reduced differences that these funds have in terms of the regulatory frameworks that they are under. Even if they are considered similar from a regulatory point of view, as this thesis is only concerned with funds operating with equity trading, CTAs are accordingly not included in any of the further discussions.

In general hedge funds can be considered as being profoundly different from mutual funds in many different aspects and one of the differences is undoubtedly the regulatory contrasts between the two. Fung and Hsieh (1997) consequently note that the returns and performance that hedge funds are able to obtain are particularly different from those of mutual funds. This is likely caused by the lesser regulation that hedge funds face, as such they are more at liberty to choose what trading strategies to employ.

The analysis of hedge funds in will first go through some of the main characteristics within the industry, before the different trading styles of funds used in this thesis are observed in detail. Both discretionary and systematic funds are included along with funds combining both approaches, but funds using AI are taken as their own category.

4.1 Main characteristics

As we have seen so far, through both the theoretical aspects and the analysis of past literature, hedge funds seem to defy some of the base assumptions of EMH. While the persistence of their overperformance remains disputed, general consensus is that on the average they are still able to generate overperformance, but similarly disputed is whether the case is the same for their investors when their high performance fees are taken into account. BF has served as our theory for distinguishing between different types of hedge funds and as has been noted, the differences can be quite far reaching. Still some general characteristics are present for hedge funds of all trading styles and these are explored further in this subchapter.

The research paper by Fung and Hsieh (1999) is especially relevant for this purpose as it provides a robust general overview of the field. One thing that becomes immediately apparent is the great amount of secrecy surrounding the industry, as the authors note that for a lengthy amount of time ever since their existence, hedge funds were able to remain out of the knowledge of the general public. Sun et al. (2012) are ones to note the same, as they detail that the amount of secrecy employed by hedge funds is so great that even the trading strategies that they employ aren't disclosed in great detail to their investors. This in term is done to protect the uniqueness of their investment ideas, and as we have seen this is especially crucial for the profitability of these trading strategies.

Fung and Hsieh (1999) continue by disclosing how hedge funds are primarily designed as managers of capital for the wealthy, whether it be individuals or institutions. As one of the prerequisites for hedge funds to receive the reduced regulation from the FSAs, their investors must be solely constituted of wealthy individuals and institutions with a sufficient amount of knowledge. As such these types of sophisticated investors, also referred to as accredited investors mean that they are generally speaking more knowledgeable of the risks involved in investing in these funds, which in term enables these funds to pursue more risky and alternative strategies as opposed to mutual funds.

Hedge funds are therefore not accessible to the general public but as discussed this is by design as otherwise, they would face added regulation which would in turn essentially make them become mutual funds. Capocci and Hübner (2004) are ones to note that especially the limited access to hedge funds sets them apart. Fung and Hsieh (1999) note that one of the usual designs of these funds is also the large involvement of their fund managers in terms of their personal wealth. As they also invest a large portion of their net worth behind their own ideas, different types of agency problems are greatly reduced and interests amongst all participants become more aligned.

Performance fees are of obvious focus in the research paper by Fung and Hsieh (1999), as it is one of the notable differences between hedge funds and other types of investment vehicles. Mainly two types of fees are charged from investors, both based on the amount of capital that the investors have invested. A set management fee charged yearly and a set performance fee, which is only charged based on outperformance. As such charging of the performance fee might have some fund-based restrictions and conditions, for example requiring a performance that beats a certain benchmark or a performance that adds to the cumulative performance that the fund has obtained, also referred to as the high-water mark.

Fung and Hsieh (1999) note an average management fee of 1-2% and an average performance fee of 15-20%. Additionally, many funds require high minimum investments from their investors, which is detailed by Capocci and Hübner (2004). As such the performance fee component represents the most lucrative part of being a hedge fund manager and therefore it can be seen that especially performance is being incentivized with this structure that has been largely unchanged ever since the inception of the first hedge fund. Overall, hedge funds are expensive for their investors as noted by Sun et al. (2012) and therefore expectations for their performance are equally high.

Agarwal et al. (2009) find in their research paper that higher incentive fees are linked to better performance by the fund managers and Goetzmann et al. (2003) see the performance fee almost as an embedded option for the manager. They also note that fund managers might be incentivized to take on high and unique risks in order to achieve extreme performance and to obtain individual gain. This possible negative development is also noted by Fung and Hsieh (1999) as they detail the asymmetric fee structure that is in place. As managers are not required to compensate investors based on losses, fund managers are therefore only part of the upside and as such might be tempted to take on very unreasonable odds to obtain returns. The researchers still note the high level of personal wealth that the managers typically put in along with the permanent damage to one's reputation for such actions which would naturally serve as limiting factors for such behavior.

Figure 1 shows the recent developments for the management fee portion of the hedge fund fee structure as this is naturally the most disputed part of the costs incurred to investors. As a manager would be entitled to these fees no matter the performance, one can imagine that situations of continued losses would make them difficult to justify. As was discussed in the beginning of this thesis, hedge fund fees are facing increased pressure, and this is especially true when it comes to the management fee. Caused mostly by increased competition, such as the rise of passive investing, along with general lack of performance as is shown by the Preqin (2021, p. 25) global hedge fund report, the figure details the declining permanent compensation that managers are to expect as their compensation is shifting more towards an incentive-based framework.

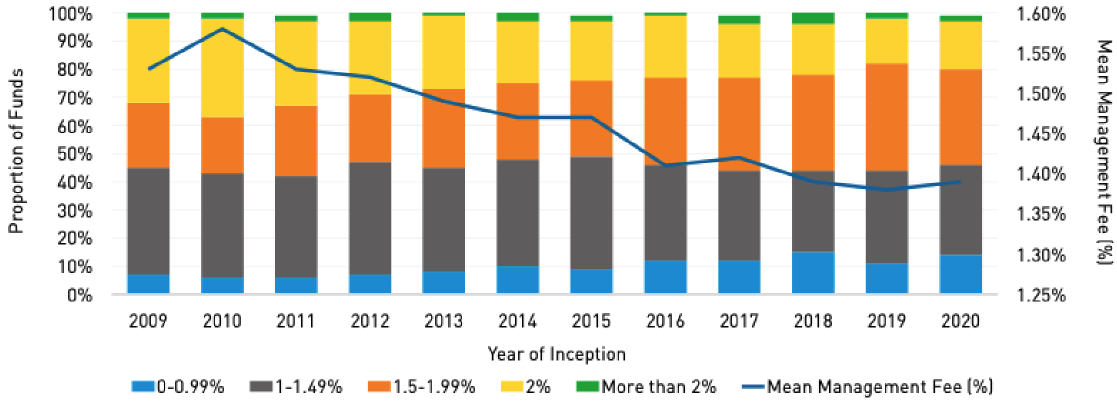

Figure 1. Hedge Fund Management Fee Distribution and Mean Management Fee by Year of Inception (Preqin 2021, p. 30).

Hedge funds are domiciled in various different countries, but the U.S. is still by far the dominant country both in terms of the number of hedge funds, and by the amount of AUM. This can also be seen from figure 2.

Region	No. of Managers	Q3 AUM ($bn)
North America	4,288	2,878.1
Europe	1,297	650.3
Asia-Pacific	909	147.2
Rest of World	291	21.0

Figure 2. Distribution of Hedge Fund Managers and Industry AUM by Manager Location (Preqin 2021, p. 26).

As such hedge funds can still be considered as a rather U.S. phenomenon. On the topic of figures, the AUM for the entire industry which was detailed at the beginning of the thesis stands at 3,87 trillion dollars as of November 2020 according to Preqin (2021, p. 5) and their report also notes that this represents a 6% increase from the AUM levels of 2019. For the future this industry wide AUM is expected to grow at an annual rate of 3,6%, reaching as far as 4,28 trillion dollars by 2025 as is shown by Preqin (2021, p. 5).

The Preqin (2021, p. 5) report discloses that 18 303 hedge funds are currently active and operational and in terms of the trading strategies that these funds employ, the equity long-short strategy is by far the most common. Fung and Hsieh (1999) define the trading style as reflecting the one used by the first ever hedge fund, where long and short positions within equities are taken as a mean to limit exposure to the equity market as a whole.

The authors additionally continue on their findings relating to hedge fund strategies, noting that while costs represent a huge differentiating factor for hedge funds along with their investor base, it is especially the strategies that these funds employ that set them apart from the rest. The differences in strategies are also noted by the authors as the biggest difference in the returns obtained by hedge funds as opposed to those by mutual funds. Hedge funds are seen as using trading strategies of a dynamic nature, whereas mutual funds deploy static buy-and-hold type strategies. Additionally, the regular use of leverage by hedge funds is noted, as positions are typically taken with the help of margin and through the proceeds from short sales.

One of the main observations by the research paper of Fung and Hsieh (1999) is the fact that hedge funds are seen as so-called absolute return vehicles and as such this is also reflected upon their choice of trading strategies. The investors of hedge funds expect absolute returns as a consequence for the large fees they pay, meaning that hedge funds are expected to outperform regardless of differing market conditions. The authors note that this inherent hedging carried out be hedge funds is further proven by their dynamic strategies, which show that their returns are uncorrelated to the markets that they themselves operate in. Harvey et al. (2017) on the other hand dispute this notion that hedge funds actually hedge, noting that the exposures shown by hedge funds against common risk-factors are both significant and economically meaningful.

Figure 3 details the commonality of different types of hedge fund strategies, both in terms of the number of funds employing them and in terms of the AUM that is allocated under them. From the figure we can see that especially equity and macro strategies are relevant, but that equity strategies are by far the most commonly used strategies for hedge funds.

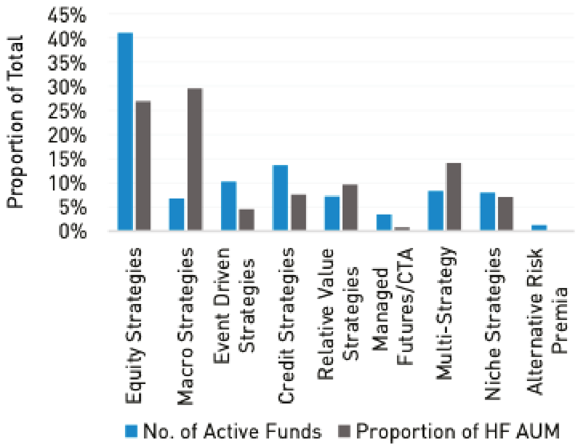

Figure 3. Proportion of Number and AUM of Hedge Funds by Top-Level Strategy (Preqin 2021, p. 27).

Preqin (2021, p. 15) report also shows that especially long-only funds are on the rise. This is noted as being caused by both the strong continuous growth experienced in the equity markets over the past decade, along with the outperformance shown by passive strategies. The Preqin (2020, p. 43) report on the other hand details some of the reasons why investors are choosing to invest in hedge funds in the first place. The main reasons outlined are the diversification benefits, high absolute returns, high-risk adjusted returns and low correlation to other asset classes shown by the returns of hedge funds. As such, Asness (2004) justifies the fee structure, noting that hedge fund alpha should be more expensive.

As discussed, hedge funds pursue alternative and different trading strategies as this is enabled by the reduced regulation they face and also rather mandated by their investors as a consequence of the high fees they pay. As such, especially the wider risk exposure noted by Agarwal et al. (2018) in terms of exposure to so-called exotic risk factors and the low correlation of these funds towards the market they operate in as detailed by

Fung and Hsieh (1999) show the diversification benefits that investing in these funds is able to offer.

The high absolute returns in any market conditions and the high-risk adjusted returns are shown in multiple research papers as we have seen so far, but especially the persistence of these returns and the ability of the investors to obtain outperformance after the hefty fees often comes to question. The low correlation to other asset classes is also seen in the research papers that have been reviewed so far and Fung and Hsieh (1997) are able to show how hedge fund return dynamics are fundamentally different from their mutual fund counterparts.

Therefore, the reasoning for investors to invest in hedge funds becomes apparent and this is also a trend that can be noted as increasing. While the Preqin (2021, p. 5) report shows the strong expected cumulative growth for the industry wide AUM, the fund managers of these hedge funds can be seen as agreeing with this view, as is shown by figure 4.

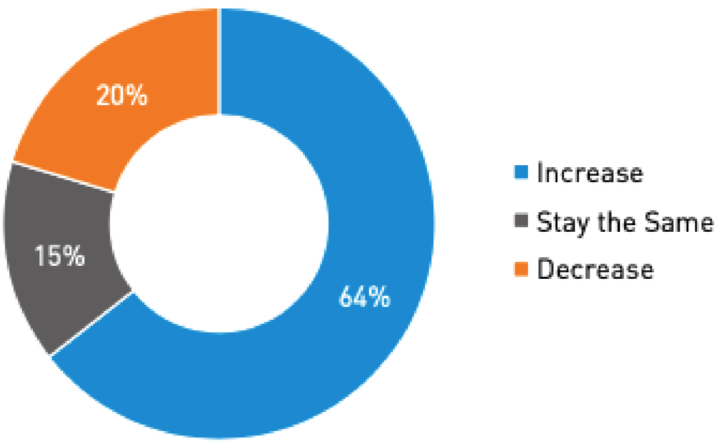

Figure 4. Fund Manager Expectations for Hedge Fund Industry AUM in 2021 (Preqin 2021, p. 124).

The figure shows the results of the Preqin manager survey from November 2020, where the fund managers are tasked with evaluating their own expectations for the growth of the hedge fund industry during the following year. As can be seen, the wide majority of managers expect that the industry wide AUM figures will rise, but conversely the report also details that 47% of the investors surveyed in the Preqin investor survey are not planning to increase their allocations toward hedge funds in the following year.

Preqin (2021, p. 120-124) notes the differing views on the current market outlook as an explanatory factor for this disconnect, as some investors and fund managers have altering views on whether the current market cycle has already reached its peak. Hence, some investors and managers have a risk-off approach, whereas others want to increase their exposures to obtain better returns.

For this future outlook on the growth in the field, especially the returns that investors are to expect are key. Here a similar disconnect can be seen between fund managers and hedge fund investors, as 34% of investors surveyed in the Preqin investor survey expect that hedge funds will perform better in the following year, which is notably different to the views of fund managers based on the Preqin manager survey as can be seen in figure 5.

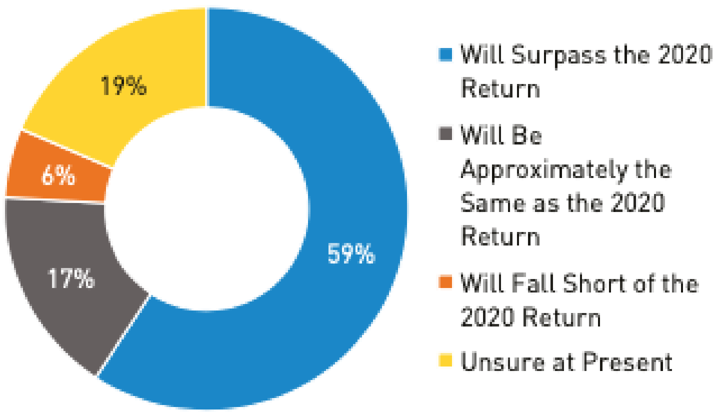

Figure 5. Fund Manager Expectations for the Performance of the Preqin All-Strategies Hedge Fund Benchmark in 2021 (Preqin 2021, p. 123).

