Manager skills of long/short equity hedge funds : the factor model dependency

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MANAGER SKILLS

OF LONG/SHORT EQUITY HEDGE FUNDS:

THE FACTOR MODEL DEPENDENCY

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ABSTRACT

Performance analysis of hedge funds has proven to be challenging in the past since these entities have the flexibility to choose between a wide variety of dynamic trading strategies without being compelled to report their holdings. That being said, using bootstrap procedures, some authors in the academic literature have succeeded in quantifying the proportion of funds which demonstrates persistent performance. Yet, these methodologies are based on an extensive range of multifactor models to estimate the performance of hedge funds. Four different models which seem particularly adapted to assess hedge fund returns will be replicated, with both buy-and-hold and optional factors incorporated. The research aims at demonstrating the potential bias and/or outperformance brought by some factor models used when defining hedge fund manager skills. Using robust bootstrap simulations, evidence was found that superior hedge fund performance cannot be explained by luck alone and that, regardless of the multifactor model used.

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1. INTRODUCTION

After several years of steady growth during the last decade of the 20^{th} century, hedge funds have won the favour of the investors in the financial world. Nevertheless, the mixed results delivered these last years and more specifically those in the wake of the financial crisis are increasingly questioning their merits and their ability to generate absolute returns, regardless of the market trends (Agarwal and Naik, 2004). Although one of the main arguments of this investment vehicle was a slight dependence on the market, these inconclusive results emphasized a certain kind of correlation between the hedge fund performance and the market performance (Patton, 2009).

A feature specific to hedge funds is that they are considered as private investments and as a matter of fact, they are subject to less strict rules than those applicable to traditional investments such as mutual funds. This way, they have unlimited access to leverage, they have the opportunity to invest in a large group of financial assets and they can use various strategies such as short selling (US President's Working Group on Financial Markets, 1999). Furthermore, they are not compelled to disclose their trading positions, which makes the understanding of their functioning and the evaluation of their actual performance even more challenging (Gregoriou and Duffy, 2006).

As a first step, it is very interesting to inquire about the reasons explaining their popularity and the actors who keep this alternative investment under close scrutiny. Five main items can be considered.

First of all, hedge funds have been increasingly present in the investors' portfolio. Currently, most institutional investors decide to invest in alternative funds in order to benefit from the advantages provided in terms of portfolio diversification (Lhabitant and Learned, 2005). In a context where the international diversification is limited, the exposure profile of hedge funds is a very valuable feature. Furthermore, by being included in the composition of the managed funds offered to their clients, the influence of hedge funds has gained importance at the expense of savings and retirement plans (Cao, Liang, Lo, and Petrasek, 2014).

Secondly, the strategies implemented by hedge funds have impacts on the development and the financial situation of many companies. If they speculate downwards, these funds can rapidly cause the value of the stock price of a company to fall, and therefore affect its financial strength and its potential future growth. On top of that, alternative funds are demonstrating an actual shareholder activism (Greenwood and Schor, 2009). A perfect example to illustrate this is the takeover of the Arcelor S.A. company, which took place early 2006. By encouraging the appreciation in the stock exchange value of Arcelor, hedge funds have to a large extent influenced the acceptance by the Arcelor's Board of Director of the initially hostile tender offer initiated by the Mittal group. Surprisingly, the structure of the European steel industry was therefore decided by several hedge funds managed in New York and London, registered in tax heavens and holding Arcelor securities listed in Luxembourg (Brav, Jiang, Frank, and Randall, 2008).

Thirdly, the activity of hedge funds is given especially close attention by market surveillance authorities. Since the scandal of the LTCM[1] fund which posed a serious risk to financial markets and more globally to the international banking system, legislators have assigned great importance to hedge funds. In the view of the potentially harmful impacts of those funds on the proper working and stability of the markets, it has become vital to track them carefully (Moschella, 2011). Such vigilance is particularly appropriate given the fact that no specific regulation exists in order to monitor their management practices. This special interest shown towards hedge funds and especially towards their underlying risk is justified by a willingness to protect investors and to ensure the smooth functioning of the market (Aglietta and Rigot, 2009).

Fourthly, the analysis of hedge fund results provides the opportunity to evaluate the effects of a remuneration policy of managers based on performance (Bali, Atilgan, and Demirtas, 2013). That way, traditional funds can estimate the benefits and disadvantages of implementing performance-related fees conditional upon the involvement and outcome of their management team.

