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Evaluating the performance of European hedge funds in the period 2000-2020

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Abstract

This paper evaluates the performance of investment strategies of hedge funds domiciled in developed European countries over the past two decades through the use of several performance measurements. This research aims at providing a better understanding of the hedge fund industry, but also of this industry in the less-studied European countries. Through reviewing previous academic literature, questions are formulated regarding the alpha, beta and performance of multi-strategy hedge funds. Empirical analysis reveals that investment strategies in developed European countries show significantly different betas and alphas and the underperformance of multi-strategy funds and funds of hedge funds. Further data suggests that future studies should attempt to dissect to overperforming strategies that are defined as 'other'. The hedge fund industry is a mystic industry and further research should aim at demystifying it.

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1. Introduction

For a long time the stereotypical image of hedge funds has been one of financial cowboys, such as George Soros, that use unconventional investing strategies to achieve high returns with low risk. Soros, famously know as '*The man who broke the Bank of England*', betted against the pound sterling and accumulated himself a fortune. Another may immediately think of catastrophes like Long-Term Capital Management (LTCM). LTCM was raking in a return of more than 40% a year, at its highest point a total return of 300% in 4 years (Lowenstein, 2002, pp. xvi-xix). Accompanying these outstanding results was (seemingly) almost no risk. LTCM assumed, including the two Nobel laureates in economics M. Scholes and R. Merton, miniscule risks in the long-run which only held until it did not, notoriously collapsing. Even though both LTCM and Soros' Quantum fund were classified as hedge funds, their investment strategies differed to a great extent. These two funds are just examples of (in)famous hedge funds in a dynamic world of finance where the diversity between hedge funds defines its industry.

One of these diverse characteristics is the type of investments that hedge funds use to achieve their goal. Investment strategies differ between hedge funds in terms of how a fund would generate returns. An example is an event-driven strategy called 'Risk arbitrage' (sometimes called Merger arbitrage) where a fund aims to make profit off an announced merging of companies (Ineichen, 2003). The collection of investment strategies and their classifications is dynamic, changing over time and never inclusive of the strategies in a similarly-dynamic financial market. As Stefanini (2006) puts it:

"…hedge funds are no static universe, rather they are subject to constant change and expansion."

While hedge funds before the 1990s were mainly existing in the United States of America, the rapid spread in Europe began from the mid 90s (Athanassiou, 2009). As a result, the year 2007 came to an end with about $500 billion in Assets Under Management (AUM) and more than 1500 funds located in the European Union. Hedge fund data provider Eurekahedge (2020) reports that this increase stagnated in the last decade and as of May 2019 the AUM in the European hedge fund industry was totalled around $489.5 billion. Preqin (2017) observes a decreasing popularity of hedge funds among European institutional investors because of global concerns about the performance and fees of hedge funds.

Using the examples of Soros' Quantum Fund and John Meriwether's Long-Term Capital Management (LTCM) as 'stereotypical' hedge funds that first come to mind, we can also use them to underline the heterogeneity within the industry of hedge funds. Where both funds chased absolute returns, and absolute returns define hedge funds (Jaeger, 2003, pp. 1-3; Liang, 1999), their means to the end differed. The Quantum Fund was betting against macroeconomic trends to make money by shorting the British Pound and Italian Lira along with the use of leverage (Stefanini, 2006). LTCM's main operation was fixed income arbitrage, a relative value strategy that seeks profit from arbitrage transactions between, for example, on-the-run and off-the-run bonds. The two funds differ significantly in their investment strategies, but their end goal ever was the same: absolute returns.

As there is a wide (dynamic) scale of used investment strategies that a hedge fund can apply in their quest for returns, questions arise for fund managers which applied strategy performs best. The answer to this question likely becomes a subjective matter with regards to the definition of 'best', as risk is a significant part of this question. Academic research in this field is limited, usually focus on US data and renowned papers often stem from the late 90s to early 00s. Because of this, a question arises what one would find if this research is focused on European hedge fund data from the last two decades. Therefore, this paper searches an answer to the information gap that is covered by the question:

How do different investment strategies of developed European hedge funds perform in the period 2000 to 2020?

The quest for an answer to this research question aims at contributing to and supporting further studies regarding hedge fund performance in European countries. The academic gap also bears with it a relevancy to investors in terms of understanding the dynamic and difficult-to-comprehend industry. As stated, most available research on hedge funds appears to been conceived about two decades ago, which underlines the relevancy of the timespan in the question by performing a more recent study about this part of the world of finance.

This paper will be structured as follows: first a look will be given upon the context of the research question, followed by an analysis of available previous research. This literature review aims at providing a basic understanding of current knowledge about hedge funds and is followed by three sub-questions with relevant hypotheses. After this theoretical framework, the used data will briefly be described in order to conceive what information is worked with in the proceeding section that describes used methodology. Then, after presenting the results, an interpretation will be given in the discussion section. Finally, a conclusion will be laid out and is followed by the bibliography and appendices.

2. Theoretical framework

2.1 Hedge funds

The more regulated mutual funds are usually limited to long-only strategies and the first fund of this type dates back to the 18th century in the Netherlands (RouwenHorst, 2004). From the first mutual fund it would take almost two centuries until the first hedge fund would be created in 1949. The relative novelty of hedge funds combined with the dynamic characteristics of it creates a, for many, unknown area of investments area. So, what are hedge funds? And how did they come into being? Then, why did hedge funds start using different investment strategies? What different investment strategies are there? In order to provide a completer context of our research, these four questions will be answered.

2.1.1 What is a hedge fund?

An investment fund is a financial intermediary which raises money that it subsequently invests in financial assets. One form of such an investment fund is a mutual fund. Using the book *Principles of Corporate Finance* by Braeley et al. (2017) a description of mutual funds can be determined. According to them, a mutual fund pools money that is gathered from selling shares of that fund to investors. This pooled money is used by managers of the fund to buy a portfolio of securities. Mutual funds can specialize in different investments strategies, like ‘value stocks’, ‘high-tech growth stocks’ or particular countries. The management of such a fund usually charges a management fee in exchange for their services. Participating in a mutual fund is done through buying shares that the management is ready to issue and the fund is also ready to buy back their shares if one desires to exit, this is called *open-end*. The opposite is a *close-end* fund that issues a certain amount of shares at a given time, so the only way to participate in a close-end fund is to buy the share(s) from another shareholder.

Since the first hedged fund by Alfred W. Jones in 1949, a diverse collection of hedge funds have existed. Simply stating that a hedge fund is a fund that 'hedges' itself against the drops in the market does not justify the complexity of hedge funds. The widely cited article *On the Performance of Hedge Funds* by Bing Liang (1999) describes hedge funds as "private investment partnerships in which the general partners make substantial personal investments. These funds are allowed to take both long and short positions, to use leverage and derivatives, to invest in concentrated portfolios and to move quickly between various markets.".

In a consultation paper published in the proposal for the Alternative Investment Fund Managers and amending Directives (AIFMD) by the Commission of the European Communities for the European Parliament and Council, several questions regarding hedge funds were asked to European and Non-European organizations, professionals, citizens and authorities. In the first consulting question confirmation was sought if hedge funds can be effectively distinguished through the following:

"Hedge funds:

- focus on delivery of absolute returns;
- have a relatively high and systematic use of leverage;
- are confined to institutional or other sophisticated investors;
- are exempt from direct regulatory requirements."

This set of criteria was not agreed upon among the opinions as 79% of the responses expressed that hedge funds are too heterogenous to satisfy those criteria. The majority of this 79% mentioned that there are, in their eyes, other relevant criteria for hedge funds. An important concluding statement of the answers to this question concludes that the ever-evolving character of hedge funds would make any strict set of criteria to determine hedge funds outdated quickly.