The clear majority of fund managers expect that hedge funds will be able to obtain better returns in the following year on average as all strategies are concerned. While this remains to be seen, a clear dependence can be noted between the views of fund managers and investors on the current market cycle and their outlook on the growth and performance of hedge funds. Implicitly revealing that as was shown by Harvey et al. (2017), the actual notion of hedging done by these funds to remain investment vehicles of absolute returns, bringing performance regardless of market conditions, is to be disputed.

As we have now been able to see, the hedge fund industry is in general very different from a multitude of other types of investments for their investors. U.S. serves as the main domicile for these funds both in terms of the number of funds and the combined AUM and different types of equity strategies are the most common for the industry. While some characteristics generally associated with hedge funds, such as their hedging practices, remain disputed a general consensus on both the growth and increased relevance of hedge funds can be seen in the future.

4.2 Discretionary funds

As we have seen so far in the section on discretionary trading, the discretionary approach to investing involves the use of mechanical trading rules as is shown by Fung and Hsieh (1999), but the actual process of making decisions is done by humans as is shown by Harvey et al. (2017). Therefore, while the growth in technology is also seen as impacting the discretionary approach, these types of funds can be seen as using technology solely as helpful tools and not as a means to automate their entire processes.

Discretionary funds are therefore hedge funds that utilize the discretionary trading style and as such they are the closest to the methodologies present ever since the start of the industry. Discretionary funds can be seen as placing a higher emphasis and weight on their managers and therefore especially the professionalism and skill of the manager is important to avoid some of the behavioral biases seen before and to showcase true out-performance as is shown by Kooli and Stetsyuk (2020).

The Preqin (2021, p. 96) report details some of the key figures relating to discretionary funds, noting that 6 960 such funds are currently active, managed by 2 636 fund managers and invested in by 1 152 investors. It can also be seen from the report that discretionary funds are a lot more common when compared against their systematic counterparts.

As is noted by Harvey et al. (2017), discretionary funds exhibit a stronger exposure against the well-known risk factors present in factor models. They also note the increasing investments made by these funds towards some of the latest technologies as a means of helping their day-to-day investment processes. In their research paper the authors also detail the inherent preferences that some investors show towards investing in discretionary funds, as the returns of these funds are considered to be less homogenous and their strategies more easily understandable when compared against systematic funds.

Also, the effects of algorithm aversion uncovered by Dietvorst et al. (2015) show that some investors are vary of investing in more technology driven funds due to general fears relating to the use of algorithms and wrong perceptions that are not backed by evidence, as algorithms are shown to be better forecasters. As such the greater popularity of discretionary funds can be explained as being caused by a wide variety of reasons, but it is especially due to their longer history as opposed to the other trading styles.

Discretionary funds are human-driven, but as discussed there are still multiple places where technologies are being used. Treleaven et al. (2013) detail different types of processes related to the pre-trade analysis, such as data cleaning and signal generation and the authors note that these are highly automated even in discretionary methodologies, where the human involvement truly begins after this analysis of raw data is carried out.

The usage of fundamental analysis is also seen as important in discretionary funds, with Treleaven et al. (2013) noting that this entails the usage of different types of data sources in addition to technical analysis. Using a more fundamental approach would then render a fund more focused on external variables and factors affecting the prices of securities instead of only focusing on the prices of the securities themselves.

Therefore, discretionary funds can be seen as also focused on both macroeconomic and company specific external factors, but modern systematic funds can be noted as taking similar factors as a part of their automated processes. Therefore, as detailed by Harvey et al. (2017) the historical differences between the two are being reduced, at least as far as data is concerned.

The differences in data can also be hypothesized similarly as was done before in the discussion related to discretionary trading, as it can be easily seen that humans are more adaptive and can for example take advantage of direct conversations with the management of companies, different gossips and rumors and other such varying sources to further their understanding. For algorithms other than AI, this would naturally need to be specifically programmed, removing such flexibility. With such adaptability would naturally also come possible behavioral biases, as a discretionary fund manager might weight some information to a too large extent.

One of the main factors setting discretionary funds apart from more automated funds is their reduced use of different types of mathematical quantitative models as a part of their trading strategy. Preqin (2021, p. 106-109) notes this reduced focus on models, as discretionary funds are seen as more skill focused. As a consequence, this creates some inherent differences in terms of their return dynamics.

Based on Preqin (2021, p. 96) data, discretionary funds can be seen as being more volatile than systematic funds and this finding is especially interesting, when considering that they are operated by human managers, and still aim to apply similar rule-based strategies. Therefore, one could assume that behavioral factors are the cause for this added volatility in the returns of these funds, as some deviation from these trading plans seems a likely explanation.

Additionally, Chincarini (2014) note that discretionary funds are more illiquid, and issue more strict restriction clauses to their investors in regard to withdrawals. While these two factors are connected as having a stable asset base is essential for investing in illiquid securities, Aragon (2007) notes that these practices are also linked to higher average returns for hedge funds, as they earn a premium as a compensation for taking on these illiquid securities.

Therefore, discretionary funds can be concluded as being on the whole very similar to their systematic counterparts, as the differences are mostly driven by the execution process of trading strategies. Still multiple differences can be noted amongst them, with the models, philosophies and general data consumption often being different.

4.3 Systematic funds

Systematic funds on the other hand are funds which employ an extensive quantitative framework, along with a strong focus on statistics as trading strategies are automated with the use of different types of trading algorithms. As such the involvement of the human manager is greatly reduced as opposed to discretionary funds and as Chincarini (2014) details, behavioral errors are completely eliminated.

The Preqin (2021, p. 96) also details key figures relating to systematic funds, noting that 2 173 such funds are currently active, managed by 1 161 fund managers and invested in by 776 investors. As such, we can see that there are substantially less systematic funds compared to discretionary funds, and this finding is also reflected by Harvey et al. (2017) and Chincarini (2014).

Chincarini (2014) also shows that while the management and performance fees do not differ between discretionary and systematic funds, systematic funds demand a notably higher minimum investment from their investors. The author also notes that the average size of a systematic fund is notably larger than that of a discretionary fund, which is seen as a sign of systematic funds trying to reach the reduced trading costs associated with economies of scale. As such, it can also be deducted that most systematic funds are therefore not aiming to benefit from small market dislocations as their size would render it impossible to profit from them. Interestingly one can also presume that automated trading would lead to a lot more trading being carried out and if systematic funds are aiming to benefit from economies of scale, it can be deducted that they aim to pursue a very active trading strategy that would benefit from such a move.

All hedge funds can be seen as using a somewhat similar top-level step-by-step process in coming up with their trades, but notable differences can be seen when a more detailed analysis into this process is carried out. It is difficult to describe the process of discretionary funds after the data has been preprocessed as described by Treleaven et al. (2013), as after this step discretionary funds will follow the overall high-level logic employed by systematic funds, but the more specific details are likely to showcase a lot of variation amongst funds as the process is highly human-driven. Therefore, this was not described separately in the previous subsection on discretionary funds, but the following high-level methodology can also be seen in discretionary funds and as such in all hedge funds to some effect.

Treleaven et al. (2013) detail the trading process of systematic funds in great detail. Firstly, funds need to consider what types of data sources to employ and especially financial time series technical data and economic fundamental data are of importance. This data then needs to be automatically retrieved, cleaned, organized and sorted so that it can be used, and this is especially relevant for systematic funds as this data is being fed into even more algorithms. After this comes the pre-trade analysis, which involves data analysis to find overall trends and other underlying information, followed by signal generation, in which different trading setups are identified.

The authors continue, noting the trade execution stage which can be done as market orders based on some key levels of supply and demand or through direct trading within the market. The final step of the process is noted as being the post-trade analysis, in which the profitability and other statistics of the decisions are analyzed.

The research paper also notes a more detailed analysis of the process above, in which the pre-trade analysis is split into three different subsections. Here the alpha model is dedicated to forecasting the future prices of the instrument in question, the risk model assesses the exposure and the accompanied risk, and the transaction cost model calculates the estimated costs of carrying out the strategy.

The signal generation stage involves a portfolio construction model, where inputs are taken from the three before mentioned models, as the model determines both the position sizes and securities that are to be included within the portfolio. The trade execution involves the choice amongst the correct trading strategy to employ, along with the order type, and the post trade analysis section is mainly concerned with calculating profit and loss and risk-adjusted performance.

As was seen in the previous subchapter, systematic funds are less volatile and as we hypothesized before, this is likely caused by the absence of behavioral factors that might intervene with the trading process described before. A discretionary fund generally runs the same pre-trade analysis, but for example in generating trading signals and executing trades, behavioral factors might take effect. If something unexpected happens within the markets, the discretionary manager might be motivated to deviate from his trading plan.

This deviation should also not be noted as only a negative aspect as it enables discretionary funds to have a lot more flexibility and ability to adapt if there really is a need to, and consequently this lack of ability to adapt is noted by Chincarini (2014) as a main weakness for systematic funds. Still the authors note that systematic funds are actually able to perform better during periods of crisis which might in term by explained by their inherent ability to stay cool under the pressure.

As we have seen, systematic funds have a lot of different advantages over their discretionary counterparts and as mentioned before, there are also some fundamental similarities when observed at a high level. As was noted by both Chincarini (2014) and Harvey et al. (2017) both types of trading styles still have their own advantages, and different types of trading situations in which they are best suited for. Therefore, one could consider whether a combined approach using the best parts of both the systematic and the discretionary trading styles would yield the best outcome. Additionally, one could question whether using AI would enable an investor to similarly obtain the best of both worlds, but in a more capable, bias free setup.

4.4 Combined funds

Combined funds can simply be understood as hedge funds using both the systematic and discretionary trading style with the aim of using the best aspects of both approaches. As such these funds can be considered as employing a sort of hybrid approach where they are highly automated, but the human manager is still somewhat involved throughout the process.

As there is no general definition for combined funds, these funds using both approaches might choose various ways in which this is implemented in practice and as such it is not possible to give a more detailed analysis into how they operate. This is due to the widely varying choices of the funds themselves, where one combined fund might be a lot closer to a full-on automated systematic fund whereas another might be a lot closer to a discretionary fund. As an example, a combined fund might employ the systematic trading style but manually choose when a trade is closed, when in profit and when in loss. One could expect that especially the market timing ability of systematic funds as noted by Chincarini (2014) would be taken advantage of in a combined fund in search of outperformance.

As such, as far as correlations between different trading styles are concerned, the combined funds are expected to be fairly similar to either systematic or discretionary funds, depending on their setup. Accordingly, their returns dynamics are to be expected to follow a similar pattern and therefore nothing new is presented with the introduction of combined funds, instead existing elements are simply cherry-picked to include both automation and emotionless execution, but also adaptability and human involvement.

Combined funds are noted in the Preqin (2021a) hedge fund database as their own trading style and their usage of both the systematic and discretionary frameworks are considered similarly as discussed above.

4.5 AIML funds

So far, we have been able to observe all the main different trading style available within the Preqin (2021a) hedge fund database, but in terms of the topic of this thesis the most essential trading style remains, AI funds. These funds are listed in the database as systematic funds using AI, discretionary funds using AI and as combined funds using AI, but as AI and ML can be considered as a revolutionary new approach altogether that changes the overall style of a fund regardless of its underlying trading style, all hedge fund trading styles using AI are grouped into one. The term AIML, artificial intelligence machine learning, refers to AI and ML being used in the funds and this is the same notation as used in Preqin (2020, p. 36-37) report, hence its usage in this thesis.

The choice to combine funds into AIML funds is also due to the themes of this thesis where AI usage in general is to be compared against more conventional hedge funds. Additionally, the findings by Harvey et al. (2017) have motivated this decision, as they found that discretionary funds using AI and ML frameworks and systematic funds doing the same are more common than generally believed, and as such the differences amongst these trading styles will be negligible in the future.

AIML funds can be therefore seen as combined funds in this thesis, in the regard that they also combine approaches used by both systematic and discretionary funds. Still as discussed before AIML funds are to be considered as their own trading style due to the large fundamental differences when compared to the other conventional fund styles discussed before.

As we have seen in the literature review part of this thesis, AI is very different from traditional algorithms in multiple different aspects. In terms of AIML funds the same conclusions can be drawn. As noted by both Sun et al. (2012) and Stein (2009), the uniqueness of trading strategies is especially important for performance, as common strategies will have their abnormal returns disappear due to increased competition surrounding the same anomaly. Matias and Reboredo (2012) on the other hand were able to uncover that AI models are more suited for dealing with nonlinear market data as opposed to traditional algorithms and Gerlein et al. (2016) note the general consensus that AI models are better for financial forecasting. Mullainathan and Spiess (2017) on the other hand detail how AI models do not require specific programming as they are simply given an input along with a desired output, and the model itself finds the best course of action in terms of a function.

As such AIML funds can be noted as being inherently better than systematic funds and as being notable better at uncovering unique trading strategies that were seen as a key source of outperformance. If the costly process of creating a trading strategy isn’t needed and an AI model is able to find it automatically, one can hypothesize that an AI model will be able to find near infinite combinations of possible strategies as the parameters and the complexities of these models are adjusted.

Therefore, at least in theory AIML funds should not have similar issues with commonality in trading strategies and when compared against the conventional hedge fund trading styles seen so far, it can be noted that the nearest fund style is the combined approach. As AI models are able to learn and are not static trading algorithms as was the case with systematic funds, AI models are also able to adapt. Combined funds were seen as taking this combined approach to especially benefit from the advantages of having more human involvement, which can also be noted as their ability to adapt. Conversely to combined funds AIML funds do not need to try to find a balance between this level of human involvement which is necessary, and involvement caused by behavioral biases and as such the AIML approach can already be considered superior on paper.

AIML funds are therefore able to operate without emotion like systematic funds, and follow their own set strategies to perfection, have the ability to adapt and learn that discretionary human-driven funds are able to leverage and to have all the before mentioned aspects without fundamental issues, such as the difficulty of combined funds to decide when human involvement is appropriate.

Chen et al. (2004) note that while unique strategies are difficult to obtain in the first place, these are also difficult to scale up. As discussed, AI models are able to learn, and these models can also be retrained so that new strategies can be obtained. The difficulty in scaling up strategies has been noted by other research papers so far and in terms of AIML funds this issue is naturally also present. The Preqin (2021, p. 19-20) report notes that especially managers of small funds are able to pursue more risky and exotic trading strategies, and one could say that AI trading can still be categorized in this group. Hence, AIML funds can be theorized to be small in terms of AUM and further confirmation for this can be obtained by observing the algorithm aversion shown by investors detailed by Dietvorst et al. (2015).

Gerlein et al. (2016) are able to show in their research paper that AI models have shown great successes in forecasting asset prices and that they are also able to uncover hidden patterns in data that can lead to the creation of completely different strategies than what human traders could imagine or even comprehend. As such the understanding of why AI models operate the way they do might become blurred and this is also noted by Harvey et al. (2017). Gerlein et al. (2016) also detail that while all the before mentioned advantages are present, AI models and hence AIML funds still need to focus on periodic retraining of models to keep them relevant due to the dynamics of the markets.