[1] Long-Term Capital Management (LTCM) was a large hedge fund, led by renowned Wall Street traders and Nobel Prize-winning economists, which nearly caused the collapse of the global financial system in 1998. This was mainly due to high-risk arbitrage trading strategies.

Lastly, hedge funds are subject to a theoretical and empirical challenge. On the one hand, the hedge fund universe is an area of interest for the financial theory because their management strategies, their performance, their underlying risks and their exposure profile are very different from other financial products (Capocci, 2013). As a result, as will be exposed later, their specificities emphasize the limits of the mean-variance framework on which numerous valuation methods and models are based (Agarwal and Naik, 2002; Favre and Galeano, 2002). The study of these funds also allows judging the efficiency of the traditional market risk measures and the models developed to assess performance. On the other hand, the study of hedge funds brings a methodological contribution since it requires statistical techniques adapted to the features of their time series.

It is therefore undeniable that hedge funds currently have an important role in the financial sphere but the relevant question that must be asked is whether this investment vehicle is able, or not, to provide superior performance.

The investors' interest in hedge funds comes to a large extent from the objective of absolute performance stated by the managers (Liang, 1999). In fact, hedge funds would have the ability to generate returns uncorrelated with those of the market. In addition, they would offer investors the opportunity to diversify the risk exposure of their portfolio. These advantages attributed to alternative management have substantially contributed to the hedge fund success and this, principally when the reversal of the markets happened, in March 2000. By relying on a dynamic risk allocation policy, managers of alternative funds reached positive abnormal returns at that time while traditional managers were barely able to outperform market indices and registered sharp falls. It is precisely the disappointment of institutional investors and pension funds with traditional management which fostered a gradual transfer of wealth to the hedge fund industry. The caveat is that this significant inflow of capital has progressively caused a performance decrease for many alternative strategies and, in particular, arbitrage strategies. According to many experts (e.g., Kaissar, 2018; Strauss, 2017; Vaidya, 2017), hedge funds suffer from an overabundance of investors and hedge funds' success eventually hinges on two rare resources: managers possessing skills and market anomalies that can be exploited. Indeed, the more rapid industry growth in comparison with the number of potential arbitrage opportunities led to a gain dilution between actors exploiting the same opportunities. In order to return to their past performance level, many managers chose to adjust their strategy. Based on the famous financial law assuming that a better performance corresponds to greater risks, several managers decided to move thus towards riskier strategies.

On top of that, hedge funds have somewhat failed to deliver the diversification that investors expected during important market downturns, delivering then substantial losses (Agarwal and Naik, 2004; Amin and Kat, 2003; Fung and Hsieh, 2004). This caused the disappointment of many investors who questioned the actual ability of hedge funds to produce absolute returns over time and thus, the legitimacy of their popularity.

Since the mid-nineties, these topics have fed into a very controversial debate which seems to be intensifying over the course of the years as the industry is gradually growing. Speeches flaunting manager skills and their ability to deliver persistent uncorrelated performance can be distinguished from speeches emphasizing their poor performance, including substantial losses (e.g., Kosowski, Naik and Teo, 2006; Chen and Liang, 2007; Avramov, Kosowski, Naik and Teo, 2011; Chen, Cliff and Zhao, 2012).

This controversy reflects the difficulties posed by the measurement of the hedge fund performance and of the underlying risk involved. The very many estimation methods, applied in different studies, also seem to support this observation. As a result, the first step is to determine beforehand the indicators and analysis methods enabling to assess, as accurately as possible the risk-adjusted performance of hedge funds.

Many papers have emphasized some particularities of hedge fund time series which turn out to be incompatible with the conventional analysis tools used in finance. Indeed, the leptokurtic and asymmetric return distribution questions the use of risk measures based on the normality hypothesis (Agarwal and Naik, 2000; Liang, 2000; Amin and Kat, 2003; Mitchell and Pulvino, 2001). Still, it must be noted that the majority of newspaper articles at the disposal of the investors continues to draw conclusions based on indicators such as the Sharp ratio or the classical Value-at-Risk. The issue with these performance and risk measures is that they do not take into account the extreme risk of alternative strategies while investors are very sensitive to this kind of risk (Scott and Horvath, 1980; Pratt and Zeckhauser, 1987).