As hedge funds are too diverse to define them by a certain set of strict criteria, the definition of these funds is wide, so all varieties of them are included. Agarwal & Naik (2004) explain that, opposite to mutual funds, hedge funds trail more dynamic investing strategies because of limited Securities and Exchange Commission regulation (in the United States of America). This means that those alternative investment vehicles, hedge funds, can use both long and short positions in combination with leverage to find positive returns. The more liberal investment strategies provide the market with exposure to the market that regular (long-only) funds cannot. Liang (1999) mentions how hedge funds align interests of managers and investors by imposing an incentive fee, usually related to realized profits/losses, that is not existent among mutual funds.

Filippo Stefanini, in his book *Investment Strategies of Hedge Funds* (2006), agrees that defining hedge funds as funds that use hedging strategies or subject them to a set of characteristics could be misleading because of the diversity of them. Stefanini rather uses the definition: “A hedge fund is an investment instrument that provides different risk/return profiles compared to traditional stocks and bond investments”. He continues to underscore that even this definition requires remarks, such as the use of (alternative) investment strategies, (alternative) styles of management, regulatory limitations and more differences between hedge funds and mutual funds. Combining Stefanini’s description and the one by Agarwal & Naik (2004), a more extensive, but not constraining, definition can be obtained. In this research hedge funds will be defined as pooled investment funds that aim at providing risk/return profiles that differ to traditional investment vehicles, by using dynamic and alternative investing strategies, such as the use of leverage, short positions, etc.

2.1.2 Brief review of hedge fund history

In 1949, an Australian man named Alfred Winslow Jones created the first ‘hedged’ fund. Jones and four friends created A.W. Jones & Co with an accumulated $100,000 to invest in stocks (Rappeport, 2007). Jones’ intuitively argued that by using leverage and a mixture of long- and short positions he could reduce portfolio risk and assemble a conservative portfolio, ‘hedging’ them against drops in stock prices (Stefanini, 2006). In order to convince other investors, Jones invested all his savings and his compensation for services would come from a 20% fee of performance. That means that he brought together the interests of investor and manager by incentivizing profits for the manager.

Alfres W. Jones' promising returns inspired many investors to start their own 'hedged' fund and Stefanini (2006) reports that by 1969, the US Securities and Exchange Commission (SEC) experienced difficulties keeping an overview of the market for hedged funds because of the rapid increase in numbers of them. At this point in time hedged funds managed about $1.5 billion in assets over 200 funds. According to Ineichen (2003) the so-called hedgers increased their long positions during the bull market of the 1960s. This resulted in a lack of short positions during the bear market that manifested itself in the early 1970s and, thus, putting many of the new hedge fund managers out of business. Until the 1990s hedge funds lacked the popularity it endured in the years before the bear markets of the early 70s. In 1992, however, the world regained attention for hedge funds as the Quantum Fund of George Soros made significant profits after famously shorting the British pound. Following this, the number of existing hedge funds kept rising and the variety of strategies widened.

The popularity of hedge funds resulted in a $1.93 trillion value of assets under management in 2008 (Herbst-Bayliss, 2011). The financial crisis of 2007 and 2008 decreased the popularity of the funds, but the funds quickly recovered. According to the Financial Times (2017) hedge funds totalled $3.1 trillion in AUM as of July 2017.

2.1.3 Investment strategies

When Alfred W. Jones brought his hedge fund to life in 1949 he aimed at increased returns while at the same time reducing net market exposure. Ineichen (2003) describes the hedge fund industry in the next three decades as being overwhelmingly dominated by the so-called 'Alfred Jones model'. Ineichen continues that in the 90s the industry 'became extremely heterogenous'. This meant that the long/short equity strategy of Alfred Jones was not a sufficient way to describe a hedge fund, as many other strategies were used by this time to generate absolute returns (Eichengreen & Mathieson, 1998) and the long-short equity strategy itself became a doming name of heterogenous strategies within this category. As Stefanini (2006) puts it: "The change in the weight of the various strategies over time reflects the ups and downs of their returns.", implying that proportions of used strategies between hedge funds are a result of historical good and bad times for each strategy.

What distinguishes hedge funds from long-only mutual funds is the usage of alternative investment strategies (Scharfman, 2020). Whereas a mutual fund usually is constrained, by regulation, to long-only investment strategies (i.e. acquiring an asset on the assumption the value will increase), hedge funds have a wider range of investment strategies to deploy in pursuit of returns. Defining this wide range of investment strategies, though, is difficult in an always-changing industry. This especially holds when one attempts to define strategies as narrowly as possible where it may come at the cost of the amount of observations. An example would be dividing directional trading into categories for emerging markets, geographical areas, etc. Stefanini (2006) classifies the heterogenous strategies in five major classes: Directional, Event Driven, Relative Value, Long/short equity and an overarching class Other strategies.

An example of such a class are relative value strategies that seek to profit from arbitrage between two securities. One of such an arbitrage transaction is a hedge fund that seeks to make a profit from the difference in relative prices between two highly correlated stocks, also know as pairs-trading. An infamous example of a hedge fund that operated in, but not exclusively, relative value strategies was the infamous Long-Term Capital Management (LCTM). LTCM's main operations were in convergence trading, in which the managers of LTCM looked at securities and identified the ones that were relatively mispriced, going short in the 'expensive' and long in the 'cheap' security (Lowenstein, 2002). This way LTCM could profit from the arbitrage between two of such mispriced securities. An overview of the descriptions of classes are found in appendix A.

2.2 Literature review

In this section the empirical sub-questions of the research questions are presented, accompanied by their respective hypotheses. These sub-questions aim at aiding in answering the central research question by examining the role of alpha, beta and multi-strategy hedge funds. To get to a hypothesis, a literature review of previous academic research is performed for each topic in question. Then, hypotheses are formulated such that testing the hypotheses will provide an answer to the sub-questions.

2.2.1 Alphas of hedge funds

Hedge funds, as stated, are defined by absolute returns. This means that hedge funds attempt at returning positive gains whatever the situation of the market is. Therefore 'beating a benchmark' is less relevant for most hedge funds compared to mutual funds, who keep long-only positions in securities (Jaeger, 2003, pp. 3-4). In academic literature these hedge funds abnormal returns explained through managerial skill are described as 'alpha' (Agarwal, Mullally, & Naik, 2015). This alpha can be traced back to Jensen (1967) who introduces a factor alpha as an 'absolute measurement of performance'. He, Jensen, puts the so-called alpha in the context of measurement to which extent a [mutual fund] manager is able to forecast security prices. He continues to describe alpha as a factor that consumes this part of returns not explained by market risk: absolute returns.

In a survey regarding hedge funds by J.P. Morgan Capital Advisory Group (2019), which was sent out to institutional investors globally, the question is asked for the reason for investing in hedge funds. From the correspondence can be concluded that the main reason for investing in hedge funds is alpha generation, with more than 50% of the correspondents describing it as their primary reason for investing. Further proof for this is provided by Agarwal, Green & Ren (2018) whose findings strongly suggests that there is a positive relationship between investors capital flow into hedge funds and alpha. They find that this relationship holds for multiple asset pricing models.

In order to understand what investment strategies are most attractive for investors in terms of alpha, it is interesting to determine this alpha for these strategies. This helps in understanding the dynamic and shady world of investing in hedge funds and what drives capital flows. Although researching these capital flows goes beyond the extend of this research, estimating the alphas provides an academic foundation for further research in alpha generation and consequences of alpha. In order to provide a better understanding in alphas that will be approximated, further estimates are done in what drives these alphas.

A sub-question 1 will be formulated as follows:

What are the alphas of different investment strategies of hedge funds?

Null hypothesis 1: There is no significant difference in alpha generation for different strategies.