Thus, concludes our analysis of the different hedge fund trading styles in the scope of this research, organized similarly as is seen in the Preqin (2021a) hedge fund data in the following chapter. It can be seen that all funds of conventional trading styles are rather similar, with differences coming mostly from the data that is being used and the way trading strategies are executed. Additionally, it can be noted that AIML funds are fundamentally different from conventional style funds in various aspects and now it remains to be seen if this difference is reflected as outperformance against the other hedge fund trading styles.

5 Data and methodology

The hedge fund data for this thesis is obtained from the Preqin (2021a) hedge fund database. The database covers the hedge fund industry on a global scale and aims to especially provide a wide coverage of the funds that are included. Preqin itself serves as a data vendor for a wide variety of different stakeholders, from academic institutions to hedge funds and the database also contains additional datasets for topics ranging from private equity to infrastructure. The company was founded in 2003 with their hedge fund database being started in 2007.

The database on the whole contains 59 438 funds and when excluding different share classes that relate to the same underlying fund, 35 885 funds remain. Then if we only select funds which display performance figures, the sample becomes 11 944 funds and 8 729 funds when only considering hedge funds. In this regard we follow the data processing employed by Bali et al. (2007) as they also eliminate CTAs to better focus on individual hedge funds. Though Fung and Hsieh (1999) note the similarities between the two and the non-important differences, for added clarity in regard to the objectives of this thesis these are removed. Furthermore, in the final sample the number of CTAs is not meaningful.

Preqin itself gets the performance figures and other statistics per each fund in question through multiple different sources. Based on my own interviews with both the company's business development and relationship managers, data is sourced primarily from open datahouses, SEC disclosures and other such regulatory filings, and through direct contributions by funds and direct contacts by the database. The sources of these direct contacts are naturally the fund managers themselves, but also investors and service providers are used as sources of data. Within the database especially the cross-referencing of information from these multiple sources is emphasized to maintain high data quality and accuracy.

One of the advantages of using the Preqin (2021a) database is the breadth of information available. For most funds, there is data available on variables such as the amount of leverage and the management and performance fees, on top of the performance and AUM figures. There are also a lot of different filters in place, from fund type and status all the way to the different asset types that are traded by each fund. An additional key benefit of using Preqin is also the fact that they possess one of the largest datasets available for AIML funds and their database has a specific filter in place for whether a fund is using AI methodologies as a part of its trading approach.

The database has over 350 AIML funds available, which is vastly superior to the numbers of comparative databases, such as Eurekahedge which has data for around 20 of such funds in their main performance index. Furthermore, almost all funds have a trading style in place, which is either systematic, discretionary or both, which are exactly the additional comparative aspects that are being used in this study. There is a natural possibility for backfill bias to be present within the performance figures of the database, but no return data is excluded as a cause of this, due to our relatively small time series sample, where such effects can be presumed to be negligible. Survivorship bias is handled by the inclusion of both active and liquidated funds into the analysis which is detailed by Chincarini (2014) and Fung and Hsieh (2009) as of notable importance.

The database also makes a difference between a fund being liquidated and a fund simply withdrawing from reporting its figures to the company. Both the date of inception and the possible date of liquidation or current status of a fund being active are reported, which is a differentiation that Bali et al. (2007) note as meaningful. In their research they discuss the voluntary nature of the data that is being distributed by these funds, which in term means that funds might also stop reporting at any point in time. But for the dataset used for this thesis this is not an issue and therefore the different statistics on the amount of funds through the sample period is accurate. This finding by Bali et al. (2007) also ties up to the earlier discussion on the capacity constraints of trading strategies and the advertising practices in place for hedge funds. If the limits of scale are reached for a certain strategy, a fund no longer needs to advertise itself by being present in any database.

5.1 Data description

As was discussed earlier, the sample of hedge funds becomes 8 729 after top-level filtering. This sample of funds is then further filtered with various different aspects to consider. Firstly, the methodology of the thesis which is discussed in greater detail in the following subchapter uses factor models, with CAPM, Fama and French three-factor model, Carhart four-factor model and Fama and French five-factor model being used. All of these models are used for pricing U.S. equities in their basic forms and thus the focus for the analysis needs to be on hedge funds that operate in similar markets.

Therefore, using the filters provided by the database, the sample of funds is filtered to only include hedge funds that trade equities, operate within the North American markets, with this being their main geographic focus and having their returns denominated in U.S. dollars. This reduces the sample size to 1 476 hedge funds which is then manually filtered to obtain the final sample of funds that has been used for this study. Brown and Goetzmann (1997) and Brown and Goetzmann (2003) detail this need for manual analysis as misclassifications can occur.

Firstly, the option to select funds with a main geographic focus being on North America instead of funds that have such focus directly on the U.S. is due to the way that data is reported within the database. Almost all funds that are marked as focusing on North American markets actually focus solely on the U.S. markets, which can be seen from the written description available for most of the funds. Therefore, funds with North American focus are filtered manually to only include funds that have actual U.S. geographic focus into the final sample. Similarly, one could select funds based on certain strategic focus, but this does not guarantee that all funds focused on equities get included. As such, no restrictions were put for strategies. Likewise, selecting funds that trade equities does not guarantee that they only trade equities. For hedge funds, the usage of different types of instruments is natural as is also noted by Agarwal et al. (2018). Therefore, the sample of funds is again manually filtered to only include funds with their main focus being on equities, based both on the description and asset type information.

This leads us to a sample of hedge funds that are operating within the U.S. equity markets, which in term makes it meaningful to use the before mentioned asset pricing models further on. From this sample of funds, the last manual adjustment is to remove all funds with information missing for the trading style, i.e. systematic, discretionary or combined. Thus, the final sample of hedge funds used for this research contains a breadth of information for 826 individual hedge funds and all these funds are included in the further analyses as to avoid cherry picking. The return data itself consists of monthly figures from a sample period of September 2006 to January 2021.

From table 1 one can observe the amount of funds under each individual trading style, the full sample of funds and the three most common strategies that are used by these funds that focus on U.S. equities. The split of the final sample of hedge funds into the trading style categories of table 1 is based both on the trading style filter along with the separate information available in the database to display whether a fund is using AI or not. This information for AI usage sometimes also gives blank values, but based on my own separate discussions with the company's business development manager, these are still funds that are meaningful to include as they can be considered as funds that do not use AI even if the fund itself has not provided such information outright. This is also partly due to the advertisement value for funds to be included in a database, with AI usage being seen as something to help funds stand out.

Table 1. Number of funds per trading style and most common equity strategies.

Hedge fund trading style and strategy	No. of funds
AIML	36
Long/Short Equity	18
Equity Market Neutral	6
Long Bias	3
Systematic	117
Long/Short Equity	56
Long Bias	18
Equity Market Neutral	18
Systematic & Discretionary	184
Long/Short Equity	118
Long Bias	26
Value-Oriented	13
Discretionary	489
Long/Short Equity	294
Long Bias	80
Value-Oriented	41
All	826

Therefore, the categorical split is the following. Systematic funds include funds with the trading style of systematic and the usage of AI being negative or blank. Systematic and discretionary funds include funds with the trading styles of both systematic and discretionary, i.e. combined, and the usage of AI being negative or blank. Discretionary funds include funds with the trading style of discretionary and the usage of AI being negative or blank. Lastly, AIML funds include all funds with the usage of AI being positive regardless of their trading style being systematic, discretionary or combined. This is due to the fact that in the case of AIML funds it is not really possible to say whether they are fully automatic or almost fully automatic, meaning that a separation of discretionary AIML and combined AIML funds for one is not meaningful. AI is being used by these funds to provide an edge similarly to the usage of plain discretionary and systematic methodologies and their combinations. Additionally, the findings by Harvey et al. (2017) show that the differences between AI funds of different underlying trading styles are negligible. Therefore, AIML funds can be thought of as their own distinct trading style, regardless of their underlying split.

Table 2 shows the descriptive statistics of individual funds in our sample grouped by their trading style. From the table one can also observe some of the other variables that are available within the dataset, such as the leverage and performance fees in use by these funds. Few key findings to note from the table are the low maximum minimum investment required by AIML funds along with their relatively low size in terms of AUM as shown by the last column. Additionally, one can see the lower maximum losses and gains for such funds.

Table 2. Descriptive statistics of individual funds in sample per trading style.

Hedge fund trading style and descriptive statistics	Minimum investment ($ in thousands)	Management fee	Performance fee	Leverage	Excess return	Cumulative return	Sharpe	AUM ($ in millions)
AIML								
Min	25,00	0,40 %	0,00 %	0,00	-33,67 %	-12,04 %	-0,16	0,02
Mean	836,36	1,61 %	17,81 %	2,75	0,91 %	52,83 %	0,20	45,26
Median	500,00	1,75 %	20,00 %	1,50	0,63 %	20,68 %	0,14	15,53
Mode	1 000,00	2,00 %	20,00 %	0,00	1,24 %	-	-	0,03
Max	10 000,00	2,50 %	25,00 %	9,00	40,60 %	358,36 %	0,92	443,60
Systematic								
Min	1,00	0,00 %	0,00 %	0,00	-66,66 %	-92,26 %	-0,55	0,05
Mean	3 528,35	1,38 %	19,25 %	16,74	0,46 %	53,07 %	0,14	747,72
Median	250,00	1,50 %	20,00 %	2,00	0,60 %	20,07 %	0,12	24,60
Mode	1 000,00	2,00 %	20,00 %	2,00	1,20 %	22,87 %	0,28	8,00
Max	100 000,00	3,00 %	50,00 %	400,00	91,20 %	693,00 %	1,44	35 662,00
Systematic & Discretionary								
Min	1,00	0,00 %	0,00 %	0,00	-63,01 %	-94,25 %	-0,37	0,05
Mean	1 804,50	1,39 %	17,88 %	1,71	0,70 %	94,79 %	0,13	210,09
Median	500,00	1,50 %	20,00 %	2,00	0,58 %	35,17 %	0,13	48,60
Mode	1 000,00	1,50 %	20,00 %	2,00	0,00 %	-	-	10,00
Max	25 000,00	2,75 %	50,00 %	5,00	164,62 %	2913,01 %	1,12	8 410,00
Discretionary								
Min	1,00	0,00 %	0,00 %	0,00	-57,82 %	-84,92 %	-1,35	0,05
Mean	1 239,77	1,41 %	18,50 %	6,94	0,73 %	116,52 %	0,16	215,55
Median	625,00	1,50 %	20,00 %	1,05	0,69 %	59,21 %	0,15	59,80
Mode	1 000,00	1,50 %	20,00 %	0,00	0,00 %	-	-	6,00
Max	25 000,00	2,35 %	30,00 %	175,00	88,59 %	2718,63 %	1,16	11 083,82

The excess net returns are calculated by subtracting the risk-free rate which consists of a 1-month U.S. treasury bill rate provided by Ibbotson Associates, from the monthly return data. The mean of excess returns is calculated as the geometric average of excess returns for each fund and then as a simple average across all funds in the trading style category, and in this aspect AIML funds can be seen as being able to provide more value to their investors. Also, in regard to the average of the Sharpe ratio similar findings can be observed when it comes to the risk adjusted returns.

It is interesting to note the substantially higher leverage figures that are displayed by both systematic and discretionary funds and both in terms of maximum and average values. Lastly, when it comes to the management and performance fees, the result is on average pretty similar across funds. A management fee of close to 1,5% and a performance fee of under 20% shows the additional pressure that these fees have come under with the rise of competition coming especially from the passive space. French

(2008) notes the rising management and performance fees from 1996 to 2007 and based on the sample, the classical 2 and 20 model of management and performance fees is now being reduced.

After observing the descriptive statistics on a fund-by-fund basis, our attention naturally turns into the portfolios that are created based on the trading style split of our sample of funds. An equally weighted portfolio consisting of all the funds in our final sample is created for each trading style category across the full sample period of 173 monthly observations, starting again from September 2006 until January 2021. The descriptive statistics on a portfolio basis are seen in table 3.

Table 3. Descriptive statistics of trading style portfolios.

Hedge fund trading style portfolios and descriptive statistics	Excess return	Cumulative return	Sharpe	AUM ($ in millions)	No. of funds	Observations
AIML						173
Min	-9,82 %	-2,11 %	0,14	1,50	1	
Mean	0,93 %	178,02 %	0,57	354,72	12	
Median	0,82 %	176,86 %	0,41	110,89	10	
Mode	-	-	-	3,60	2	
Max	10,82 %	392,29 %	1,68	1 448,48	30	
Systematic						173
Min	-11,48 %	-23,72 %	-0,46	93,62	23	
Mean	0,44 %	40,83 %	0,36	12 646,46	53	
Median	0,71 %	35,68 %	0,42	8 668,38	53	
Mode	-	-	-	-	27	
Max	4,96 %	112,21 %	1,28	37 478,94	78	
Systematic & Discretionary						173
Min	-9,81 %	-18,08 %	-0,53	1 701,48	49	
Mean	0,59 %	64,39 %	0,38	10 997,39	111	
Median	0,73 %	72,06 %	0,37	7 985,64	115	
Mode	-	-	-	-	149	
Max	12,19 %	177,29 %	1,31	28 552,60	152	
Discretionary						173
Min	-12,07 %	-17,64 %	-0,56	10 809,28	163	
Mean	0,70 %	82,94 %	0,46	34 055,09	312	
Median	1,04 %	92,60 %	0,31	37 115,04	336	
Mode	-	-	-	-	383	
Max	10,72 %	236,35 %	1,58	59 268,66	395	

From table 3 we can observe similar findings as were noted before, but this time on a more aggregated portfolio basis. The mean excess net returns are calculated as the geometric mean of excess returns due to the compounding of the figures and again it can be seen that AIML funds are on average superior to the other types of trading styles. Furthermore, these funds are also better on a Sharpe ratio basis, both in terms of the average and maximum values.

On a cumulative return type basis, the AIML funds are again seen as being superior and it is notable to see the small lowest value for these returns that are reached throughout our sample period. When observing the AUM column, the relatively small scale of AIML funds is again seen and when looking at the number of funds a large growth can be seen for each type of trading style as will be detailed further shortly.

All in all, the main findings so far are both the good performance of AIML funds along with the lackluster performance of systematic funds, which is interesting considering their relative closeness in terms of trading styles. It could already be hypothesized that non-AI trading algorithms and mathematical models are lacking in some respects as opposed to full AI approaches.