In this thesis, the risk-adjusted performance of hedge funds will be addressed by using bootstrap simulations, as proposed by Fama and French (2009), Barras, Scaillet and Wermers (2009) and Kosowski, Naik and Teo (2008) on a comprehensive dataset free of survivorship bias, covering the period January 1998 to May 2017. This statistical procedure emerged as being a valuable solution in order to quantify the proportion of funds that demonstrates persistent performance by distinguishing between luck and skill in the cross-sectional distribution of hedge fund α estimates.

Yet, these methodologies rely on different benchmark models to estimate the performance of hedge funds. It is therefore of great importance to select the most relevant multifactor models to assess them, based on a thorough review of the existing academic literature.

The research aims at demonstrating the potential bias and/or outperformance brought by some well-accepted factor models used when defining hedge fund manager skills. The idea is to disclose whether good performance of some hedge funds can be attributed to manager skills or if it is most likely just due to luck, and likewise, if bad returns are due to a lack of manager skills or, contrarily, simply due to bad luck. To do so, the historical distribution of actual $t(\alpha)$ estimates will be compared to a simulated distribution obtained by running 1000 bootstrap simulations from a return sample where true α is set to zero and which can therefore be interpreted as a distribution where abnormal returns can only be attributed to chance.

The contribution of this paper is manifold. First, the time period covered is lengthened until May 2017, enabling to better picture the post-crisis situation. Then, the analysis is conducted on hedge funds instead of mutual funds, whose characteristics are particularly relevant in the case of a bootstrap procedure due to the non-normality of the return distribution. Also, while Kosowski, Naik, and Teo (2006) carried out simulations independently for each individual fund which does not take into account the correlation of the α estimates, fund returns were jointly sampled in this paper, in accordance with the methodology developed by Fama and French (2010). Finally, another extension of this paper when compared with the existing literature is the comparison between several multifactor models, including both buy-and-hold and optional risk factors which enables to highlight potential false discoveries and/or outperformance.

The results obtained are striking. First, hedge fund returns do not follow a normal distribution and should not be evaluated with a mean/variance framework. Also, including optional factors in the multifactor benchmark model significantly improves the quality of the model, by taking into account the substantial losses faced during market downturns. Finally, based on a bootstrap procedure robust to many biases (self-selection, survivorship, stale price and incubation), evidence is found that the performance generated cannot be attributed to chance alone, meaning that some managers located in the right tail have superior skills. The findings remain the same even when accounting for conditional factors in the benchmark model and the false discoveries are emphasized by the results obtained when using the CAPM as benchmark.

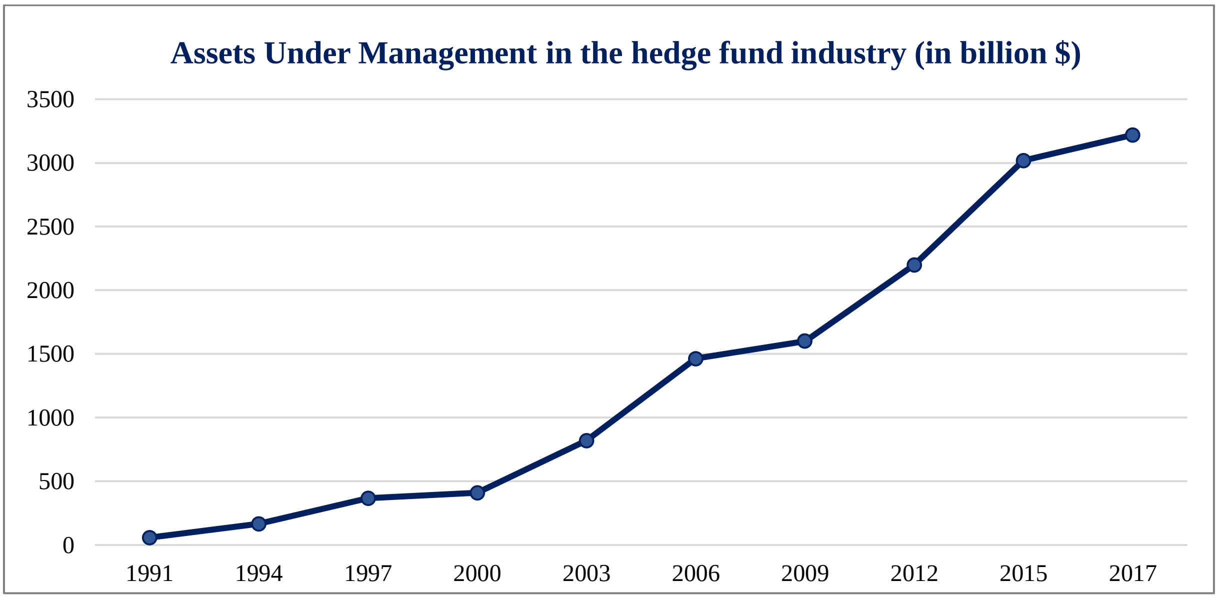
The remainder of the paper is structured as follows: Section 2 provides a literature review describing the current academic knowledge over hedge funds while section 3 presents the database used and the treatment applied to it in order to avoid the traditional biases. Section 4 details the methodology developed and a step-by-step explanation of the chosen statistical approach. Section 5 shows preliminary evidence about the hedge fund particular non-linear return structure and the legitimacy of the bootstrap procedure. Section 6 outlines and interprets the empirical results including the bootstrap analysis whereas section 7 concludes and gives avenue for further research.