2.2.2 The betas of investment strategies

Hedge funds being absolute returners means that they chase returns without benchmarking themselves (if they do, it is against a risk-free asset) and at the same time managing their volatility (Ineichen, 2003, pp. 19-34), or rather: generate returns regardless of what the market is doing. By introducing portfolios that are hedged against moments of high volatility in the market. When a relative performer suffers negative returns, but their benchmark suffers more, they perform *relatively* 'well'. When one looks at absolute returns, their target of return is independent of the performance of markets, indexed by indices such as S&P 500 (Fung & Hsieh, 1999). Ineichen (2003, pp. 114-116) continues to argue that benchmarking hedge funds against indices (e.g. S&P 500) is a not good idea. Ineichen's argument that benchmarking hedge funds against traditional asset benchmarks is not sufficient is backed by Stefanini (2006, pp. 282-283), Liang (1999) and Fung & Hsieh (2004).

While benchmarking the returns of an absolute performer against equity indices is a controversial topic, finding betas of sub-categories of hedge funds based on their investment strategy can be interesting. According to the Capital Asset Pricing Model, the beta of a stock implies its correlation to the respective regressor, being an equity market index that can be used as a proxy for a market (Brooks, 2019, p. 586). Hedge funds do advertise being absolute performers, or having returns that cannot be achieved through investing in index funds (Asness, Krail, & Liew, 2001). In the timespan of January 1994 to September 1998, Agarwal & Naik (1999), find that the betas for most investment strategies regressed onto multiple indices hover around a beta of 0.5. They, Agarwal and Naik, find that most investment strategies show a low correlation, being a beta <0.5, with multiple indices. However, Asness, Krail and Liew (2001) claim that these findings of Agarwal and Naik (1999), and others with similar findings, are likely to be understated as they do not take into account various sources of systematic risk.

The assumed low correlation of the returns of hedge funds to market indices are widely cited as a beneficial characteristic of hedge funds (Patton, 2009). When Alfred W. Jones tried to reduce his market exposure through long and short positions (Ineichen, 2003, p. 6), he did nothing more than attempting to reduce the beta of his portfolio. While Patton (2009) continues to research this presumed low correlation for the more general categorization of investment styles (e.g. event-driven strategies), it becomes a question how the strategies within these styles behave regarding market risk. Hence, researching the betas of hedge funds by investment strategy in Europe can be of academic value by determining to what extend their performance can be linked to equity indices.

A 2nd sub-question will be formulated as follows:

What are the market exposure betas of respective investment strategies of hedge funds?

Null hypothesis 2: There is no significant difference in market risk coefficient beta for different strategies.

2.2.3 Hedge funds and multiple investment strategies

From 1994 to 2004 the amount of assets under management of hedge funds that apply more than one investment strategy, rose from $4 billion to $39 billion, almost increasing by 1,000% (Agarwal & Kale, 2007). Agarwal and Kale report that this increase is mainly caused by the attraction of the beneficial characteristic of being able to allocate capital among various strategies. According to them, these strategies carry different levels of profitability that can be taken into account when distributing this capital among strategies. In the same timespan, 1994 to 2004, multi-strategy hedge funds do not report significant divergent performance (average annual return and annualized monthly volatility) compared to other strategies (Stefanini, 2006, p. 284).

Sub-question 3 is stated as follows:

Are there any notable differences in performance when a hedge fund uses multiple investment strategies instead of one?

Null hypothesis 3: There is no significant difference in performance between funds of hedge funds or multi-strategy funds and a single investment strategy.

3. Data

3.1 Database

The enigmatic characteristic of hedge funds becomes all too apparent when one starts their journey of finding an (appropriate) database for their research. In the era before 2010 hedge funds were even more secretive than in the recent years due to the lack of regulation. Ackermann, McEnally and Ravenscraft (1999) write: “Reporting of data on hedge funds is voluntary, therefore no one source is comprehensive.”, talking about both U.S. and non-U.S. hedge funds. With this they imply that, when using merely one database, they cannot fathom the entire hedge fund industry. Following the financial crisis of 2007-2008, in 2010 the Dodd-Frank Act in the U.S. and in 2011 the Alternative Investment Fund Managers Directive (AIFMD) in the E.U. passed. Part of these new directives was the implementation of regulations that aimed to increase transparency of reporting of hedge fund data to regulatory bodies. However, these regulations do not necessarily mean transparency overflows into commercial databases.

Joenväärä, Kauppila, Kosowski and Tolonen (2019) examine the use of an aggregation of seven commercial databases for hedge fund data for research purposes. They conclude that even though their aggregate database is comprehensive, it may still endure biases that are caused by the aforementioned lack of commercially available hedge fund data. Besides this, when composing a three-part aggregate database they find three high quality databases that 'stood out': BarclayHedge, Hedge Fund Research (HFR) and Lipper TASS. They argue Preqin and eVestment are rather poor-quality databases for research purposes. Due to limitations of availability of hedge fund databases at the Erasmus University Rotterdam, the possible databases for research are Morningstar and Lipper TASS. Lipper TASS is the most used database in papers that have been published in: *Journal of Finance*, *Journal of Financial Economics*, *Review of Financial Studies*, *Journal of Financial and Quantitative Analysis* and *Financial Analysts Journal* (Joenväärä, Kauppila, Kosowski, & Tolonen, 2019). Noting the upward bias of average returns of average hedge funds when using a single database (Joenväärä et al., 2019), the Lipper TASS database will be used in this research.

The Lipper Trading Adviser Selection System (TASS) database, that is part of Thomson Reuters Lipper, collecting hedge fund data for more than 20 years. This database collects monthly data of more than 20,000 hedge funds worldwide. This includes live funds and so-called graveyard funds, which have been either liquidated or have stopped reporting their returns. The TASS database reports a wide range of variables that describe fund's characteristics, but also report their rates of return over time.

In addition to hedge fund data, data of equity indices is required, more specifically the MSCI Price Index Developed Europe. Monthly closing price data for this index was collected from Global Financial Data. Using this closing price data the monthly return on the index can be calculated over the past 20 years. These returns will later on be used when determining the market return. Then, in order to determine a riskless target return we proxy the 3-month German Treasury bill yield as the risk-free rate of return. Annual yields are gathered from Global Financial Data (GFD) and transformed into monthly yield by dividing by 12.

3.2 Sample selection

Before cleaning the sample and determining whether there are biases that need to be accounted for, the sample has to be limited to a selection. The research question stated at the beginning of this paper limits the sample to developed European countries within a timespan of January 2000 to November 2020. *Developed countries* is topic to a subjective determination of what defines 'developed'. One company that offers a definition to developed countries is Morgan Stanley Capital International Inc. (MSCI). MSCI is a financial firm that, among other activities, constructs equity indices for a multiple of markets. One of those is the MSCI Europe Index, built of a portfolio of 15 developed European markets (See appendix 9.2). Luxembourg and Cyprus are not in this list of 15 countries, but MSCI does count them as part of the developed market universe. The reason for omitting them in the index is because of their modest market size (MSCI, 2019, p. 85). In the case of Cyprus, with 1 hedge fund in the data set this does not affect the dataset much. However, Luxembourg accounts for a significant proportion (35.8%) of the observations in our data sample: 681 funds.

Khelifa and Hmaied (2014) argue that the domicile country of hedge funds is influenced by investor's expectations of tax. According to them, the favourable tax regulations in Luxembourg is the explanation of why Luxembourg is such a prominent player in the housing of hedge funds globally. An interesting observation is the fact that only a few hedge funds are domiciled in the United Kingdom, while the United Kingdom is the biggest hedge fund industry in Europe (Preqin, 2017). The reason for this discrepancy is the flexible characteristic of offshore resided hedge fund bodies (Thomson Reuters, 2018), thus making it attractive for UK hedge fund managers to manage a fund from an offshore country, such as Luxembourg.