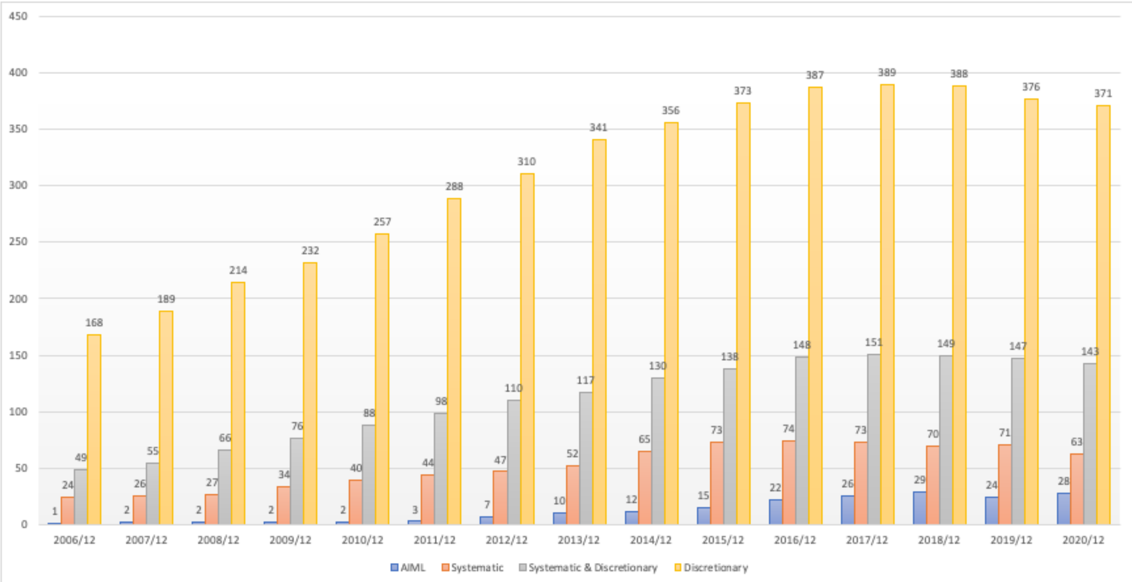

Figure 6. Number of funds per portfolio through the sample period.

Figure 6 shows how the number of hedge funds is evolving within each trading style portfolio throughout the sample period. Notable factors are the large growth experienced by every trading style until the end of 2017 along with the widely varying number of funds per style. Brown et al. (2001) detail that hedge fund survivorship is mainly driven by their ability to obtain returns, hence one could hypothesize that this is driving their growth. It can be seen that the popularity of a trading style is linked to its complexity as using a systematic or AI driven approach is naturally more complex to employ as opposed to a discretionary or combined method. This added cost of complexity is something that is also noted by Treleaven et al. (2013) and Sun et al. (2012).

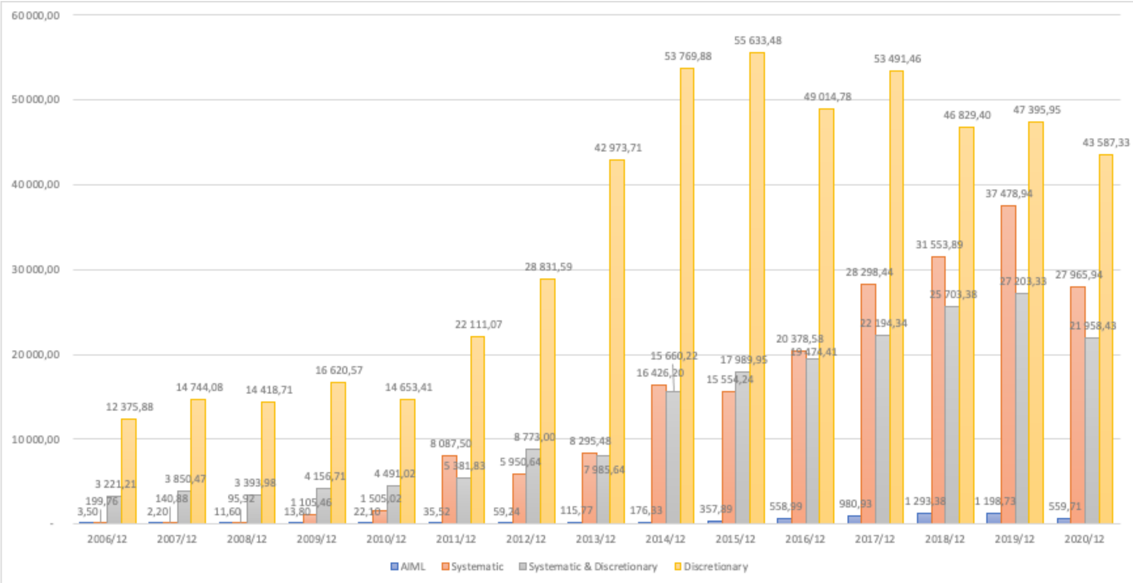

Figure 7. AUM per portfolio through the sample period.

The figure 7 on the other hand shows how the AUM of the funds has evolved throughout the sample. Especially interesting is the size difference between AIML and systematic funds, which is proportionally massive when considering that there are only around twice as many systematic funds as opposed to AIML funds towards the end of the sample. It can be seen that on average systematic funds are very large and AIML funds are very small. Also, the growth of AUM is generally coinciding with the growth in the number of funds, meaning that on an average level the growth in assets is not necessarily driven by the growth of individual funds, but by the growth of the industry as a whole

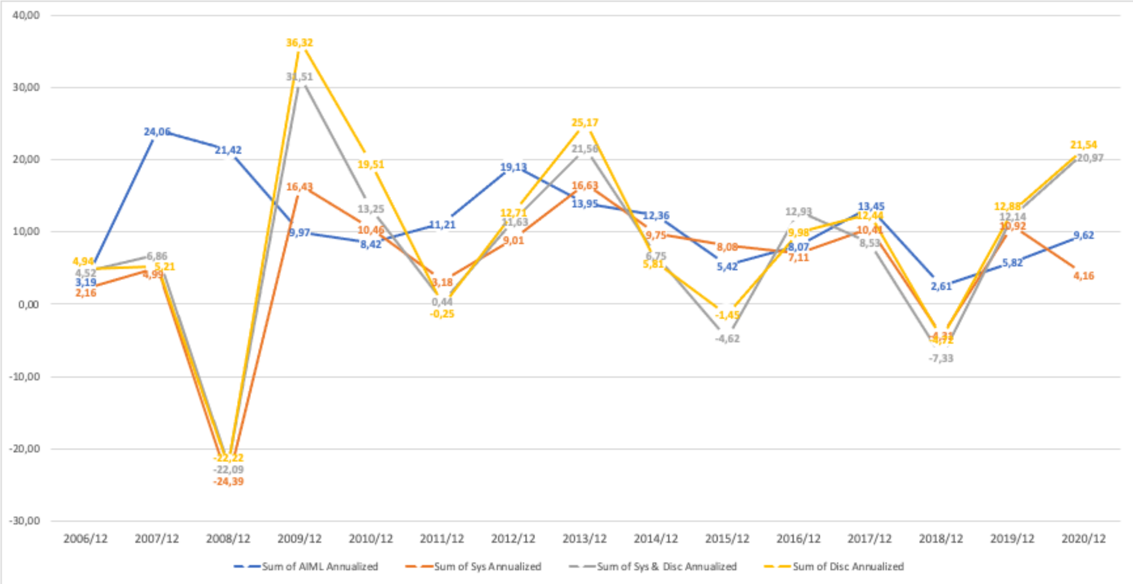

Figure 8. Annualized excess returns per portfolio through the sample period.

Figure 8 shows how the annualized excess returns have evolved and an interesting finding is the fact that AIML funds have ended every single year in profit as far as the sample period is concerned. While the sample of AIML funds is small for the first parts of the period, it can be seen that the return dynamics do not show substantial change even as more AIML funds are being introduced. It is also worthwhile to note the more stable composition of returns for these AI funds as they mostly do not reach the highest returns, but similarly they are able to keep away from the worst downturns. This can also be seen by observing the relatively low leverage levels that these funds use in table 2. The chart also shows how similar the dynamics of systematic, discretionary and funds that combine both approaches are.

Figure 9 shows the annualized Sharpe ratios per funds and including these as comparative performance measures is essential as is discussed by both Liang (1999) and Fung and Hsieh (1997). Again, the AIML funds can be seen as being above the other trading styles in terms of risk adjusted returns for most parts of the sample period. It is worth noting that AIML funds are able to maintain a positive Sharpe ratio for the entire sample, but contrary to excess returns, there is more variation in the figures. This in term shows that AI funds are able to obtain similar returns by reducing the amount of risk that is being taken as the Sharpe ratios spike up while the excess returns remain stable.

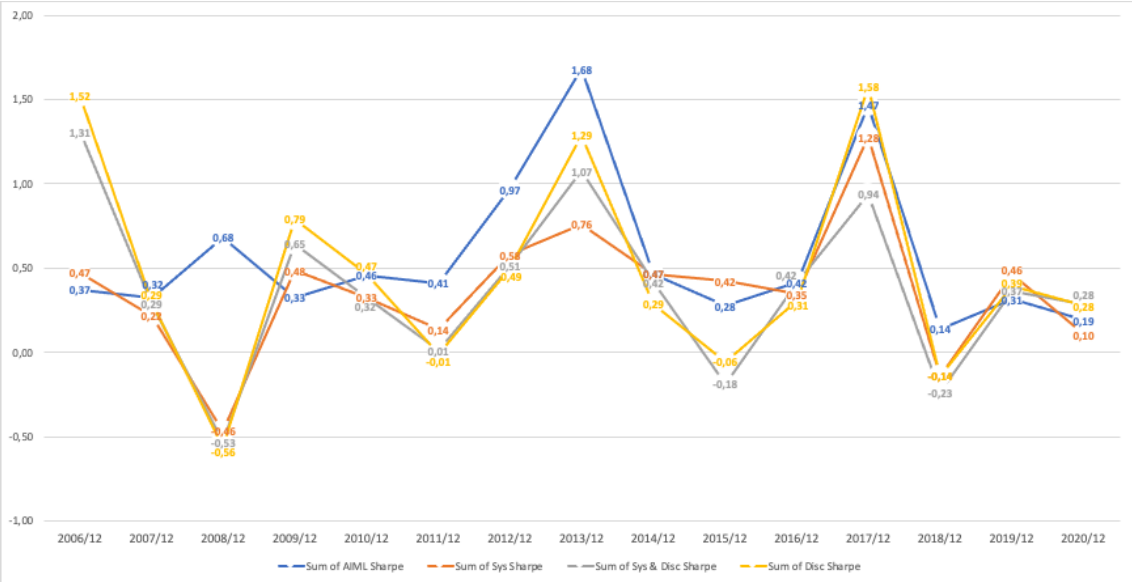

Figure 9. Annualized Sharpe-ratios per portfolio through the sample period.

Based in the past two figures AIML funds are seen as a more stable and less flashy alternative to the other trading styles that it is being compared against. The research paper by Timmermann and Granger (2004) argues that stable and predictable forecasting patterns disappear quickly while Mullainathan and Spiess (2017) note the inherent adaptability that using AI models is able to offer. Therefore, one could presume from the results seen so far that AIML hedge funds are better able to take advantage of a multitude of fleeting opportunities and adapt accordingly to market conditions, meaning that the most extreme case situations on both sides of the y-axis are averted.

The final descriptive figure of our dataset is the cumulative returns that an investor could've hypothetically obtained by investing in our different hedge fund style portfolios if different market frictions are left out of the equation. In figure 10 the stable nature of AIML returns becomes especially apparent as the cumulative year-on-year growth ends up bringing much larger returns on the whole and sets these funds apart from the rest.

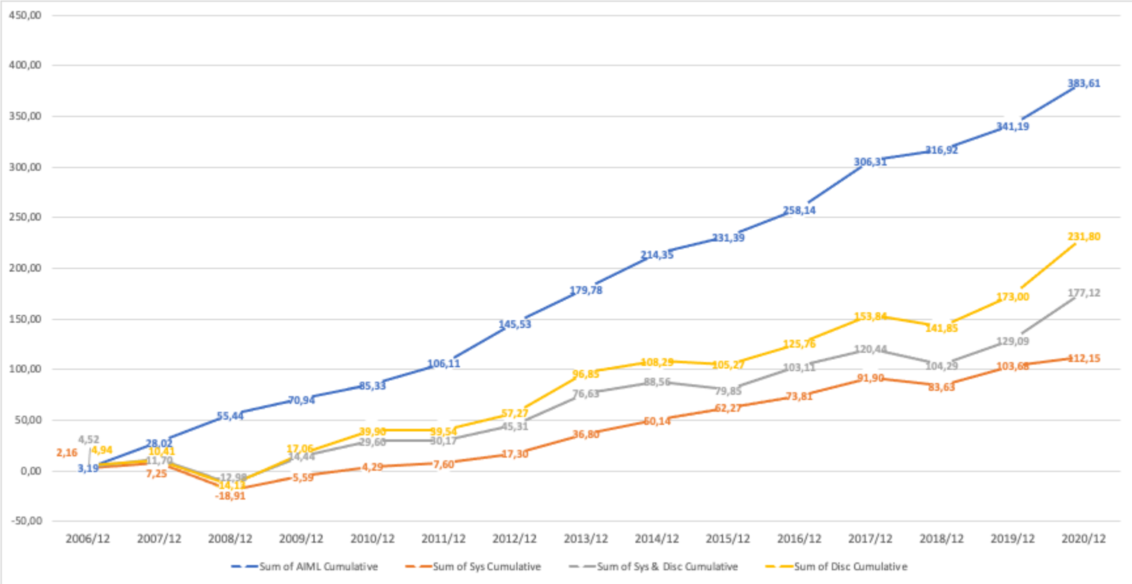

Figure 10. Cumulative excess returns per portfolio through the sample period.

5.2 Methodology

The methodologies for analyzing hedge fund performance are rather disputed when it comes to the literature in the field. Agarwal et al. (2018) are one of the many researchers noting the dilemma between choosing the right model and Capocci and Hübner (2004) for one come to the conclusion that several different models are to be used. Additionally, Sun et al. (2012) note the dynamic nature of hedge fund strategies and the need to use models that have additional factors in addition to the plain CAPM model.

On the contrary Berk and Van Binsbergen (2016) and Barber et al. (2016) are able to show that for mutual funds the CAPM is the preferrable model and Agarwal et al. (2018) demonstrate that CAPM is actually the better model for hedge funds as well. Due to this lack of consensus, multiple performance models are employed in this thesis and similarly to the recommendations by Fung and Hsieh (2004) and Ammann and Moerth (2005) factor models based on assets are being used.

To be more detailed, Fung and Hsieh (2004) actually propose their own seven-factor model which is aimed at being able to capture the wide variety of risk factors that are present in hedge fund portfolios in general. As the scope of this research is specifically on hedge funds that operate almost solely with U.S. equities, the usage of less complex factor models is more than justified. The most common factor models used for pricing U.S. equities are the CAPM, the Fama and French three-factor model, the Carhart four-factor model and the Fama and French five-factor model and therefore these are chosen to evaluate how hedge fund performance varies across these different trading style portfolios.

The methodology that we employ in the first stage is closest to the research carried out by Capocci and Hübner (2004) and Chincarini (2014). In their research papers, the authors employ the Fama and French three factor model, the CAPM and the Carhart four-factor model as their standard frameworks. Capocci and Hübner (2004) also note the dispute amongst the optimal model to choose but come to the conclusion that multi-factor models are in the end better at explaining the average returns that are obtained by hedge funds.

Therefore, following the methods by Fama and French (1993), the one month treasury bill rate provided by Ibbotson associates is used as the risk free rate, the S&P500 returns are used as the market rate, the before mentioned hedge fund excess net return data is being used to distinguish performance and the data for all factors in each factor model is being sourced from the French (2021) data library. This gives us a methodological framework that is in line with the main findings and discussions carried out in previous research papers and uses model data that is similarly sourced.