2. LITERATURE REVIEW

In this section, a thorough review of the existing literature over hedge funds is developed. First, a precise definition of hedge funds is given and the principal characteristics of this type of investment are described to have an accurate knowledge of what a hedge fund exactly is. Then, several alternative strategies can be applied in hedge funds. It is important to distinguish them and understand their mechanism. Finally, the different models and techniques developed in the academic literature to evaluate the risk-adjusted performance of hedge funds are described. The various multifactor models are detailed, what we know about manager skills is investigated and the performance persistence is scrutinized.

2.1. Development of the hedge fund industry

In recent years, hedge funds have progressively become central players in financial markets and thus, are subject to a particular attention from the academic world. Indeed, the hedge fund industry has developed at an incredible speed as illustrated by the graph below:



According to a recent study conducted by Cao, Liang, Lo, and Petrasek (2014), a significant growth of the average holding of hedge funds in publicly traded stocks can be noticed. It has increased from 3% during the period 2000-2003 to 9% in the period 2008-2012. In 2001, there were approximately 6000 hedges funds with 400 billion dollars of assets under management (Al-Sharkas, 2005). Fifteen years later, this number has been multiplied by 8 to achieve 3220 billion dollars of total assets under management (Preqin, 2017).

Moreover, while there were only 16 scientific papers addressing the subject of hedge funds before 2005 in the main financial journals (JF, JFE, RFS, and JFQA)[2], more than 105 papers on hedge funds have been identified in these journals since that time (Agarwal, Mullaly, and Naik, 2015).

2.2. Definition and characteristics

2.2.1. Definition

Finding a unique definition for the term « hedge fund » is a genuine challenge. Since the creation of the first hedge fund by Alfred Winslow which was of type long/short equity in the late 1940s, this investment vehicle has been continuously extended over the years. Initially, the basic idea of hedge funds consisted of shorting stocks that were expected to drop in value in the future while going long, and sometimes using leverage, on stocks that were expected to rise in value with the aim of eliminating the risk of market-wide fluctuations. Currently, the expression « hedge fund » can be applied to plenty of unregulated funds. However, the term does not have an official definition or even a generally accepted one (Garbaravicius and Dierick, 2005).

Some authors have examined this issue through time and there were attempts to find a concrete definition of hedge funds.

The US President's Working Group on Financial Markets (1999, p. 1) characterised such entities as « any pooled investment vehicle that is privately organised, administered by professional investment managers, and not widely available to the public ».

Garbaravicius and Dierick (2005, p. 5), for their part, defined hedge funds as « An unregulated or loosely regulated fund which can freely use various active investment strategies to achieve positive absolute returns ».

More recently, Capocci (2013, p. 2) gave his own definition: « A hedge fund is an investment limited partnership (private) that uses a broad range of instruments like short selling, derivatives, leverage or arbitrage on different markets ».

[2] JF is the abbreviation for « Journal of Finance », JFE is the abbreviation for « Journal of Financial Economics », RFS is the abbreviation for « Review of Financial Studies » and JFQA is the abbreviation for « Journal of Financial and Quantitative Analysis ».