3.3 Cleaning Data & Biases

Before working with the Lipper TASS dataset it is valuable to clear the dataset of extreme values, irrelevant data, duplicates and transform the remainder so it is ready for research purposes (see appendix C). Besides this, the collected dataset suffers biases that need to be accounted for where possible. One, already mentioned, bias is the upward bias in average performance of hedge funds when one limits itself to a single database (Joenväärä et al., 2019). This bias should be taken into mind when a conclusion is drawn from any results.

One major contributing fact of biases in hedge fund data is the fact that a hedge fund reporting to commercial databases is on a voluntary basis and in fact, hedge fund managers dó use this voluntary reporting in to their strategic decision making for the reason that their name in a database is one of the few ways they can advertise themselves (Jorion & Schwarz, 2014). Joenväärä et. al. (2019) expect that this results in poor-performing funds being reported in less, or just one, databases than a well performing hedge fund, so-called *selection bias*. And indeed, Joenväärä et. al. (2019) find that using a single database there is a probability that selection bias may arise. As aforementioned, they conclude that their aggregate database may still suffer from this selection bias as this voluntary reporting also means that there could be some funds that do not report to any commercial database.

Once a database has been selected to be used for research purposes, there is another type of bias that one needs to account for in hedge fund databases, namely *survivorship bias*. Survivorship bias occurs when a database stops reporting a hedge fund that went extinct, therefore only having data of *surviving* hedge funds. Lipper TASS database includes dead funds and therefore mitigates survivorship bias. Liang (2001) argues that, if so-called graveyard fund data is available, the survivorship bias can be found by determining the difference between the mean return of live funds and dead funds. In the case of a positive bias for live funds, Liang (2001) notes that this confirms that poor performance is a main cause of funds going extinct. Because the Lipper TASS database is used in this research, another potential cause for survivorship bias that comes into play is the database's history. In 1999, Tremont Capital Management acquires the TASS database in addition to its own hedge fund database. Aggarwal & Jorion (2010) found that when the two databases merged over a 2-year time period only the still-reporting funds were invited to join the new database. This means that the dead hedge funds from before March 1999 are not included in the current Lipper TASS database. Focusing on European hedge funds from January 2000 to November 2020, this survivorship does not apply to the dataset.

Reporting to commercial databases also results in another bias, one that can be accounted for to a certain degree: *instant history bias* or *backfill bias*. Backfill bias can be explained through an example of a hedge fund manager[1]. The manager of a new hedge fund can report to a commercial database on a voluntary basis and being reported in those is one of the only ways to make name for their fund. Usually, managers start reporting their returns to a commercial database strictly later than when they started performing. This means that after a while, with a positive tracking of results, it is favourable for a manager to start reporting to a database, as well as report their previous returns. In the case of unfavourable returns, a manager does not have any benefit in 'filling back' those poor returns into the database. Backfilled returns are reported to exist in the Lipper TASS database (Fung & Hsieh, 2000; Getmansky, Lee, & Lo, 2015) and one can find several ways to adjust for this bias:

1) Remove all returns that are reported after fund is added to database
2) From the inception date of the fund, cut off the first 12-24 amount of months
3) Remove returns returns that are reported past 12-24 months from when fund is added to database
4) Only include funds for which the date when performance reporting started is relatively close to their inception date

Getmansky, Lee & Lo (2015) use method (1) to remove any backfilled returns in the Lipper TASS database. Joënväärä et. al. (2019) also use the "generally superior" method of excluding all observations of returns prior to the date a fund was listed in the database. The first method is further underscribed by Aggarwal & Jorion (2010) over using the second method. They, Aggarwal & Jorion (2010), used a slightly stricter criterium in their earlier work *The performance of emerging hedge funds and managers* in the Journal of Financial Economics (2010). They only used returns of funds that never backfilled or where the

[1] This example is derived from, and is further analogized in: Posthuma, N. & van der Sluis, P.J. (2003). A Reality Check on Hedge Fund Returns.

difference between inception date and date added to the database was less than 181 days, in order to capture “the early performance of emerging [hedge fund]managers”. When one considers the second, third and fourth option, they swiftly come to the realization that, even though they may address the backfill bias, the damage to the sample size may be even more worrysome as it could exclude other precious performance history (Fung & Hsieh, 2009). Hence, in this research any returns are removed when they are reported prior to the inception date of the hedge fund as reported in the database.

Another required transformation of the dataset occurs when looking at the default categorization of hedge fund investment strategies. As stated before, Stefanini’s (2006) classification of investment strategies consists of 5 classes. In the dataset provided by Lipper TASS exist 14 unique values for the variable PrimaryCategory that tells what investment strategy a fund applies. Now, these 14 values range from ‘undefined’ to ‘Dedicated short bias’, the latter having very few observations. In order to find a balance between a ‘strict’ classification with just 5 classifications and a dataset that does not provide results with a lot of explanatory power, the dataset is transformed such that it allows for the 5 classes as defined by Stefanini with two additional classes for funds with a multi-strategy and fund of funds.

4. Methodology

4.1 Explanatory model

In analysing hedge fund’s returns a model is needed that offers explanatory powers of sources of return. One of such asset pricing models is the Capital Asset Pricing Model (CAPM), developed by William Sharpe, Jack Treynor (1962), John Lintner (1965, 1975) and Jan Mossin (1966). This model captures the risk-free excess returns $(\mathrm{R_i} - \mathrm{R_f})$ of an asset in terms of its sensitivity to the market (beta) and market risk premium $(\mathrm{R_m} - \mathrm{R_f})$. This CAPM model is one the most famous equations in asset pricing and looks as follows (Brooks, 2019, p. 586):

$$R_i - R_f = \beta_m [R_m - R_f] \tag{1}$$

where R_i = Return on strategy/fund i, R_f = Risk-free rate of interest , β_i = Measure of how risky an investment strategy is relative to the market, R_m = Return of the market (proxy).

This CAPM model is a fairly simplified equation to find the beta (β) of an asset. Jensen (1968) introduces returns that can be explained by managing a portfolio from a superior standpoint. He continues to explain that when managers manage a portfolio, they aim at providing an error bigger than zero (i.e. positive returns not explained by market premium) if we look at the CAPM model. Jensen states that the model needs to allow for a constant that accounts for these biased residuals. Hedge funds being characterized by abnormal returns and the idea that a hedge fund manager can 'beat the market', calls for the introduction of such a constant. When we implement this constant alpha (α) in the CAPM model we get was is called a 'single-index model' (SIM), developed by William Sharpe (1963). The CAPM model augmented to include an alpha for abnormal returns, looks as follows:

$$R_i - R_f = \alpha_i + \beta_m[R_m - R_f] \quad (2)$$

where R_i = Return on strategy/fund i, R_f = Risk-free rate of interest , β_m = Measure of how risky an investment strategy is relative to the market, R_m = Return of the market, α_i= Jensen's alpha.

In *Common risk factors in the returns on stocks and bonds* Eugene Fama and Kenneth French (1993) introduce a multiple factor model, or more commonly known as the 'Fama-French three-factor model'. Fama and French implement, in addition to the CAPM model market risk premium factor along with an intercept, two factors that mimic returns explained by size and book-to-market value.

$$R_i - R_f = \alpha_i + \beta_m[R_m - R_f] + \beta_{SMB}SMB_t + \beta_{HML}HML_t \quad (2)$$

where R_i = Return on strategy/fund i, R_f = Risk-free rate of interest , β_m = Measure of how risky an investment strategy is relative to the market, R_m = Return of the market, α_i= three-factor alpha, SMB_t = Size factor, HML_t = Book-to-market value factor.