5.2.1 Capital asset pricing model

The CAPM can be seen as one of the foundational models for the pricing of financial assets. Created in the mid 1960’s by Sharpe (1964), Lintner (1965) and Mossin (1966), it helps to understand how assets are priced in the financial markets and serves as a strong theoretical foundation for the purpose of analyzing hedge fund returns. The formula for the model is the following:

$$R_t - R_{Ft} = \alpha + \beta(R_{Mt} - R_{Ft}) + \varepsilon_t \tag{1}$$

where t = 1, 2, …, t

Where in our context, R_t stands for the net return of the hedge fund portfolio, R_{Ft} for the risk-free rate of return as the one month treasury bill rate and R_{Mt} for the market rate of return as the S&P500 stock index.

To put in simple terms, the usage of the CAPM uncovers the excess return that is obtained after controlling for the excess return of the market. In the case of our hedge fund analysis, the CAPM shows whether the different style portfolios are able to beat the markets, and this is shown by the coefficient α in the formula above. Jensen (1968) describes the alpha as a measure of the forecasting ability of the fund manager and therefore as the measure to show the true value added. As such he also notes the importance of using these factor models for performance comparisons as he details the intrinsic need to control for different degrees of risk to render the varying excess returns comparable.

As was mentioned before, the CAPM is chosen as the first model to be used for the purpose of performance comparisons due to its general acceptability within the past literature based on hedge fund performance. As is noted by Sharpe (1964), the β coefficient in the model shows the sensitivity towards the market factor and therefore it is used to uncover whether the hedge fund in question is defensive and has a low beta value or whether the fund is aggressive and has a high sensitivity. As such, the factor models are to be used to not only obtain comparative performance figures but to also uncover more underlying information based on the value of the coefficients.

5.2.2 Fama-French three-factor model

The Fama and French three-factor model can be seen as an extension to the CAPM framework discussed in the previous subchapter. Introduced by Fama and French (1993), the model aims at improving the explanatory power of the CAPM by introducing additional factors which are seen by the authors as being meaningful for explaining the average returns that are obtained for stocks. The formula for the model is the following:

$$R_t - R_{Ft} = \alpha + \beta_1(R_{Mt} - R_{Ft}) + \beta_2 SMB_t + \beta_3 HML_t + \varepsilon_t \tag{2}$$

where t = 1, 2, …, t

In addition to the variables already seen for the CAPM, the three-factor model introduces the SMB_t factor which is designed to showcase the returns related to size, and the HML_t which is included to showcase the returns related to the book-to-market equity. The SMB_t factor is calculated by subtracting the returns of three portfolios of big stocks against three portfolios of small stocks, on a monthly basis. Similarly, the HML_t factor is calculated by subtracting the returns of two portfolios of low book-to-market equity stocks against two portfolios of high book-to-market equity stocks, month-on-month.

Fama and French (1993) detail the need to use the three-factor model as opposed to the plain one-factor CAPM model due to the added benefits that these additional factors are able to bring. The authors show that the firm specific components of returns are captured well and that these factors are unexplained by the CAPM. They also detail the fundamental economic reasoning behind adding the two factors, as having the risk-factors in returns related to both the size and the book-to-market equity is able to capture the cross-section of average returns per stocks and as both of these factors are known to have an impact on these returns.

The model is widely used for the purpose of analyzing hedge fund performance as was discussed before. Capocci and Hübner (2004) additionally note the great performance of using the factor model for analyzing mutual funds and this serves as their motivation to utilize it also for hedge funds. Agarwal et al. (2018) on the other hand note the common factors that the model is able to capture for the firm specific components and come to the conclusion that more complex trading strategies of hedge funds are therefore able to show high alphas as far as the three-factor model is concerned, since their risk-factors in returns are less standardized.

5.2.3 Carhart four-factor model

The Carhart four-factor model introduced by Carhart (1997) again builds on top of the Fama and French three-factor model, by adding a fourth factor, momentum.

$$R_t - R_{Ft} = \alpha + \beta_1(R_{Mt} - R_{Ft}) + \beta_2 SMB_t + \beta_3 HML_t + \beta_4 UMD_t + \varepsilon_t \quad (3)$$

where t = 1, 2, …, t

The UMD_t denotes the additional momentum factor, which is added for the purpose of improving the explanatory power of the two before mentioned factor models. First introduced by Jegadeesh and Titman (1993) in their study on momentum anomalies, the factor is meant to capture the returns of the one-year momentum strategy. The UMD_t factor is calculated by subtracting the returns of a portfolio of stocks with the lowest performance from a portfolio of stocks that shows the highest performance. Carhart (1997) additionally notes that these returns are to be lagged by one month for the creation of the four-factor model.

Carhart (1997) can be seen as taking a negative view towards the possibility of funds being able to deliver excess returns for their investors as he notes that most of the components in returns can be accredited to the factors present in his model. He especially notes that both the usage of factor models and the deduction of different costs render the returns of most funds into easily explainable events and therefore display a lack of forecasting skill for the average fund manager.

By adding the momentum factor, Carhart (1997) details that then the four most common equity strategies are captured by the model, which are the strategies involving the purchase of stocks with varying betas, stocks with varying level of market capitalization, stocks with either a value or growth basis and stocks that experience the effects of momentum.

Chincarini (2014) additionally notes the common usage of the model to determine the skill of a fund manager but Kooli and Stetsyuk (2020) on the other hand can be seen as opposing this theme of simply adding additional factors as a way to improve the explanatory power of multi-factor models. They also note the difficulty in establishing what the true level of managerial skill really is and whether the alphas of these before mentioned models are able to capture them. Still Carhart (1997) maintains that the four-factor model is able to capture and explain variation in fund returns to a high degree and therefore show alphas that are not captured by the most common strategies.

5.2.4 Fama-French five-factor model

The final factor model used for the first stage analysis of hedge fund performance is the Fama and French (2015) five-factor model.

$$R_t - R_{Ft} = \alpha + \beta_1(R_{Mt} - R_{Ft}) + \beta_2 SMB_t + \beta_3 HML_t + \beta_4 RMW_t + \beta_5 CMA_t + \varepsilon_t \quad (4)$$

where t = 1, 2, …, t

In the model the momentum factor is discarded and instead additional factors RMW_t for the robustness of profitability and CMA_t for the aggressiveness of investing are added. The RMW_t factor is calculated by subtracting the returns of a portfolio of weak profitability stocks from a portfolio of stocks with robust profitability. Similarly, the CMA_t factor is calculated by subtracting the returns of a portfolio of high investing aggressive stocks from a portfolio of low investing conservative stocks.

Fama and French (2015) firstly note that while factors can be endlessly added to factor models, the five-factor model is truly able to perform better than their previous three-factor model and therefore it is the preferred model for explaining stock returns. The additional robustness and investing factors are aimed at capturing the firm specific components of returns to an even higher degree and therefore provide the highest explanatory power of the models discussed so far.

In regard to more complex factor models where various additional aspects are concerned, Fama and French (2015) do not rule out their usage, but mostly note the need for a theoretical framework behind each factor that is being added. The five-factor model is yet to be more widely used in the research papers analyzing hedge fund performance, but most of this can be confidently put down to the recentness of its introduction.

Fama and French (2018) also add a sixth factor into the five-factor model, creating the six-factor model by the means of adding the UMD_t momentum factor discussed before but note the similar performance that the two multi-factor models display. Therefore, coming to a conclusion that the meaningfulness of extending this five-factor model by the momentum factor is still something that needs to be researched further and hence a similar large difference as was seen between the three-factor and the five-factor model is not present to justify a switch.

5.2.5 Summary

In this thesis the above four different factor models are used to analyze hedge fund performance on risk adjusted comparative terms. From the analysis of past literature on the field, the only widely used factor model not being included is the Fung and Hsieh seven-factor model. Fung and Hsieh (2004) themselves note that their model is the factor model of choice for most research papers within the field of hedge fund research.

The seven-factor model comprises different factors for the equities, bonds, credit, currency and commodities along with trend-following factors as is summarized by Sun et al. (2012). The model is also utilized by Agarwal et al. (2018) as one of the multiple models that they employ and Fung and Hsieh (2004) note how well the model is able to capture the risk-factors that are most commonly present in hedge fund portfolios.

While the model is proven to be functional and widely used, it is not chosen for the purpose of our research as the data that we are operating with is only comprised of hedge funds trading U.S. equities. Therefore, using a model based on different so-called asset styles would not be beneficial as only equities are of focus. As such using factor models for pricing U.S. equities is the only reasonable course of action and the most common, proven and widely used such models are selected for this study.

For understanding performance, the alpha of each factor model is naturally being used. Jensen (1968) details this by showing that the actual forecasting ability of a fund is marked by positive alphas while negative values for the alpha coefficient are given by underperforming funds. Additionally, he notes that the alpha shows the true value added by the fund manager and is a comparative performance figure as all returns are run through the same risk factor models.

Jensen (1968) also remarks that positive alphas can come from both correct forecasts of the price of individual stocks or of the market as a whole. While alphas can be both positive and negative, also their size is of importance as this denotes how big of a portion of their capital the fund in question has allocated towards their estimates, implicitly revealing the level of confidence that these funds place on their own forecasts.

6 Empirical results

After discussing both the data being used and the methodologies being employed in the previous chapter, now the results of using these methodologies on the data are uncovered. Firstly, the factor models are being employed as per hedge fund trading style on the first stage and then additional tests for the persistence of our results are being carried out. Furthermore, tests are being done for the correlation between the different equally weighted hedge fund trading style portfolios and as such the seemingly unrelated regressions framework is being used and the alphas amongst portfolios are being compared.

While carrying out our methodology using the discussed factor models, the analysis of persistence of the results we obtain is especially important. Sun et al. (2012) highlight this importance by noting the varying evidence of hedge fund performance persistence. Agarwal and Naik (2000) for one are able to uncover performance persistence with quarterly horizons while Edwards and Caglayan (2001) note the same but for a yearly outlook. Malkiel and Saha (2005) especially uncover how the best performing funds continue their outperformance and Jagannathan et al. (2010) note the same for longer timeframes. For an opposing view, Agarwal et al. (2018) for one are not able to find persistence in performance when it comes to the hedge funds in their sample.

Capocci and Hübner (2004) note the importance of performance persistence also from the point of view of individual fund managers as they detail the substantially higher attrition rates that hedge funds experience compared to their mutual fund counterparts. In such cases being able to show persistence and stability in performance would be especially important as investors chasing returns might quickly lead to notable drawdowns.

The second additional aspect to consider for the interpretation of our results is the correlation amongst the different trading style portfolios of hedge funds. Asness et al. (2001) uncover in their research paper that certain hedge fund indexes suffer from serial correlation and Getmansky et al. (2004) note the same positive autocorrelation when it comes to the returns of individual hedge funds. Similarly, Liew and French (2005) are able to demonstrate the positive serial correlation amongst hedge fund returns.

Hwang et al. (2017) and Liew and French (2005) also detail this autocorrelation further by uncovering more the possible reasons for such characteristics within the hedge fund performance data. Hwang et al. (2017) firstly note the trading strategies of hedge funds which sometimes involve the usage of illiquid securities and they also detail possible return smoothing, which averages out the performance data for funds. Liew and French (2005) accordingly note the possibility of return smoothing, alongside survivorship and backfill bias as the main reasons.

As discussed in the previous chapter, survivorship bias is not present within the dataset as both currently live and liquidated funds are included within the sample. The effects of backfilling of return data detailed by Fung and Hsieh (2000) and Aggarwal and Jorion (2009), causing backfill bias, is also considered negligible as detailed before. The case for return smoothing is not as likely as all our funds trade equities and most of these are publicly traded and as such the valuations for their worth are also determined within the marketplace. Nonetheless, certainly a wide variety of equity strategies and sub-strategies are present, and this possibility cannot be fully ruled out. Also, the usage of illiquid securities is just as likely and therefore the case for taking into account the serial correlation is also to be made.

As such, in addition to the methodology discussed in the previous chapter, also the persistence of these results and the possible serial correlation amongst our trading style portfolios need to be accounted for during the interpretation of our final results. With these additional factors taken into consideration, one can expect our results to be robust both in terms of the methodologies and the results obtained.

6.1 Hedge fund performance

The first step in gathering our empirical results is to run the four different equally weighted hedge fund trading style portfolios consisting of net performance figures through our four different multi-factor models. The results from the CAPM can be seen from table 4, with *, ** and *** showing significance at a 10%, 5% and 1% level respectively, as is the case for all the following tables.

Table 4. Performance measurement CAPM.

Hedge fund trading style	Panel A: CAPM (single index model)		
	Alpha	Mkt	R_2^{adj}
AIML	0,79%***	0,19***	0,13
Systematic	0,07%	0,46***	0,79
Systematic & Discretionary	0,12%	0,60***	0,89
Discretionary	0,23%***	0,60***	0,88

The main findings to note are that both AIML hedge funds and discretionary funds have statistically significant alphas at the one percent level, but that the level of overperformance shown by AIML funds is much greater. The market factor is also significant at a one percent level, but this applies to all the different portfolios within the sample. Discretionary and funds combining both the systematic and discretionary approach can be seen as having identical exposures towards the market factor which can be reflected upon by observing both the figures 3 and 4 seen in the previous chapter where their returns appear to practically move in tandem. The last column showing the adjusted coefficient of determination shows reasonable fit for the three last portfolios, but it seems that the returns of AIML funds cannot really be explained by the model.

Titman and Tiu (2011) are able to uncover in their research paper that funds displaying low R-squared values showcase higher ratios for the alpha coefficient and also show higher Sharpe-ratios in their calculations. Additionally, they note that these funds exhibit better overall performance.

As such two different findings can already be noted based on our results. Firstly, the usage of our factor models is justified as far as the market factor is concerned, which in term shows that the funds in our sample are truly focused on U.S. equities as is shown by the high adjusted R-squared value. Second, AIML funds are less exposed against the market factor and as such are not as well explained by the model. They showcase strong overperformance and as was interpreted by Titman and Tiu (2011), higher Sharpe ratios and overall performance, which is also mirrored in figures 4 and 5 of the previous chapter.

Table 5 shows the results of the Fama and French three-factor model based on our portfolio of funds. Here the results for the alphas and the market factor are pretty close to identical with the results obtained from the CAPM, but now it can be seen that funds using both the systematic and discretionary methodologies have statistically significant performance figures, albeit at a ten percent level of significance.

Table 5. Performance measurement Fama and French three-factor model.

Hedge fund trading style	Panel B: Fama and French three-factor model				
	Alpha	Mkt	SMB	HML	R_2^{adj}
AIML	0,74%***	0,18***	0,11	-0,10	0,14
Systematic	0,02%	0,48***	0,02	-0,08***	0,80
Systematic & Discretionary	0,13%*	0,56***	0,17***	0,01	0,90
Discretionary	0,24%***	0,55***	0,29***	0,00	0,92

The adjusted R-squared values are also fairly consistent, but when observing the two additional factors, some findings can be made. All funds show a positive exposure against the size factor meaning that they invest slightly more in small stocks, but only the discretionary and combined funds show statistical significance. On the book-to-market equity side the exposures are split amongst the funds, but only systematic funds show significance in results, showing that they invest slightly more in stocks of low book-to-market equity firms.