2.2.2. Main characteristics

Complementary to the definitions, it is interesting to have a look at the main characteristics of these funds. To begin with, hedge funds are very loosely regulated in comparison with other investment entities. This low degree of regulation enables investors to construct private structures with great freedom. Indeed, in contrast to traditional investments such as mutual funds, hedge funds are neither subject to the Security Act of 1933[3], nor to the Investment Advisers Act of 1940[4]. As a result, they do not have to reveal their positions (Gregoriou and Duffy, 2006). The consequences are that an investor has to be sufficiently informed about a particular hedge fund, its strategy and the nature of the principals before deciding to invest. Another consequence of not being regulated is that hedge funds are neither required to document their positions to a general public nor to any supervisory agency.

Kazemi and Martin (2002) explained that, because managers are not forced to perform in accordance with any given benchmark, they can enjoy a greater flexibility at the level of their investment style choice. This leads to the implementation of innovative investment strategies in order to boost the funds' performance (Capocci, 2013). Amin and Kat (2003) and Agarwal and Naik (2004) showed that hedge fund payoffs are nonlinear and this typical behaviour can be explained by the use of dynamic option-like trading strategies. According to Schneeweis (2002), hedge fund managers have several investment tools at their disposal to perform these strategies.

First, the leverage – which can be defined as the ability of funds to borrow money to magnify their returns (Chen, 2011) – allows the investors to amplify their exposure to a specific security or market and therefore, increase performance. Liang (1999) argued that the vast majority of hedge funds (83%) uses leverage, and borrowing enables managers to have more capital to invest. Additionally, leverage does increase volatility: not only the standard deviation but also the spread between the two extreme returns are much higher for the levered hedge funds than for the unlevered ones. Ackermann, McEnally, and Ravenscraft (1999) demonstrated that hedge funds logically exhibit a higher volatility than market indexes or mutual funds. More generally, many researchers found that hedge funds have both higher performance and higher levels of risk (Ackerman, 1999; Liang, 1999).

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[3] The Securities Act of 1933 can be considered as the first main law concerning the offer and sale of securities.
[4] The Investment Advisers Act is a U.S. federal legislation established in 1940 that specifies the role of an investment adviser and monitors his activities.

Besides the leverage, short selling and derivatives also represent common tools in the hedge fund industry. Short selling is used when the investor believes that the price of a security will drop in value and therefore, that he will be able to buy it in a near future at a lower price which will enable him to make profits. According to Edwards and Caglayan (2001), short-selling funds have an inverse correlation with stock returns in both bull and bear markets and experience thus very high returns in bear markets. Moreover, investors make use of active trading which implies buying and selling securities with the intention of holding them for a brief period of time, usually no longer than one day. Active trading as an investment strategy aims at taking advantage of short-term price movements and arbitrage opportunities. Derivatives, such as options or forwards, are used by 71% of hedge funds (Chen, 2011) and are particularly helpful to implement dynamic trading strategies.

The liquidity of hedge funds is also a topic that has been studied in detail by several researchers. A large proportion of hedge funds has a lock-up period to avoid early redemption (Liang, 1999). A lock-up period is a predetermined amount of time before which investors are prohibited from taking back freely their investment. Many authors found a positive significant relationship between lock-up periods and returns, and demonstrated that a lock-up period increases the illiquidity of funds (Aragon, 2007; Liang, 1999; Park and Whitt, 2013). Indeed, a particularity of hedge funds is the opportunity to deal with illiquid assets associated with higher returns. Other mechanisms exist, such as discretionary liquidity restrictions on investor shares during financial crises which aim at ensuring that assets can be traded at a fair value (Aiken, Clifford, and Ellis, 2015; Park and Whitt, 2013; Titman and Tiu, 2010).

2.2.3. Fee structure

Due to the high minimum investment amount required, hedge fund investors can be grouped into two main categories: high net worth individuals and institutional investors (Garbaravicius and Dierick, 2005). Hedge fund managers receive remuneration based on a typical fee structure: they earn not only the usual management fee but also a performance fee which is a payment made to a fund manager for generating positive returns (Bali, Atilgan, and Demirtas, 2013). The performance fee is generally calculated as a percentage of the investment profits (usually 20%) and the management fee is a percentage of the total assets under management (between 1% and 2%).