Jegadeesh & Titman (1993) observe an anomaly in stock performance: the predictability of future returns based on past returns. They find that buying winners and selling losers of the past six months will result in positive abnormal returns in the next six months, a so-called momentum of positive (or negative) returns. This finding is further examined by Chan, Jegadeesh & Lakonishok (1996), who find that this 'drift' of returns cannot be explained by the size and book-to-market factor in the Fama-French three-factor model. Carhart (1997) uses the Fama-French three-factor model combined with Jegadeesh & Titman's (1993) findings to construct a new, four-factor, model that he proceeds to use to examine short-term persistency in returns of mutual funds. This Carhart four-factor model looks as follows:

$$R_i - R_{f,t} = \alpha_i + \beta_m\left[R_m - R_f\right] + \beta_{SMB}SMB_t + \beta_{HML}HML_t + \beta_{WML}WML_t \qquad (2)$$

where R_i = Return on strategy/fund i, R_f = Risk-free rate of interest , β_m = Measure of how risky an investment strategy is relative to the market, R_m = Return of the market, α_i= three-factor alpha, SMB_t = Size factor, HML_t = Book-to-market value factor, WML_t = Momentum factor.

In table 1 below, coefficient of determination (R^2) is displayed for each abovementioned asset pricing model, which tells us how much of the variation in returns of hedge funds is explained through the model. The higher this coefficient, the better a model fits the data provided by Lipper TASS database regarding hedge funds. Because the Carhart four-factor model shows the highest R^2, this model is used when estimating coefficients to answer the research questions. Using STATA software (2017) OLS regressions using this asset pricing model are performed and calculations relevant for answering the central research question are done using this software as well. All data regarding the SMB, HML and WML factors are gathered from Kenneth French's Data Library (2021) that offers data for developed European countries on these factors from the Carhart four-factor model.

Table 1. Explanatory value, as measured by R^2, for various asset pricing models regarding hedge fund data. All models provide factors that are significant at a 95% confidence level.

Model	**R^2**
CAPM	0.0712
Single Index (SIM)	0.0713
Fama-French three-factor	0.0909
Carhart four-factor	0.0968

4.2 Performance Measurements

For some investors the highest returns do not necessarily mean that hedge fund performs best. There are other variables that need to be taken into account, such as how volatile these returns are or whether these returns occur in a bullish or bearish market. In academic literature studying hedge funds there is no single measurement of performance that determines which hedge fund is the best hedge fund. An arbitrage-focused hedge fund such as LTCM may (in hindsight theoretically) be subject to almost no risk while picking up the pennies on Wall Street. In order to account for the heterogeneity in characteristics between hedge funds, a collection of performance measurements is collected and analysed. Using the Carhart four-factor asset pricing model the alphas, betas, residuals and other estimates for these measurements of performance for each hedge fund can be gathered.

4.2.1 Alpha

Jensen's alpha (α) is a measurement of performance given the market risk associated with each strategy (Jensen, 1967). More specifically, Jensen's alpha can be interpret as the constant in the SIM: α. This Jensen's α captures the forecasting abilities of [in his 1967 paper: mutual] fund managers, being superior skills if α is positive and inferior skills when negative. In the Carhart four-factor model one does not speak of *Jensen's alpha* anymore, but rather uses the term four-factor alpha. Although the naming of this alpha differs among asset pricing models, their meaning is essentially the same: a constant capturing absolute returns explained by managerial skill (Carhart, 1997; Jensen, 1967). Now, as hedge funds advertise being absolute returners it becomes relevant to measure such an α (but also β) that measures abnormal returns through managerial skill.

4.2.2 Sharpe ratio

The Sharpe ratio puts the excess returns of a hedge fund in perspective to its standard deviation (Sharpe, 1994). The ratio, although being used commonly in hedge fund research, is sensitive to some deficiencies caused by methodology. The Sharpe ratio is calculated by dividing the average excess returns by the standard deviation of these excess returns. In order to not dilute the standard deviation by calculating the Sharpe ratio over an aggregate for multiple funds, Sharpe ratios are calculated for every fund and then the average is calculated. The Sharpe ratio is calculated as follows:

$$S_h = \frac{\frac{1}{T}\sum_{t=1}^{T}\left(R_{i,t} - R_{f,t}\right)}{\sigma_i} \tag{4}$$

where $R_{i,t}$ = Return on fund i at time t, $R_{f,t}$ = Risk-free rate of interest at time t , σ_i= standard deviation of excess returns of fund i, T = Total number of observations for fund i. With σ is being calculated for each fund as follows (Sharpe, The Sharpe Ratio, 1994):

$$\sigma_i = \sqrt{\frac{\sum_{t=1}^{T}\left(ER_{i,t} - \overline{ER}_i\right)^2}{T-1}} \tag{5}$$

where $\mathrm{ER}_{i,t}$ = Excess return of fund i at time t, $\overline{\mathrm{ER}}_i$ = Average excess returns , T = Number of observations for fund i.

4.2.3 Sortino ratio

Returns and their deviation from a target can be split into downside and upside deviation, returns below target return and returns above target return respectively. When upside deviation occurs (e.g. a 10% monthly return compared to 1% target), this would not be experienced as an ‘unpleasant’ deviation. Opposed to this ‘pleasant’ deviation, a hedge fund can experience downside deviations which are monthly returns that are below the target monthly return. In this research, as stated above, the risk-free monthly yield on a three-month German Treasury bill is taken as the target return as this is a return one can earn on capital almost riskless. The Sharpe ratio takes into account this favourable deviation and therefore the final measurement becomes lower (where higher is better) as upside deviation increases. Another method to measure performance is the Sortino ratio. The Sortino ratio only uses the values of downside deviation from the desired target return and is calculated as follows (Rollinger & Hoffman, 2013):

$$S_o = \frac{\frac{1}{T}\sum_{t=1}^{T}\left(R_{i,t} - R_{f,t}\right)}{\sigma_D} \tag{5}$$

where $R_{i,t}$ = Return of fund i at time t, $R_{f,t}$ = Risk-free rate of interest at time t , σ_D= downside standard deviation of excess returns, T = Total number of observations for fund i. With σ_D being calculated for each fund as follows:

$$\sigma_{D,i} = \sqrt{\frac{\sum_{t=1}^{T}\left(\min(0, R_{i,t} - R_{f,t})\right)^2}{T-1}} \tag{5}$$

where $R_{i,t}$ = Return of fund i at time t, $R_{f,t}$ = Risk-free rate of interest at time t , σ_D= downside standard deviation of excess returns, T = Number of observations for fund i.

As the sortino ratio takes the minimum value of either zero or excess returns, the ratio achieves extreme values if a fund reports almost only positive excess returns, or is even impossible to compute when there are no downside deviations (cannot divide by zero). Therefore, in order to keep the ratio clean of an outlier bias, only the sortino ratios below 5 are taken into account in our means.

4.2.4 Treynor ratio

As the beta of a hedge fund implies its correlation to the equity market proxy, one is able to measure excess returns against each unit of beta. This is especially relevant when measuring the performance of investment strategies that aim for low betas specifically. With the beta taking values in the range (-2,3) there also exists betas that approach 0. This means that in our equation with an excess return not equal to zero, some Treynor ratios become extremely high (less than -20,000 observed). In all cases where the absolute Treynor ratio is concluded to be higher than 20 the beta lies within the range (-0.04, 0.08), while the nominator values all are within one standard deviation of the mean. In order to account for the extreme values caused by a denominator approaching zero, the Treynor ratio will be capped at an absolute value of 20. The Treynor ratio is calculation looks as follows (Kenton, 2021):

$$T_r = \frac{\frac{1}{T}\sum_{t=1}^{T}\left(R_{i,t} - R_{f,t}\right)}{\beta_i} \tag{6}$$

$R_{i,t}$ = Return on fund I at time t, $R_{f,t}$ = Risk-free rate of interest at time t , β_i= Beta of fund i (significant at 10%). Only calculated if beta is significant at 10% significance level.