Table 6 shows the results from the comparative performance measurements using the Carhart four-factor model and again the results in the first three columns along with the R-squared values are similar to the tables analyzed before. The main difference being the additional significance for the alpha that the combined funds using both the systematic and discretionary approaches are able to obtain. The book-to-market equity factor stops showing significance for any fund style, but the additional momentum factor shows significance at one percent for the discretionary and combined funds but reduces to five percent for systematic funds.

Table 6. Performance measurement with Carhart four-factor model.

Hedge fund trading style	Panel C: Carhart four-factor model					
	Alpha	Mkt	SMB	HML	UMD	R_2^{adj}
AIML	0,74%***	0,18***	0,11	-0,10	-0,01	0,13
Systematic	0,02%	0,49***	0,02	-0,05	0,05**	0,81
Systematic & Discretionary	0,14%**	0,54***	0,17***	-0,03	-0,06***	0,91
Discretionary	0,24%***	0,54***	0,28***	-0,03	-0,04***	0,92

Discretionary and combined funds exhibit negative exposure towards the momentum factor, meaning that they invest in stocks with the lowest performance. Interestingly, systematic funds on the other hand are investing in the highest performing stocks. Again, the AIML funds are not showing statistically significant exposure to any of the common risk factors added to the models so far, besides the market factor.

Table 7 shows the results of the performance analysis using the Fama and French five-factor model and the results are rather interesting. Firstly, the first three columns are again fairly identical to the results seen in the four-factor model, but AIML funds can be seen to be reaching identical levels of the alpha coefficient as was the case when using the CAPM. For the book-to-market equity factor systematic funds are again showing statistical significance similar to the three-factor model, albeit at a five percent level.

Table 7. Performance measurement with Fama and French five-factor model.

Hedge fund trading style	Panel D: Fama and French five-factor model						
	Alpha	Mkt	SMB	HML	RMW	CMA	R_2^{adj}
AIML	0,79%***	0,16***	0,12	-0,05	-0,02	-0,22*	0,14
Systematic	0,04%	0,47***	0,01	-0,08**	-0,04	-0,02	0,80
Systematic & Discretionary	0,16%**	0,55***	0,17***	0,00	-0,05	-0,04	0,90
Discretionary	0,28%***	0,53***	0,27***	-0,02	-0,11**	-0,09*	0,93

The robustness of profitability factor is showing statistically significant negative exposure against discretionary funds, meaning that these funds invest more in stocks with weak profitability and the aggressiveness of investing factor is showing statistically significant negative exposure against both the AIML and discretionary funds, meaning that they invest more in high investing aggressive stocks. It is also to be noted that all funds exhibit negative exposure against both of the added factors, even if statistical significance is only seen for the ones discussed above.

Now that the results of all the factor models have been analyzed and the first stage of the performance comparison is done, some overall observations can be seen. Firstly, all funds invest in high beta aggressive stocks as they all show positive statistical significance at the one percent level against the market factor. Additionally, the justification of the usage of factor models used for pricing U.S. equities for the purpose of performance comparison for our sample of hedge funds is further reinforced as both the market factor and the adjusted R-squared remain strong throughout the models, albeit the low R-squared value for AIML funds. This again shows that our sample of funds is truly focused on U.S. equities. The second main finding is that AIML funds do not show any meaningful additional values for the R-squared as factors are added, meaning that their returns are driven by factors that are unexplained by these models.

The values of the alphas are fairly stable and especially AIML and discretionary funds can already be seen as showing persistence across the factor models. AIML funds only show significant exposure against the aggressiveness of investing factor but otherwise the models do not help to uncover where this clear overperformance is originating from, besides the market factor.

Now that the results from the factor models have been analyzed, our attention turns next into the time varying evolution of the beta coefficients per factors that are present in our factor models. For this purpose, the Fama and French six-factor model is used as it contains all the individual factors that are present in each of our four distinct factor models used before.

$$R_t - R_{Ft} = \alpha + \beta_1(R_{Mt} - R_{Ft}) + \beta_2 SMB_t + \beta_3 HML_t + \beta_4 RMW_t + \beta_5 CMA_t + \beta_6 UMD_t + \varepsilon_t \quad (5)$$

where t = 1, 2, …, t

As discussed earlier only the UMD_t factor from the Carhart four-factor model is added to the Fama and French five-factor model to create this six-factor model. Then the variation across time per the six beta components visible in the equation above are estimated for each trading style portfolio by running year-on-year regressions using the six-factor model.

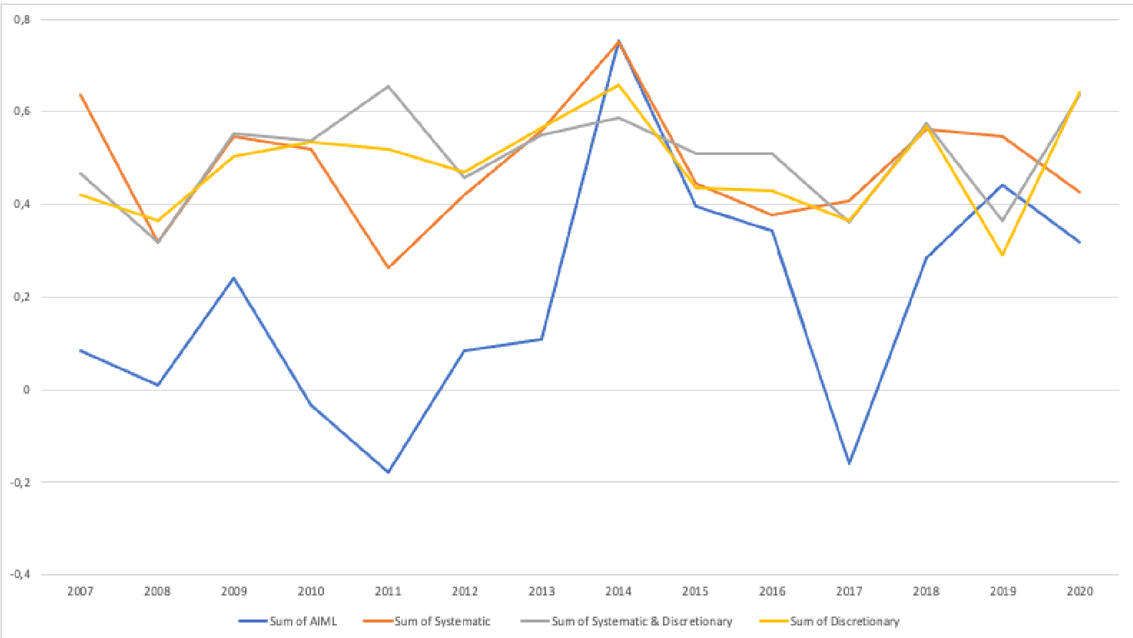

Figure 11. Time-varying MKT-factor.

Figure 11 shows the time variation of the market factor for each of our four portfolios. From the figure one can firstly see the similarity of the discretionary, systematic and combined funds, all of which show slight time wise variation, but staying constantly positive and on the side of high beta aggressive stocks. Secondly one can observe the very different type of behavior shown by AIML funds which greatly vary their exposures and also switch to mostly defensive low beta stocks on two occasions during the sample period.

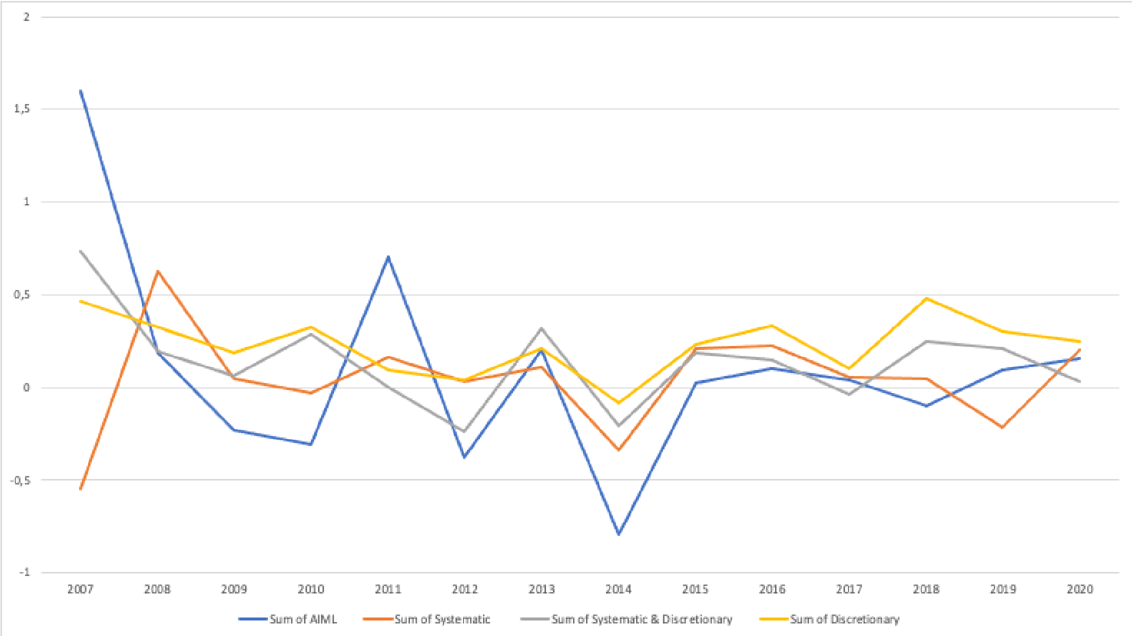

Figure 12. Time-varying SMB-factor.

Figure 12 shows the same methodology being done but this time in regard to the size factor. Here the main findings to note are the variation of the exposure of all funds, which go from positive to negative depending on the year and also the large discrepancy between AIML and systematic funds at the beginning of the sample. On the whole when excluding AIML funds, the rest of the funds show similar time-variation towards the size factor and large movements are uncommon. Again, AIML funds can be seen as standing out from the rest in their quick adaptation towards different exposures of size and also by their different levels of these exposures in the beginning of the sample. It is to be noted as well that towards the end of the sample period all fund styles show similar smooth variation when it comes to their exposures.

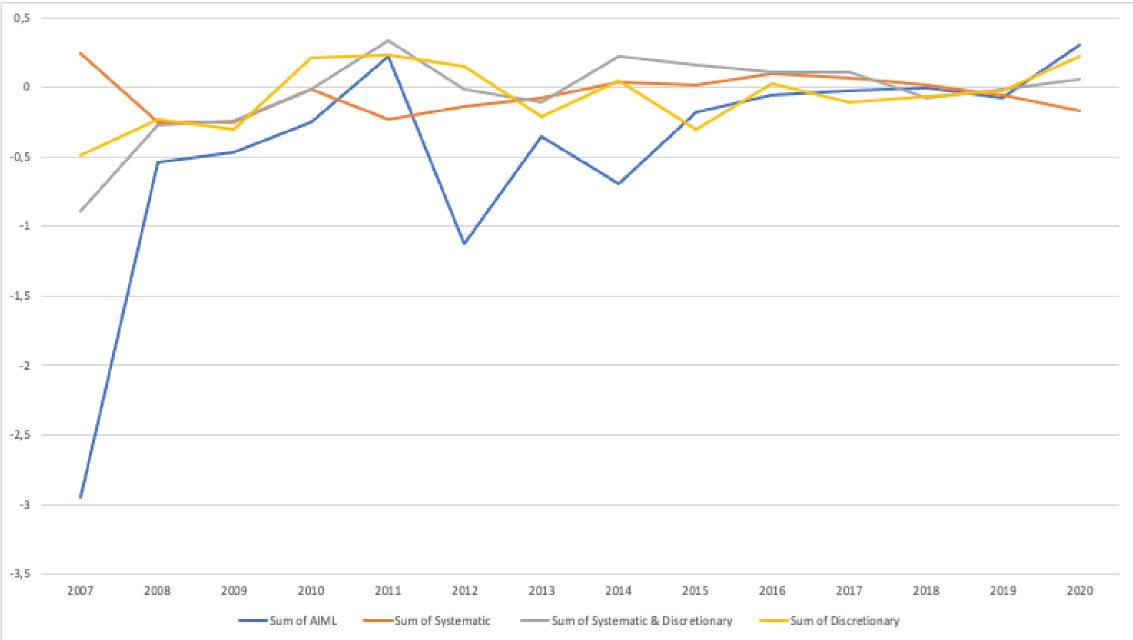

Figure 13. Time-varying HML-factor.

Figure 13 shows the time variation against the book-to-market equity factor and here especially the extremely negative beginning value of AIML funds draws attention. Also, the other fund styles exhibit great similarity for the factor in question. AIML funds on the other hand showcase far greater variation in their exposures and this is especially apparent towards the middle of the sample period. Here it is interesting to note that exposures are varied not in opposing directions as was the case for the size factor, but in overall strength as the exposure towards the book-to-market equity remains negative for most of the sample.

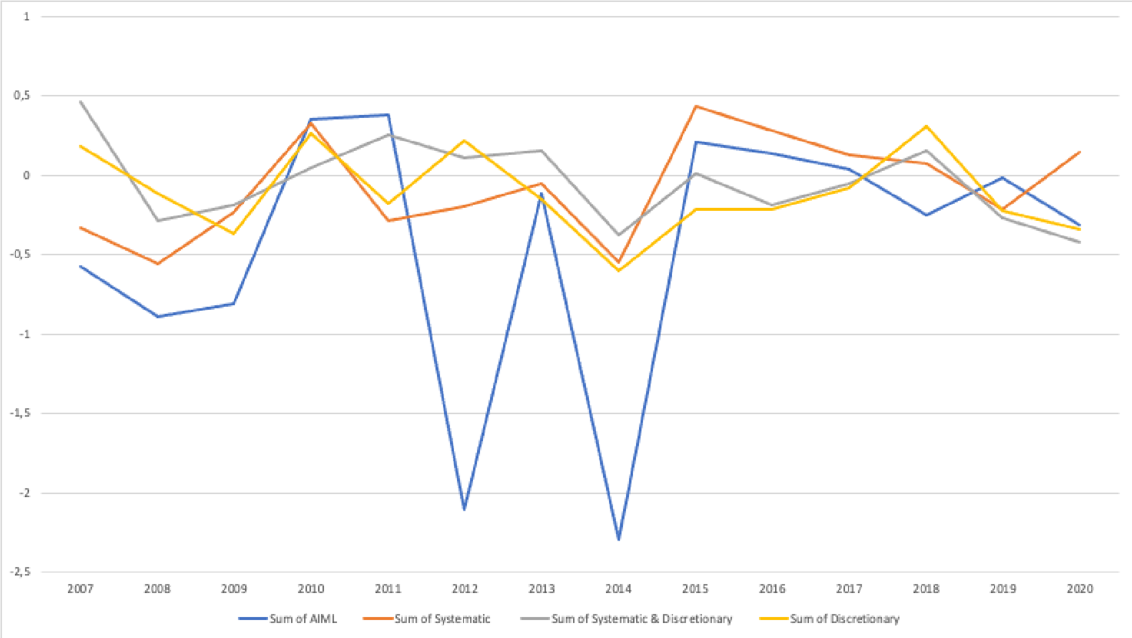

Figure 14. Time-varying RMW-factor.