The high-water mark and the hurdle rate are two mechanisms used to limit the performance fees received by the managers. A high-water mark makes the distribution of performance fees conditional upon the exceedance of the maximum share value. This mechanism allows preventing situations where investors receive performance fees for bad performance or fees paid twice for the same performance. Goetzmann, Ingersoll, and Ross (2003) showed that managers usually earn a percentage of the fund's return in excess of the high-water mark and, as a result, this mechanism limits the importance of performance fees. An alternative to this method is the use of the hurdle rate which is a mandatory minimum level of return that must be achieved before starting the distribution of proportional performance fees (Capocci, 2013).

2.2.4. Drawbacks

Hedge funds also have shortcomings that must be acutely examined during the portfolio construction process. Indeed, investors are facing several difficulties when determining the appropriate amount of exposure to hedge funds in their portfolios. Fung and Hsieh (2004) explained that the opaqueness of hedge fund operations coupled with the lack of performance-reporting standards make it especially challenging to express precise expectations for hedge fund performance. On the one hand, reliable data started only in the 1990s which do not represent a sufficiently important history to evaluate the performance of hedge funds in a variety of market environments. On the other hand, because hedge funds are private investment vehicles, they do not disclose information. Consequently, the historical return statistics are of questionable quality.

Kosowski, Naik, and Teo (2006) stated that evaluating the significance and persistence of hedge fund returns is fraught with many difficulties. First, the best-qualified managers are among a huge cross-section of hedge funds, what increases the probability that some top performers achieve outstanding results only because they are lucky. Moreover, due to the dynamic trading strategies established by the managers and their holdings of derivatives securities such as options, the hedge fund returns typically do not follow a normal distribution (Eling, 2006; Malkiel and Saha, 2005). Finally, the complexity of these strategies makes benchmarking their performance troublesome and leads sometimes to model misspecification.

To sum up, hedge funds differ from mutual funds on three main features: the disclosure of their positions and activities, the use of financial leverage and the use of derivatives (Anson, 2012).

2.3. Investment strategies

The choice of a primary investment strategy is of paramount importance when a new hedge fund is opened. Hedge funds use a variety of alternative investment strategies whose use is always justifiable. However, many strategies can be grouped into some major categories based on their main characteristics. Consequently, the database providers have divided them into groups based on differentiating figures as compared with peers (Capocci, 2013).

Different classification mechanisms are available in the scientific literature to sort the different hedge fund strategies. Fung and Hsieh (1997) emphasized two main aspects: the location choice, which represents the asset classes in which the manager wants to invest and the trading strategy, which corresponds to the direction (long or short) and the leverage used by the managers to generate the desired level of return.

Another method to group hedge funds consists of separating funds that are market neutral from those that are directional. On the one hand, market-neutral funds are really complex and designed to provide returns that are uncorrelated to those of the overall market and therefore, have the potential to boost returns and reduce risk. On the other hand, directional trading strategies, as the name suggests, have a strong exposure to the market.

In this section, the main hedge fund strategies are briefly explained, primarily based on the book written by Bali, Atilgan, and Demirtas (2013), with a particular focus on long/short equity as the analysis will be conducted on this type of hedge funds.

2.3.1. Convertible arbitrage funds

Convertible arbitrage funds consist of exploiting anomalies in the progression of the price relationship between the underlying equity and corporate securities that are convertible into common stocks. Convertible means that the holder has the opportunity to exchange the security against shares between the issuing date and the maturity date (Capocci, 2013). These convertible funds are therefore hybrids and their returns can be explained by stocks, options, bonds or fund factors (Amman, Kind, and Seiz, 2010). In a typical convertible arbitrage transaction, a hedge fund manager will buy the convertible bond and short sell the stock in anticipation of either an increase in the bond price, a decrease in the stock price, or both effects simultaneously.

2.3.2. Emerging market funds

An emerging market hedge fund is a hedge fund that specializes its purchases in securities of emerging market countries such as India, Brazil, Russia or China, which tend to have higher inflation and volatile growth (Amenc, Curtis and Martellini, 2003). These markets are differentiated by a lack of advanced investment tools and the presence of high illiquidity, resulting in potentially large returns (Fung and Hsieh, 1997).

2.3.3. Event-driven funds

Event-driven funds attempt to benefit from events occurring in the course of the business life such as mergers, reorganizations, acquisitions or recapitalizations, that could possibly result in the short-term mispricing of a company's stock. Managers of event-driven funds can take positions on corporate events in two basic ways (Fung and Hsieh, 1999). First, some funds actively take positions in corporate bankruptcies and reorganizations and are often referred to as « distressed securities » funds. The other ones are called « merger arbitrage » funds and invest in announced merger and acquisitions, usually by purchasing the equities of the targets and going short the equities of the acquirers.