4.2.5 Appraisal ratio

Another performance indicator is the Appraisal ratio which captures the alpha per unit of systematic risk (Bacon, 2013, pp. 86-87). This ratio measures at alpha against the level of risk that is unsystematic, being the standard deviation of the residuals of our Carhart four-factor model. This means that a relatively high Appraisal ratio tells us that the alpha of a hedge fund comes with a relatively low level of taken risk. The equation for the Appraisal ratio looks as follows (Agarwal & Naik, 2000; Bacon, 2013, pp. 86-87):

$$A_p = \frac{\alpha_i}{\sigma_{residuals\ i}} \tag{7}$$

α_i= Alpha in four-factor Carhart model, $\sigma_{\text{residuals i}}$= Standard deviation of the residuals of the four-factor Carhart model of fund i. Only calculated if alpha is significant at 10% significance level.

5. Results

In this section results are presented based on the methodology that is described in the fourth section Methodology. The earlier stated sub-questions will be repeated and all relevant results will be mentioned. Then the corresponding hypothesis will be rejected or not depending on the findings. After this, further results relevant to the central research questions will be presented and clarified.

After adjusting the data as described in appendix C the number of European hedge funds is brought down from 4,507 to 1,901. Most of this decline in number of funds can be blamed on the currency filter that accounts for any duplicate reporting of a hedge fund (i.e. hedge fund X reported in EUR but also in USD). In this remaining data one can find non-normally distributed monthly rate of returns as seen in table 4, which is well-known in hedge fund research (Kat & Miffre, 2006). In table 2 more descriptive statistics for hedge fund returns are displayed. In table 3 the results of the four-factor Carhart model are found, together with the estimated ratios.

In answering our question regarding the differences in alpha between investment strategies of hedge funds, regressions using the Carhart four-factor model were performed. In the fourth column of table 3 the average (four-factor) alphas are shown for each hedge fund strategies. In order to test the first null hypothesis that states that there is no significant difference in alpha generation between different strategies and the population mean, a one-sample t-test is performed and displayed in the fourth column table 3. The null hypothesis should cannot be rejected if none of the investment strategies shows a significant difference in alpha compared to the total average alpha. Hence, we can reject the null hypothesis that there is no difference among strategies regarding alpha.

The second null hypothesis states that there is no significant difference in the beta coefficient that tells the risk of a hedge fund associated with the market premium. In order to test this, a one-sample t-test is performed to test whether the beta of a specific strategy differs from the mean. The results are displayed in the second column of table 3 and the findings are coherent with the finding of Agarwal & Naik (1999) that hedge funds show low correlation to market proxies (beta < 0.5). It can be concluded that the beta coefficient differs from the mean for some strategies, hence we also reject the second null hypothesis. It should be noted that the beta only differs significantly for 3 investment strategies, while for alpha this number is 5. In a way, this makes sense if one takes into consideration the nature of each strategy together with the meaning of the beta. The strategy long/short equity hedge is a strategy where a manager tries to long (short) the stocks he is bullish (bearish) about in order to beat passive (long-only) funds. Stefanini (2006) suggests this type of strategy is a directional strategy as most hedge fund managers in this category keep their net market exposure positive, resulting in a higher beta, which corresponds with the relatively high (significant) beta. Stefanini also mentions how relative value strategies do not seek to profit from the direction of the market, but rather from arbitrage, which also corresponds with the findings in table 3.

The third null hypothesis to support an answer to the central research question states that funds using a multi-strategy approach do not perform significantly different than funds using a single investment strategy. As seen in table 5, comparing both multi-strategy funds and funds of funds against single investment style funds, we can reject the third null hypothesis for all performance measurements (except for one) at a 1% confidence level. This suggests that there is a performance difference between multi-strategy hedge funds and ones that use only one strategy, but also a significant difference between performance of funds of hedge funds and single investment style hedge funds. Remarkable findings are the values of (excessive) returns, alpha and for funds of funds all the performance ratios. More specific, in contradiction to the findings of Agarwal & Kale (2007) there does seem to be any significantly benefit to the ability to allocate capital among different strategies (or funds). So, we can reject the null hypothesis that states there is no difference in performance between funds of hedge funds or multi-strategy funds and single investment strategy funds.

Table 2. Descriptive statistics of the (excess) returns of the classified hedge fund investment strategies.

	# of		Mean				Description of Returns		
Category	**Total funds**	**Dead funds**	**Return (%)**	**σ (%)**	**Excess Return (%)**	**σ (%)**	**Median**	**Skewness**	**Kurtosis**
Directional	66	50	0.088	4.809	-0.009	4.811	0.120	-0.851	39.768
Event Driven	26	15	0.424	3.583	0.351	3.592	0.340	-0.286	24.644
Fund of Funds	1,211	1,072	-0.024	3.352	-0.143	3.354	0.276	-10.605	332.151
Long/Short Equity Hedge	169	130	0.218	3.290	0.134	3.295	0.315	-3.726	84.388
Multi-Strategy	191	136	0.093	3.165	0.024	3.171	0.222	-8.058	238.752
Other	107	52	0.590	5.242	0.579	5.242	0.369	1.221	30.572
Relative Value	131	97	0.185	3.749	0.084	3.758	0.294	-2.932	74.667
All funds	1,901	1,552	0.063	3.521	-0.040	3.525	0.275	-6.855	214.863

Table 3. Descriptive statistics regarding the performance measurements for each of the hedge fund investment strategies. Tests for significance are done through one-sample t-test that tests whether the found sample mean is different from the population mean. */**/*** = significant at a 90%/95%/99%

	Beta		Alpha		Sharpe		Sortino		Treynor		Appraisal	
Category	**μ**	**σ**	**μ**	**σ**	**μ**	**σ**	**μ**	**σ**	**μ**	**σ**	**μ**	**σ**
Directional	0.396	0.565	0.002	1.101	-0.032**	0.134	-0.030**	0.218	-0.135	1.098	-0.104	0.318
Event Driven	0.348	0.334	0.450***	0.644	0.077*	0.191	0.171**	0.357	0.779**	1.743	0.135**	0.277
Fund of Funds	0.279***	0.141	-0.523***	0.812	-0.042***	0.177	-0.019***	0.286	-0.364***	1.377	-0.250***	0.301
Long/Short Equity Hedge	0.391***	0.266	0.008**	0.927	0.029**	0.170	0.082***	0.281	0.298***	1.281	0.034*	0.381
Multi-Strategy	0.310	0.291	-0.247	1.154	0.213***	0.250	0.032	0.285	0.101*	1.871	-0.094	0.538
Other	0.414**	0.349	0.581***	1.066	0.342***	0.832	0.240***	0.501	0.629	4.907	0.790***	1.231
Relative Value	0.387	0.492	0.068**	1.035	0.054*	0.365	0.192**	0.759	0.671*	3.690	0.213***	0.673
All funds	0.306	0.237	-0.276	0.968	0.001	0.293	0.025	0.359	-0.149	1.874	-0.070	0.600

Table 5. Performance measurements of multi-strategy & funds of hedge funds compared to single strategy hedge funds. It should be noted that numbers in the single strategy row are means of table 3. $^{*}/^{**}/^{***}$ = significant at a 90%/95%/99% confidence level.