Figure 14 displays the time varying exposures of the portfolios of funds against the robustness of profitability factor. This figure shows very interesting developments as both at the beginning and at the end of the sample AIML funds behave similarly towards the other funds, but during the middle of the sample period very negative exposures are taken against the factor. Here the other funds are again experiencing similar developments amongst each other but AIML funds can be seen as adapting at an extreme pace in their exposures. While other funds vary between +0.5 and – 0.5 exposures, AIML funds are able to take on notably larger exposures even if the overall direction is the same.

Figure 15 shows the variation faced by the aggressiveness of investing factor and here the strength of the varying exposures can be seen as being somewhat similar between AIML funds and funds of other trading styles. While the exposures revolve around positive and negative values throughout the sample, especially in the beginning AIML funds take on a more conservative exposure near zero while the other funds, systematic and combined funds in particular, take on very negative values.

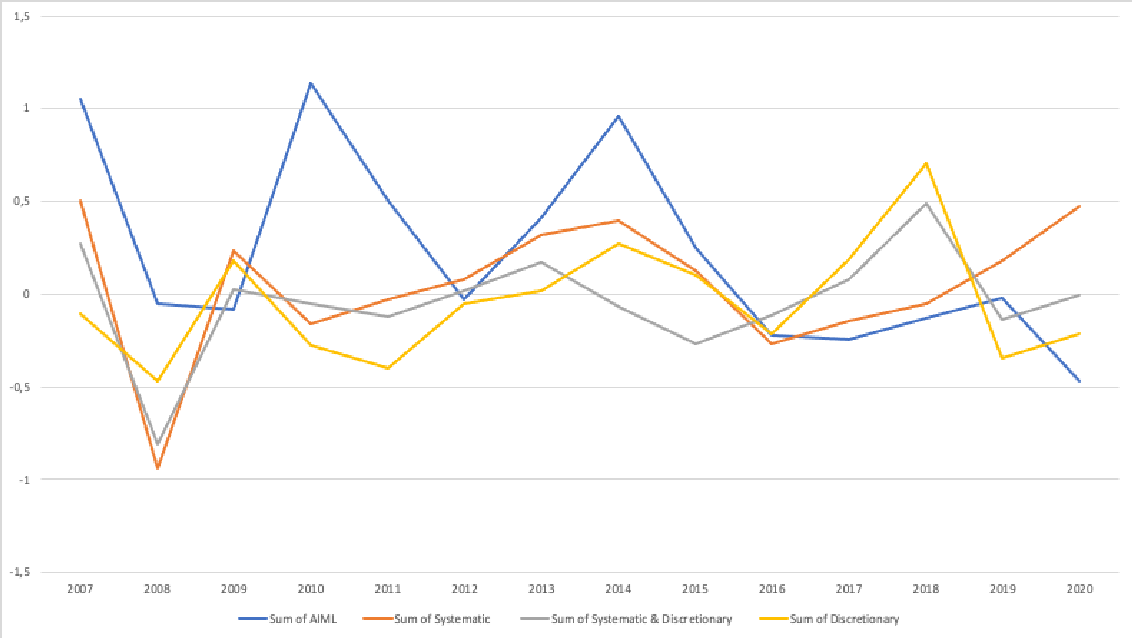

Figure 15. Time-varying CMA-factor.

From the figure we can also see discretionary and combined funds taking on a rather sharp positive exposure towards the end of the sample and again AIML funds keep their exposures closer to zero. It is closer to the mid-point of the sample period where the very quick adaptations made by AIML funds come to be seen. Again, exposures are very quickly varied between positive and zero on several occasions, meaning that AIML funds take positions on low investing conservative stocks very quickly and then vary their outlook during the next period.

Figure 16 shows the final factor that is part of the factor models used for this thesis, the momentum factor. When observing its time variation in terms of AIML funds, it can be seen as being rather similar towards the robustness of profitability factor. While AIML funds exhibit very positive values at the beginning of the sample, overall they remain similar to the other trading style funds in the beginning and end of the sample. In the middle of the sample period, AIML funds are seen as rapidly changing their exposures between positive and negative and attaining large exposures in doing so.

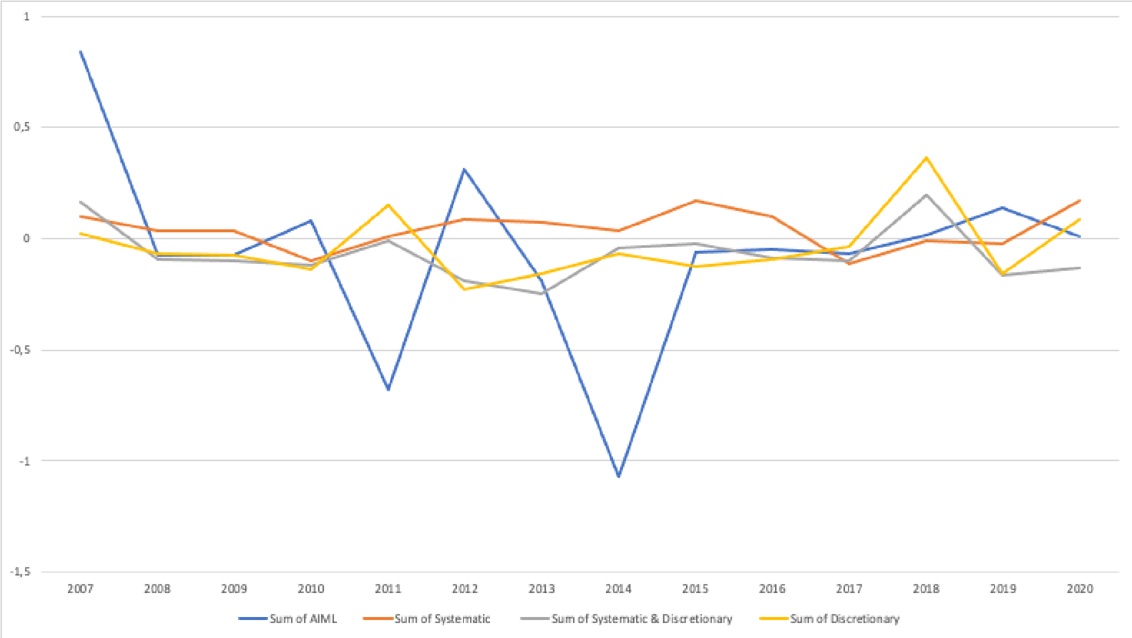

Figure 16. Time-varying UMD-factor.

AIML funds are therefore more aggressively taking on positions on the highest and lowest performing stocks while the other trading style funds keep their exposures very close to zero throughout the sample. It is especially interesting to see how AIML funds display such extreme movements during some periods and then settle on similar smooth evolutions of exposures during the next and almost mirror the movements of the other funds. It is similarly interesting to see how closely related the other funds are towards the momentum factor as they take on almost no exposure.

All in all, multiple findings can be made from the analysis of the time-variation of the beta coefficients that are used in our factor models. While the statistical significance of these variations is to be kept in mind, the analysis of the overall changes shows that firstly, the systematic, discretionary and combined funds take on very similar exposures for each of the factors in question and secondly, AIML funds take on exposures that differ greatly from the rest of the group.

AIML funds rarely show the smooth incremental changes in exposures that the other funds are able to demonstrate and instead they take on rapid changes in exposures both size-wise and direction-wise. Thus, one could say that AIML funds are both better and quicker at adapting and are therefore able to show the overperformance that we have seen so far. While this is still not statistically proven, the clear finding from observing the time-variation of these exposures is the fact that AIML funds are very different compared to the other trading style funds in the sample and this is a very likely reason for the overperformance that they are able to show across the factor models that we previously analyzed.

6.2 Hedge fund performance persistence

The performance of hedge funds has now been analyzed in great detail in regard to their level of automation and hence different trading styles. Additionally, their time-varying exposures towards the factors used to evaluate this performance are uncovered. Our attention now turns to the persistence of the results that we've obtained in our performance analysis. As we noted in the beginning of the chapter in addition to using factor models to render the performance in comparative terms, one also needs to take into account the persistence of said performance.

Using the split sample test methodology, we are able to uncover whether the results we have seen so far also stand when observing different subperiods. As our sample of fund returns for each trading style portfolio is 173 monthly observations, starting from September 2006 until January 2021, we split these observations into two groups of relatively equal size of 88 monthly observations from September 2006 until December 2013 and 85 monthly observations from January 2014 until January 2021. Then we run the same factor models as per methodology in the previous subchapter and do so for both of the two subperiods in question, hence uncovering possible persistence in our results.

Table 8 shows the CAPM model applied per each of our trading style portfolios and per each of our two subperiods.

Table 8. Performance persistence CAPM.

Hedge fund trading style	1 subperiod			2 subperiod		
	Panel A: CAPM (single index model)			Panel B: CAPM (single index model)		
	Alpha	Mkt	R_{2}^{adj}	Alpha	Mkt	R_{2}^{adj}
AIML	1,17%***	0,06	0,00	0,30%**	0,36***	0,59
Systematic	0,06%	0,50***	0,79	0,09%	0,42***	0,82
Systematic & Discretionary	0,31%***	0,57***	0,89	-0,09%	0,63***	0,89
Discretionary	0,44%***	0,57***	0,89	-0,01%	0,65***	0,88

From the results we can see that AIML funds are able to obtain statistically significant positive alphas at a one percent level of significance and the same is true for the second subperiod, but for a five percent level of significance. Additionally, the scale of the alpha is reduced but it is still of a meaningful size, beating the results of all other funds when considering our performance analysis in the previous subchapter. In the case of AIML funds it is also interesting to see how the adjusted R-squared value climbs substantially during the second subperiod while the alpha stays simultaneously significant.

When looking at the alphas of the other trading style portfolios, it is interesting to note that none are significant during the second subperiod. This is a result that can be seen as mirroring those found by some earlier research paper discussed before where especially the persistence of hedge fund performance is of importance due to evidence of its disappearance.

Table 9 displays the results of a similar type of analysis, but this time using the Fama and French three-factor model for analyzing the performance per each subsample. The results are again fairly similar, and it can be seen that only AIML funds are able to demonstrate statistically significant performance also in the second subsample.

Table 9. Performance persistence Fama and French three-factor model.

Hedge fund trading style	1 subperiod					2 subperiod				
	Panel C: Fama and French three-factor model					Panel D: Fama and French three-factor model				
	Alpha	Mkt	SMB	HML	R_2^{adj}	Alpha	Mkt	SMB	HML	R_2^{adj}
AIML	1,09%***	0,11*	0,00	-0,22*	0,02	0,34%**	0,33***	0,12**	0,02	0,60
Systematic	0,00%	0,52***	0,07	-0,16***	0,81	0,06%	0,43***	-0,01	-0,04	0,82
Systematic & Discretionary	0,27%***	0,57***	0,14***	-0,09**	0,90	0,00%	0,58***	0,17***	0,09***	0,92
Discretionary	0,39%***	0,54***	0,26***	-0,07**	0,92	0,08%	0,58***	0,28***	0,05*	0,94

Again, while discretionary funds and funds combining both approaches are able to show statistically strong alphas at a one percent level of significance during the first subsample, this outperformance completely disappears in the second subsample. Also, interesting to note is how systematic funds are unable to show almost any type of performance both in terms of the coefficient values for the alpha and in terms of significance.

Table 10 shows our performance persistence analysis using the Carhart four-factor model. The results in terms of alphas are almost fully identical when compared to the three-factor model and again only AIML funds are able to showcase both better performance in the first subperiod and performance persistence with statistically significant alphas also in the second subperiod.

Table 10. Performance persistence Carhart four-factor model.

Hedge fund trading style	1 subperiod						2 subperiod					
	Panel E: Carhart four-factor model						Panel F: Carhart four-factor model					
	Alpha	Mkt	SMB	HML	UMD	R_2^{adj}	Alpha	Mkt	SMB	HML	UMD	R_2^{adj}
AIML	1,09%***	0,11	0,00	-0,22*	-0,01	0,01	0,34%**	0,33***	0,12**	0,01	-0,01	0,60
Systematic	0,00%	0,53***	0,07	-0,14**	0,03	0,81	0,04%	0,46***	0,00	0,03	0,11***	0,84
Systematic & Discretionary	0,27%***	0,55***	0,14***	-0,12***	-0,05***	0,91	0,02%	0,56***	0,16***	0,04	-0,08***	0,93
Discretionary	0,38%***	0,53***	0,26***	-0,11***	-0,05**	0,92	0,08%	0,58***	0,28***	0,03	-0,03	0,94

Table 11 demonstrates the results of the performance persistence analysis using the Fama and French five-factor model. As we can see the results are again very similar to the ones seen in the persistence analysis using all our other factor models. AIML funds are the only ones showing statistically significant alphas during both subperiods and the alphas for both the discretionary and combined funds are not persistent. It is also interesting to note that for both subperiods the level of overperformance for AIML funds is the strongest when using the five-factor model, while the R-squared value is also the highest.

Table 11. Performance persistence Fama and French five-factor model.

Hedge fund trading style	1 subperiod							2 subperiod						
	Panel G: Fama and French five-factor model							Panel H: Fama and French five-factor model						
	Alpha	Mkt	SMB	HML	RMW	CMA	R_2^{adj}	Alpha	Mkt	SMB	HML	RMW	CMA	R_2^{adj}
AIML	1,29%***	0,05	0,00	-0,22	-0,35	-0,14	0,03	0,37%**	0,31***	0,08	0,10	-0,15	-0,27**	0,64
Systematic	0,09%	0,49***	0,07	-0,14**	-0,13	-0,13	0,81	0,06%	0,43***	0,01	-0,05	0,07	0,03	0,81
Systematic & Discretionary	0,34%***	0,55***	0,14***	-0,09*	-0,11	-0,10	0,91	0,01%	0,59***	0,13***	0,08**	-0,14**	-0,01	0,93
Discretionary	0,51%***	0,50***	0,24***	-0,12***	-0,25***	-0,06	0,93	0,10%	0,57***	0,25***	0,06*	-0,14***	-0,12**	0,95

Overall the performance persistence analysis brings forth some compelling results. Firstly, the R-squared value either increases or stays the same for all funds during the second subperiod. This is especially notable for AIML funds, but it can be seen that also the trading styles that are well explained by the factor models in question are able to improve their coefficients of determination to some degrees. The second main finding is that similarly to our performance analysis, systematic funds are unable to show performance during the full sample, let alone any subperiod, and more worryingly the values for the alphas are also the smallest of any trading styles while not even being statistically significant at any reasonable level.

The third main finding is the fact that while funds combining both the systematic and discretionary trading styles and especially discretionary funds show statistically significant alphas in all or most of the factor models used for the performance analysis, neither of these funds is able to show performance persistence by the means of the second subperiod for any of the factor models. Therefore, for these funds we can see that their performance is indeed significant, but in the end not of persistent nature.

The fourth and last main finding based on the performance persistence analysis is naturally the great performance and the persistence of said performance for AIML funds. These funds are able to show statistically significant and clearly positive coefficients for the alphas in both the performance analysis section along with this further analysis on performance persistence.