2.3.4. Global macro funds

Global macro funds, as its name implies, emphasize that close attention is paid to macroeconomic factors. Macro events represent changes in global economies, typically brought about by changes in government policy. These changes impact interest rates which, in turn, affect all financial instruments such as stock, bond and currency markets. In this instance, managers make use of leverage on expected movement in equity, interest rate, currency, commodity markets or fiscal policy (Capocci, 2013).

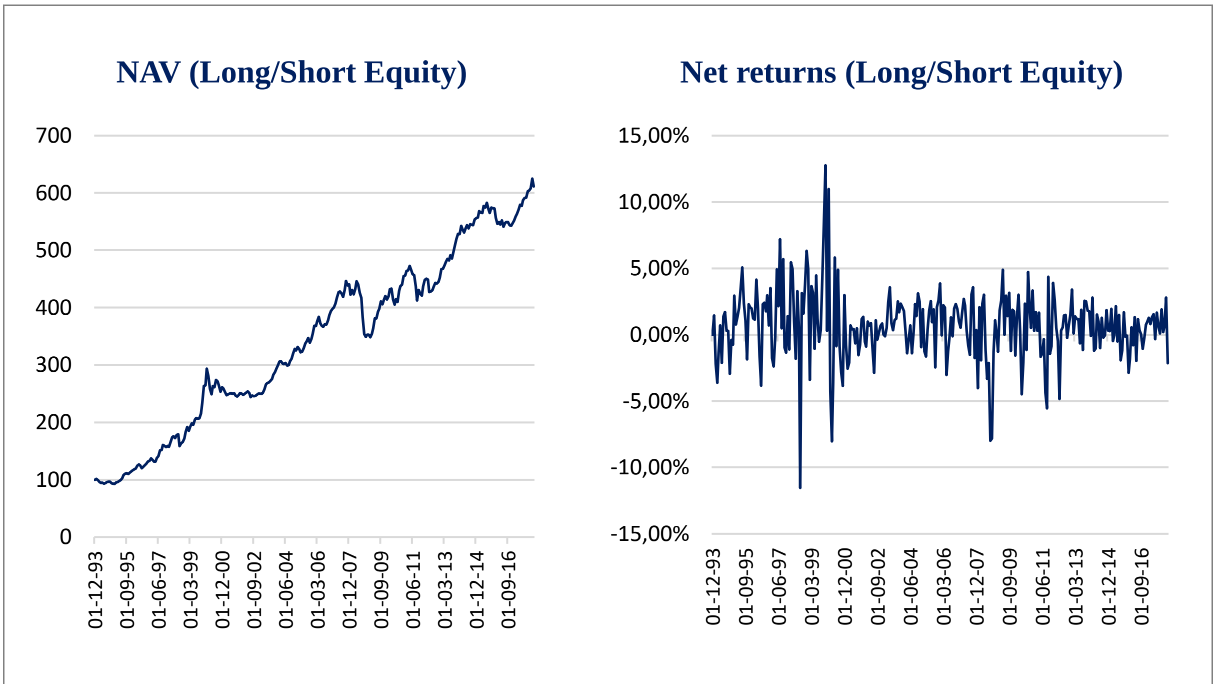
2.3.5. Long/short equity funds

Long/short equity funds are by far the oldest and the most frequent in financial markets. It consists of investing in long as well as short positions on the equity market. When hedge fund managers adopt this strategy, they can either purchase stocks that they feel are undervalued or short sell stocks which seem to be overvalued. The identification of these securities is based on an in-depth fundamental analysis, generally supplemented by technical analyses designed to improve the investment timing.

Fung and Hsieh (2011) calculated that roughly 40 percent of all hedge funds are classified as having long/short equity as their primary investment style which approximately represents 27 percent of this industry's total assets under management (AUM) based on the estimate provided by the Lipper-TASS database.

An important aspect of portfolio management is the manager's ability to control his net exposure to the market whereas the market conditions are continuously changing over time because it enables to generate excess returns. The short positions in a long/short portfolio are useful to hedge against the market risk but can also contribute to the generation of positive returns. Besides, it is common to note that funds which make use of this type of strategy are often characterised as funds with double alpha and low beta, as managers attempt to generate alpha by efficient stock picks in both their long and short positions.