	Alpha		Sharpe		Sortino		Treynor		Appraisal	
Category	**μ**	**σ**	**μ**	**σ**	**μ**	**σ**	**μ**	**σ**	**μ**	**σ**
Fund of Funds	0.279^{***}	0.141	-0.523^{***}	0.812	-0.042^{***}	0.177	-0.019^{***}	0.286	-0.364^{***}	1.377
Multi-Strategy	-0.247^{***}	1.154	0.213^{***}	0.250	0.032^{***}	0.285	0.101^{**}	1.871	-0.094^{***}	0.538
Single Strategy	0.222	0.955	0.094	0.338	0.131	0.423	0.448	2.544	0.214	0.577

Now that the hypotheses have been, all three, rejected the main question remains how different strategies of hedge funds perform in a different way among each other. While multiple performance measurements are presented, it continues to be question whether there is one type of measurement that tells us whether one specific measurement is the best to determine differences. Therefore, all ordinal ranks of performance ratios are displayed in table 6. For each investment strategy the mean rank is displayed in order to observe what the position of a strategy is on an overall level regarding these performance measurements. As seen, the funds classified in ‘Other’ (an aggregate for all other strategies that cannot/are not classified in the other 6) are together ranked ‘best’ if one looks at just these measurements. However, this is of little explanatory value in academic research and dissecting ‘Other’ into more concrete strategy types proves to be hard in this particular dataset.

Table 6. Ranks of hedge fund investment strategies regarding the performance measurements. For all 5 measures, higher is perceived as ‘better’. Mean ranks of all ranks displayed in column seven.

Category	Alpha	Sharpe	Sortino	Treynor	Appraisal	Mean rank
Other	1	1	1	3	1	1.4
Event Driven	2	3	3	1	3	2.4
Relative Value	3	4	2	2	2	2.6
Long/Short Equity Hedge	4	4	4	4	4	4
Multi-Strategy	6	5	5	5	5	5.2
Directional	5	6	7	6	6	6
Fund of Funds	7	7	6	7	7	6.8

One of the performance measurements is the alpha in the Carhart four-factor model. We rejected the first null hypothesis that stated there is no significant difference between the alphas of different investment strategies of hedge funds. This suggests, as stated, that there is a difference between alpha values of investment strategies of hedge funds. A next question would be why such a difference exists and what the drivers are, but this steps beyond the scope of this research. Some preliminary results regarding the composition of the four-factor alpha are shown in table 7, but does not provide any explanatory power when answering the central research question of this research due to lack of relevancy. The results in table 7 do, however, provide explanatory power for findings of alpha in table 3 and 5.

Table 7. Alpha regressed against factors, all significant at a 99% confidence level. Insignificant factors, such as the dummy variable whether a hedge fund is leveraged, are left out. Same goes for time fixed-effects.

Variable	Coef.	Std. Err.	t-value	P-value
Incentive Fee	0.011	0.002	5.12	0.000
Offshore	0.166	0.035	4.78	0.000
Small		OMITTED		
Medium	0.161	0.040	3.99	0.000
Large	0.234	0.046	5.07	0.000
Constant	-0.499	0.037	-13.65	0.000

6. Discussion

A conclusion can be drawn from table 6 that the category of investment strategies classified as 'Other' outperforms the other strategies in almost all measurements of performance, except for the Treynor ratio where it cannot be rejected that the value for this category differs from the mean. However, the vague 'Other' class (see appendix A) remains of little explanatory value to the central research question, thus leaving out this strategy type allows for a better observation the better defined investment strategies. Within these six are two strategies remaining in the 'upper' part of the 'leader board' (table 6): Relative Value and Event Driven. The rankings of these two investment strategies suggests that they, on average, score better on all measurements of performance. One of the noteworthy findings regarding the Event Driven strategy is the relatively high four-factor alpha (0.450) that suggests returns are more affected by managerial skill than, for example, hedge funds focusing on relative value. Besides this, the Event Driven strategies appear to yield higher excess returns than the other strategies (excl. ‘Other’). For both these two strategies the Sortino ratio values suggest that each unit of excess return comes at less downside deviation. Another finding is the significant underperformance of European multi-strategy funds and funds of hedge funds contradicts previous academic literature, mainly US focused, that mention the rise and benefits of these categories, such as the possibility of capital allocation.

The rejection of all three hypotheses suggests there is a significant difference between performance between different investment strategies, but the question what those differences are remained to be answered. It can be deducted from table 6 that funds categorized as having an ‘Other’ investment strategy than the ones provided by Lipper TASS significantly outperform the other six investment strategies. But this emphasizes the question what exactly the strategies within this category are and thus requires further investigation. Therefore, further research should explore these unclear strategies and take an attempt at dissecting the category into more concrete investment strategies.

In this research the Carhart four-factor model was used to estimate several factors, but academic literature remains divided about an ‘ideal’ asset pricing model as illustrated by Harvey, Liu & Zhu (2016). One of such asset pricing models is the extended multi-factor model introduced by Capocci & Hübner (2004) which is a melt of multiple asset pricing models (including Carhart’s model) and is designed to take into account several characteristics of the hedge fund industry. Exploring such (new) more extensive models could result in better suited models for hedge fund research.

In the fifth section of the results a brief mention was made regarding the factors affecting the alpha of hedge funds in developed Europe. With alpha being the main reason for investing in hedge funds further breakdown of this factor could provide academic insight in its drivers: is it truly managerial skill or mere luck?

One of the mentioned limits of this research is the hurdles that come with the nature of hedge fund data. The most limiting bias to this research is the use of one single database instead of an aggregate one, as underwritten by Joënväärä et al. (2019). Joënväärä et al. conclude that using a single database results in upward biased data, therefore this needs to be taken into consideration when interpreting the finding in this research. Besides this, as explained in section 3.3, solely using the Lipper TASS database appears to come with limitations in terms of amount of observations after the described data cleaning (appendix C).

Finally, attempting to demystify the strategies of hedge fund may undermine any findings that are deemed representative for the hedge fund industry. Research is based on past-returns and Agarwal, Green & Ren (2018) observe the flow of investors' capital based on past alpha that turns out to be non-persistent. Stefanini (2006, pp. 292) adds to this that successful strategies result in exhausting performance due to overcrowding, which results in the hedge fund industry turning to new or other strategies, notoriously pictured by the demise of LTCM's performance due to overcrowding caused by success (Lowenstein, 2002).

7. Conclusion

The dynamic and mystic industry of hedge funds as portrayed by various researchers appears in various ways in the performed research in this paper. Literature review shows that findings regarding various factors differ among research and several causes are mentioned. One of such causes is the bias caused by the voluntary nature of hedge fund reporting that affects the representability of commercial databases of hedge fund data, a significant obstacle in this research. Some solutions to the caused biases are mentioned and implemented, but further exploration of databases is required in order to minimize biases. Another future effort in optimizing the Lipper TASS dataset is the transformance of the data that is caused by self-reporting.

On the basis of the available data, all three hypotheses were rejected which suggests there is a significant difference between alpha and beta between distinct investment strategies of hedge funds. But also that multi-strategy funds and funds of hedge funds seem to perform differently than hedge funds using a single investment strategy. In fact, findings indicate that focusing on a single strategy goes hand in hand with better performance, contradicting the popularity in multi-strategy funds in the US. This may imply that the performance of these multi-strategy and funds of hedge funds is different from US hedge funds, further underwriting the relevance of extended academic research regarding European hedge funds. One particular investment strategy sticks out: the aggregate 'Other' for all other strategies. The results imply that these other strategies are among the best performers according to ratios used to measure performance, but what this 'Other' category consists of remains a question that should be investigated in further research. Beyond this vague category are the better-defined categories that appear to have the event-driven and relative-value strategies among the better performers.

Besides dissecting the categories even more, there are several other aspects of this research that are applicable to further research, ranging from databases to asset pricing models. Beyond the statistical results is the academic relevance in detecting such unmapped fields as it lays the groundwork of future research.