Therefore, based on the results seen so far it can already be seen that AIML funds are able to obtain alphas after controlling for the returns through the factor models and the persistence of these returns is in line with the literature supporting hedge fund performance persistence. AIML funds are able to provide clear excess returns for their investors and more importantly this is something that stands the test of time as we have seen in the subperiod analysis. Still before the final case for AIML funds being superior to the other trading style funds included in this thesis can be declared, one also needs to account for the possible autocorrelation amongst hedge funds returns as was noted before.

6.3 Multiple equation models

As we have seen, hedge fund returns often showcase serial correlation amongst funds, which would in term render the results of our earlier factor models both biased and inconsistent. In order to handle such issues and to prove that the results we have obtained so far are valid, the seemingly unrelated regressions framework is to be used. But first we want to observe whether there truly is positive serial correlation amongst our hedge fund trading style portfolios.

Table 12 show the correlation between our different hedge fund portfolios and it becomes immediately apparent that some level of correlation between the portfolios is present. Firstly, all the coefficients are statistically significant at a one percent level of significance and secondly, all the coefficients show positive values, showing positive serial correlation.

Table 12. Correlation between different trading style portfolios.

Hedge fund trading style	AIML	Systematic	Sys& Disc	Discretionary
AIML	1,00			
Systematic	0,42***	1,00		
Systematic & Discretionary	0,43***	0,97***	1,00	
Discretionary	0,34***	0,84***	0,85***	1,00

From the table it can also be seen that as we’ve noted throughout our analysis so far, the similarities between discretionary, systematic and the combined funds using both styles are more than just coincidence, as the three show high levels of correlation, with especially the systematic and the combined funds being very closely correlated in terms of returns.

Interestingly, also matching the findings we've noted so far, AIML funds are far less correlated to the rest of the hedge fund portfolios, displaying only around half the values that the other fund types are showing. Therefore, the case for the unique nature of AIML funds can again be made. But the results from the table also mean that the seemingly unrelated regressions methodology needs to be employed.

Table 13 shows the results from the seemingly unrelated regressions using the Fama and French six-factor model and when observing the values for the alphas, it can be seen that the results are closely mirroring the ones originally obtained in our performance analysis. AIML funds are again able to display great statistically significant outperformance even after accounting for positive serial correlation between the different trading style portfolios and similarly the discretionary and the combined funds are able to display significant alphas as before. But as we already noted in the performance persistence analysis, these significant alphas were not persistent and therefore the results are not that meaningful anymore at this point.

Table 13. Seemingly unrelated regression.

Hedge fund trading style	Alpha	Mkt	SMB	HML	RMW	CMA	UMD
AIML	0,79%***	0,16***	0,12	-0,05	-0,02	-0,22*	0,00
Systematic	0,03%	0,48***	0,02	-0,04	-0,03	-0,04	0,05***
Systematic & Discretionary	0,16%**	0,54***	0,16***	-0,05	-0,05	-0,02	-0,06***
Discretionary	0,28%***	0,52***	0,27***	-0,05*	-0,11***	-0,07	-0,04**

So far, we have been able to prove that AIML funds have better performance, this performance is statistically significant, they are able to show significant performance persistence and to show significant performance even after controlling for autocorrelation between the other portfolios. Therefore, only one more step in our empirical methodology remains, which is the comparison of AIML alphas against the alphas of the other trading style portfolios, by the means of the Wald coefficient test.

Table 14 shows the results for the Wald coefficient test based on the seemingly unrelated regressions analysis. When controlling for autocorrelation and comparing the alpha of AIML funds against the other hedge fund portfolios, it can be seen that AIML funds show very clear outperformance that is statistically significant at a one percent level of significance. The coefficient values of the alphas are clearly positive, and this is across all of our other hedge fund portfolios.

Table 14. Wald coefficient test.

Hedge fund trading style	Systematic Alpha	Systematic & Discretionary Alpha	Discretionary Alpha
AIML Alpha	0,75%***	0,63%***	0,51%***
Chi-square	(15,25)	(13,90)	(8,62)

AIML funds are able to obtain significant alphas that beat all the other trading style portfolios used in this thesis. Our original null hypothesis was that AIML hedge funds do not outperform conventional funds and based on the results from Table 14 we can confidently reject our null hypothesis and accept our alternative hypothesis that AIML hedge funds are truly able to outperform hedge funds of conventional trading styles.

6.4 Summary of the results

Based on our empirical results, the following summary can be made. Firstly, in the analysis of performance per trading style portfolio, AIML funds and discretionary funds are able to show performance in terms of significant alphas for all of our chosen factor models. As more factors are added also the funds using a combined systematic and discretionary approach are able to obtain statistically significant performance figures. Based on our results we can see that systematic funds are unable to obtain any significant alphas in any of our factor models.

When we analyze the persistence of these performance figures using two different subperiods as a split sample test, we can see that the statistically significant performance exhibited by both the discretionary and the combined funds becomes insignificant during the second subperiod. In the case of AIML funds the same cannot be said, as these funds are able to display statistically significant performance during both subsamples in all of the factor models employed.

When we carry out an analysis into the correlation between our hedge fund trading style portfolios, we can see that varying levels of positive serial correlation are present. This in term requires us to carry out an additional analysis using the seemingly unrelated regressions framework which shows that AIML funds are still able to display statistically significant positive alphas of the same level as with our performance analysis, when accounting for this autocorrelation.

Lastly, the Wald-coefficient test based on the seemingly unrelated regressions shows the statistically significant differing alphas when compared to the alphas of our other hedge fund trading style portfolios. This in term leads us to accept our alternative hypothesis that AIML funds are able to outperform the other types of hedge funds under consideration. They exhibit better performance, this performance is persistent and this performance is statistically better than the performance of hedge funds using other types of trading styles. Thus, leading us to make the claim that using the latest AI technologies enables hedge funds to obtain better overall performance.

7 Conclusions

In this research paper we've been able to observe the different types of trading styles employed by hedge funds and to see whether the usage of AI is as beneficial in the field of asset management as it has been in other areas. We have conducted our analysis by the level of automation employed by our sample of hedge funds through sorting them based on their trading styles, from human-driven discretionary funds all the way to AI-driven AIML funds. By using the EMH and BF as our theoretical frameworks and by observing past literature we are able to observe hedge fund outperformance and conclude that this is in line with the EMH as the persistence of this performance remains disputed. Accordingly, the EMH does not rule out the existence of few persistent performers and the usage of EMH also helps us note the motivation for the existence of these active strategies and the rise of their passive counterparts.

The BF in term helps us to uncover the main differences amongst our different hedge fund trading styles and also shows what types of behavioral factors human fund managers are potentially affected by. As such the usage of this theory also helps in uncovering one key motivation for the development for these automated systems.

One could simplify the findings of EMH reflecting more the automated hedge fund trading styles and the BF as showcasing the more manual styles employed by hedge funds. This is due to the fact that trading algorithms and AI are inherently efficient and as we have detailed, they are not impacted by behavioral factors as opposed to human-driven trading styles.

The results obtained in this thesis are very meaningful as they open up interesting analysis in terms of the theories that have been used, the literature that has been reviewed, and the real-world implications that can be deducted. Additionally, the findings open interesting paths for future research.

As the main contribution by this thesis, we are able to see that the usage of AI technologies in terms of AIML funds is beneficial for hedge fund performance and we are able to observe that the performance of these funds is notably greater than the performance of the more conventional trading style funds. As such we reject our null hypothesis and accept our alternative hypothesis, showing that these funds are genuinely able to stand out from their peers in terms of performance.

When observing our findings from a theoretical point of view, we can see that while the strict forms of EMH rule out market beating excess performance, the more common way to understand the theory is the ruling out of persistent excess performance. Our results can be seen as mostly agreeing with this view, as none of the conventional trading style funds are able to show persistent performance. AIML funds on the other hand are able to display persistence in terms of performance, but as far as EMH is concerned one could hypothesize that as these funds are relatively new, small in terms of AUM when compared to conventional hedge funds and employing strategies that are very different both in terms of their foundations and exposures towards common risk-factors, they are able to find new and relatively small market dislocations and inefficiencies where they are able to obtain profits. AI models are also noted as being able to generate new forecasts and trading strategies on a consistent basis and as such it is not likely that they would only be pursuing the similar market inefficiency on a continuous basis. This is also proven by their widely varying risk factor exposures.

As such we can see that our findings do not violate the more common findings of EMH based on two main discoveries. Firstly, as these funds are small and go after opportunities that other market participants might not be able to observe, due to their advanced technologies, they do not overcrowd the abnormal opportunity based on both position size and competition. Therefore, they are likely able to use a market dislocation more persistently as long as it stays hidden and their fund size remains small. Secondly, these funds can be seen as dynamically shifting from one opportunity to another and therefore it can also be theorized that they simply maintain market efficiency.

As such, both of these findings would result in performance persistence and would also not violate the EMH, as they theory states that the opportunities for abnormal returns need to disappear which would also be the case in our findings. In terms of the BF frameworks our findings are interestingly able to show that while only AIML funds show persistent performance, discretionary funds perform well in all our factor models used for risk-adjusted performance measurements.

Therefore, it can be seen that standard algorithmic trading is not able to able to outperform, which from a behavioral point of view would then be noted as being due to their inability to learn and adapt as they follow their static rulesets. Combined funds on the other hand likely struggle with the deciding of when to intervene on the decisions of the algorithms and when to trust them, rendering them to have less in terms of returns when they are significant.

As such, the ability to adapt and showcase true skill can be seen as the key factor for outperformance as both discretionary and AIML funds perform well. But when it comes to both the size of the outperformance along with the persistence of said performance, on can hypothesize that here the negative aspects showcased by BF come to play. Different types of biases seem to limit the size of the return when discretionary funds are compared against their AIML counterparts and especially the lack of persistence of discretionary funds is interesting from a behavioral point of view. AIML funds are naturally not impacted by behavioral factors, but it can be seen that when discretionary funds obtain good outperformance, they are unable to maintain this level of success, which could be marked by factors such as overconfidence and anchoring where the managers start to showcase an inability to adapt as the market changes, believing that past sources of profits are still relevant. This in term would render the before mentioned advantages of discretionary funds in terms of adaptability and the ability to learn out of the equation, explaining our results.

AIML funds on the other funds are consistently able to maintain their ability to adapt, as they continuously learn and can also be periodically retrained. As this ability doesn't become biased overtime as can easily be the case for discretionary funds, they are able to show both outperformance and performance which remains persistent over time.

In regard to past literature in the field, our findings can be seen as both accepting and opposing the findings by other research papers. Carhart (1997) writes that after controlling for risk-factors, the returns of funds can be attributed to random factors and Jensen (1978) agrees that no outperformance can be present. Based on our findings we oppose to these views and acknowledge the findings by Kooli and Stetsyuk (2020) who show that an average hedge fund manager is able to beat the market. While systematic funds are unable to show any performance throughout our factor models this can be seen as agreeing with the findings by Chincarini (2014) as they note that systematic funds outperform in terms of macro strategies, but not in terms of equity strategies.

In regard to performance persistence, Agarwal et al. (2018) note this as being either mixed or nonexistent, but Agarwal and Naik (2000), Capocci and Hübner (2004) and Jagannathan et al. (2010) show that performance persistence is present within hedge fund returns. Edwards and Caglayan (2001) and Agarwal and Naik (2000) on the other hand only find performance persistence in short time-periods and research papers generally note that the evidence regarding this performance is rather mixed. Therefore, this is very much in line with our findings, as we also find mixed evidence of this performance persistence in terms of our trading style portfolios and additionally our view for measuring this persistence is very long, in line with findings that persistence can possibly only be seen within a short time-period. Additionally, Sun et al. (2012) show that unique trading strategies are the key for this performance persistence and as discussed, this can especially be the case when it comes to AIML funds, further explaining our findings. Similarly, Antweiler and Frank (2004) and Matias and Reboredo (2012) note AI as producing better forecasts and this can be seen by both our results and the size of the alphas obtained by AIML funds.

Harvey et al. (2017) also note that hedge funds do not often hedge their positions as they have meaningful statistically significant exposures against various risk factors. We can also note the same based on our analysis, but interestingly for AIML funds, no meaningful exposures can be found for factors other than the market factor and the aggressiveness of investing factor. As these exposures are not economically as meaningful as the alphas earned by these funds, we can determine that the returns by AIML funds are mostly driven by other factors and also hypothesize that AIML funds run a more hedged portfolio against these factors.

Finally, in the analysis of the economic implications of our results, some interesting findings can be deducted. Firstly, as for the meaningfulness of investing in hedge funds, this cannot truly be answered as these funds are on the most parts able to show outperformance and in regard to the persistence of this performance a long-term view was taken in this thesis. Hwang et al. (2017) on the other hand note that the median age for a hedge fund is only around 80 months, meaning that performance persistence might still be present within shorter timeframes.

AIML funds show strong outperformance throughout but from the viewpoints of both fund managers and investors, if AUM figures are grown and more capital is both invested and accepted within the funds, the ability of these funds to obtain a similar level of profit might quickly disappear. Furthermore, increased competition would also play a role. On the whole the main economic implication of the findings in this thesis can be noted as being the fact that using AI is able to further the profits of hedge funds, as AIML hedge funds can be seen as practically dominating the other fund types as they show higher general performance, this performance is the only persistent one, and their alphas are statistically greater than the alphas shown by conventional funds and economically meaningful.

As such, in terms of real-world implications of our findings it is to be expected that this trend of using AI models within hedge funds will only increase as more studies within the topic are published. As for the future research for the themes studied in this thesis, multiple different approaches can be noted.

This thesis is only concerned with hedge funds that invest in U.S. equities which is driven by both the noted significance of U.S. for the hedge fund industry and the equity strategies being seen as the most relevant one employed by hedge funds along with the usage of our factor models which are meant for pricing U.S. equities. As such a natural progression would be to take on a larger scope for any future research, without putting limits on asset types or geographies and then using the popular Fung Hsieh 7-factor model designed for the purposes of analyzing this unrestricted sample of hedge funds in general. Also, additional factors could be taken as part of the models used in this thesis.

Additionally, one could examine the impact of different strategies, and geographies individually, control for fund specific characteristics, observe what are the impacts if HFTs are taken as its own category separate from systematic and AIML funds and also whether examining AIML funds by their underlying trading style would yield different results. For AIML performance one could also research to what factors can this performance be attributed to and what is the main driver of said performance, for example are AIML funds able to time the market better similarly to systematic funds or are their models simply better at forecasting general directions?

Finally, it would also be interesting to see how the results of this thesis would change if an identical methodology would be applied after 5 to 10 years as the AIML hedge fund industry would likely be more mature and contain both more funds in general and funds with larger AUM.

As such we can conclude that AI usage within hedge funds will likely grow as their advantages become more well-known and established, and algorithm aversion and other behavioral factors shown by prospective investors slowly disappear. Still, the small size of AIML funds gives them the added ability to pursue these alternative methods and models more easily and perhaps the findings in our results can be put especially down to size and as such future growth is likely going to make both the persistence and the size of the returns of these models very different. Still it needs to be remembered that AI is a wide topic so various new methods are similarly likely discovered as competition increases. A lot remains to be seen and as always, the only thing that remains constant is change.

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Appendices

Appendix 1. List of funds

Due to licensing agreements with Preqin (2021a) this list is available by request only and therefore cannot be shared publicly.