Concluding, a bewildering industry seems to come with a puzzling world of academic literature and data. This is highlighted by one of the most famous hedge funds LTCM causing a 'trillion dollar gap' in the derivative market, while under the assumption that the Nobel Prize laureates in the management understood the world of risk better than everyone else. When George Soros succeeded his famous bet against the British pound, he ignited a rebirth of hedge fund popularity as he upheld the financial cowboy image of hedge funds. In a more recent time, the GameStop short-squeeze as triggered by the stand-off between retail investors and hedge funds that were shorting GameStop further emphasized the Wild West image of the hedge fund industry. Whether this short squeeze ignites a new boom of popularity in hedge funds is what only time can answer, but the cowboy picture was unquestionably reinforced.

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Appendix A. Investment Strategies of Hedge Funds

Class	Investment strategy	Description
Directional	Global Macro[3]	Based upon the manager's opinion of the market a selection of securities is made that reflects this view. Soros' Quantum Fund bet against the British pound would fall in this category. Funds in this category invest in both developed and emerging global markets.
	Managed Futures[1,2,3]	Although similar to Global Macro strategies in terms of following trends as interpret by managers, this strategy usually uses a computerized model to determine moves in financial and commodity futures. Usually referred to as Commodity Trading Advisors (CTAs).
	Dedicated Short Bias[2,3]	Hedge funds following this strategy have a net short position in their portfolio
	Emerging Markets[2,3]	Funds in this category invest in equity/fixed income markets of emerging countries. Investing in complex financial products can be hard in these markets, so long-only funds are common.
Event Driven	Merger Arbitrage Risk Arbitrage[2]	Returns in this category are derived from acquisitions. The fund will go long in the to-be-acquired company and short the acquirer. Risk comes from acquisition deals failing.
	Shareholder Activism[1]	Shareholder activism is the operation of generating shareholder value by taking a role in corporate governance. Or as Stefanini (2006) puts it: "... hedge funds managers [in this category] have an active role in generating catalyst events that unlock shareholders value.".
	[Other] Event Driven[3]	A remainder category for investment strategies that could be defined as strategies that aim at profiting from pricing inefficiencies driven by corporate events. Examples are investments surrounding regulation D or distressed debts.
Fund of Funds[1,3]	-	These types of hedge funds invest in multiple hedge funds (or CTAs). The manager of such a fund of hedge funds allocates capital to each fund. This means a fund of hedge funds can have returns from both Directional and Relative value funds.
Long/Short Equity Hedge[1,2,3]	-	The first hedge fund of Alfred W. Jones would be categorized in this strategy as the strategy includes fund that attempt to be market neutral by going both long and short in (usually) equity. Positions could be attempted to hedge using more complex financial products such as futures and derivatives.
Multi-Strategy[1,3]	-	Funds in this category apply multiple strategies within the hedge fund. For example, using both an event driven strategy and directional strategy to generate returns.
Other	-	This class does not provide any clear set of categories defined within it based on Refinitiv but also other literature.
Relative Value	Convertible Arbitrage[1,2,3]	Convertible securities are securities like convertible bonds. Hedge funds in this category attempt to profit from an arbitrage arising from inefficiencies. A classic move would be to short a stock and longing a convertible bond.
	Fixed Income Arbitrage[1,2,3]	Fixed income securities such as government bonds provide arbitrage opportunities that can be exploited. LTCM was mainly operating in this category. An example is the arbitrage between on-the-run and off-the-run government bonds.

1. Stefanini, F. (2006). Investment Strategies of Hedge Funds. West Sussex: John Wiley & Sons Ltd.
2. Asness, C., Krail, R., & Liew, J. (2001). Do Hedge Funds Hedge? Journal of Portfolio Management, 6-19.
3. Getmansky, M., Lee, P. A., & Lo, A. W. (2015). Hedge Funds: A Dynamic Industry In Transition. Annual Review of Financial Economics, 483-577.

Relative Value	Equity Market Neutral[1,2,3]	This strategy seeks to turn a profit from the arbitrage that arise in equity and fixed income. A usual strategy is to long and short matched portfolios within the same country.
	Options Strategy	Refinitiv describes this strategy as managers that seek gains from the spreads between similar inefficiently priced options.
	Mortgage Backed Securities[1]	Hedge funds in this category base their returns on arbitrage opportunities that arise from mortgage-backed securities, that are securitizations of mortgage cash flows and their underlying collateral real estate.

Although Wharton Research Data Services does not provide a direct manual regarding definitions of categories, a file from Refinitiv (2019) provides many of them. Classification of strategies is based upon descriptions provided by Stefanini (2006)[1], Asness, Krail & Liew (2001)[2] and Getmansky, Lee & Lo (2015)[3]. Superscript describes source(s) additionally used.

Appendix B. MSCI Europe Index

- Austria
- Belgium
- Denmark
- Finland
- France
- Germany
- Ireland
- Italy
- The Netherlands
- Norway
- Portugal
- Spain
- Sweden
- Switzerland
- United Kingdom

*Cyprus and Luxembourg are not in this index, but are counted as Developed Markets.

Appendix C. Cleaning the Lipper TASS data using STATA

In the light of the research question the variable PrimaryCategory needs to be transformed as good as possible as to sufficiently categorize investment strategies. Lipper TASS provides a list of twelve different strategies of funds. When a fund is classified as Other, Undefined or Event Driven, we further specify its investment strategy by determining if they only report using one investment focus (IF_* variables). We end up with six new investment strategies: Distressed Bonds, Distressed Markets, Merger Arbitrage Risk Arbitrage, Mortgage Backed Securities, Regulation D and Shareholder Activism.

The dataset provided by the Lipper TASS database is not a ready-to-go perfect dataset as one can observe extreme outliers, such as an observation of a 2,000,000% rate of return. Besides this, some funds are reported more than once, but in a different currency. An observation should be rejected if the rate of return is detected as an outlier based on the following criteria:

- less than -100%;
- more than 200%;
- exactly equal to the return of the two previous months.

Besides data-entry errors, some funds are being listed more than once due to the occurrence of reporting in different currencies (e.g. a fund listed for both EUR and USD). However, duplicates are not limited to reporting in various currencies, thus removing duplicates solely on the basis of multiple currencies will not solve the issue entirely (Aggarwal & Jorion, 2010b). Aggarwal & Jorion (2010) suggest that in these other situations where duplicate reporting occur, a method to address this is by eliminating one of the funds if the correlation is equal to or higher than 0.99. Then, the eldest fund will be kept if the remaining reporting dates are the same. If they started reporting at the same date, the fund with the longest tracking record of returns is kept. In the case they report in the exact same months, the fund with the highest assets under management (AUM) is kept.

The following steps are taken chronologically in cleaning the dataset:

1. Drop irrelevant variables
2. Only keep countries included in MSCI Developed Europe index (appendix B)

3. Remove any backfilled observations (Date of observation < Inception date)
4. Drop returns that are reported gross-of-fees
5. Re-categorize investment strategies according to appendix A.
6. Remove outliers in rate of returns (see above)
7. Remove duplicates due to reporting in multiple currencies. Remove non-EUR returns.
8. Remove hedge funds that report less than 2-years of returns.

Appendix D. Tables

Table 8. Tests for normality for each investment strategy by measuring skewness & kurtosis.

Category	H_0: No skewness (at 1% sign.)	H_0: No kurtosis (at 1% sign.)	Normality?
Directional	Reject	Reject	No
Event Driven	Reject	Reject	No
Fund of Funds	Reject	Reject	No
Long/Short Equity Hedge	Reject	Reject	No
Multi-Strategy	Reject	Reject	No
Other	Reject	Reject	No
Relative Value	Reject	Reject	No
All funds	Reject	Reject	No