It is also important to mention that funds do not necessarily want to remain in a market risk neutral position. Jacob and Lévy (2000) indicated that a rigorously-build long/short portfolio can control the market risk without inevitably having neutral positions. The long/short universe is heterogeneous because the investment approach differs from one manager to another.



The graphs are retrieved from Preqin (2017)

Some long/short funds are qualified as specialized in some sectors while others are said to be more generalists. Ineichen (2003) noticed that those specialized funds are highly correlated with their sector benchmark index. However, he also stated that those funds can manage their risk so that the performance grows more rapidly than the one of the sector benchmark indexes. Yao, Clifford, and Berens (2004), for their part, showed that sector specialist hedge fund managers do not outperform generalist hedge fund managers in terms of exposure to systematic risk. By adjusting for the volatility, the fraction of funds producing a positive performance is almost identical between specialists and generalists.

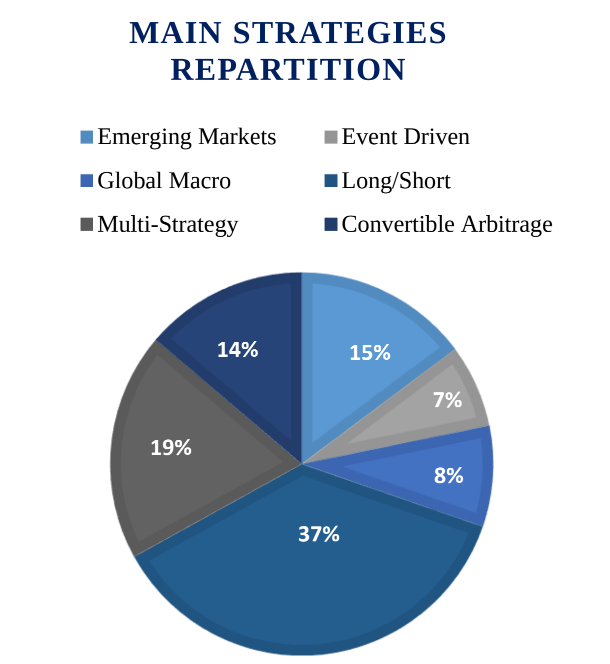
Contrary to other hedge fund strategies, Fung and Hsieh (2001) exposed that hedge funds following the long/short equity strategy do not have significant exposures to option-based factors and consequently, bear risks similar to equity mutual funds. This strategy is therefore liquid and particularly easy to implement (Bali, Atilgan, and Demirtas, 2013). Long/short strategies can also be differentiated in numerous ways such as market geography, industry sector, investment philosophy…

The repartition between the different strategies according to 5 main databases (TASS, HFR, Barclay, Eureka and Morningstar) is displayed below:

Aggregate Database

(TASS, HFR, Barclay, Eureka and Morningstar)

Main Strategy	# Funds
Emerging Markets	3170
Event Driven	1510
Global Macro	1822
Long/Short	7874
Multi-Strategy	4136
Convertible Arbitrage	2954



Retrieved from Joenväärä, Kosowski and Tolonen (2016)

2.4. Return-generating process

Being able to properly evaluate performance has always been the main focus of attention in the hedge fund industry. Based on a plethora of assumptions, several authors have tried to explain, using a model, the general performance of all hedge funds. The scientific literature addressing this topic has considerably grown, especially in the past years. In this section, a part of this extensive literature is discussed to provide the reader with an overview of the current knowledge.

To understand the return-generating process of hedge funds properly, several studies have developed linear multifactor models, decomposing hedge fund returns into alphas and betas. Betas (β) correspond to the components of the fund's return related to its exposure to systematic risk factors and the alpha (α) is the portion of the fund return that cannot be explained by the risk factors and which is therefore called « excess return ».

The logical starting point in identifying the relevant hedge fund risk factors is to examine whether funds are exposed to market or systematic risk. Although many managers explain to their clients that their returns are uncorrelated with the traditional asset classes, several scientific papers have proved that the estimated correlation considerably underestimates the actual exposure of hedge funds to those asset classes. Indeed, Patton (2009) analysed the market neutrality of hedge funds and discovered that around 25 percent of funds designated as « market neutral » have significant correlation with the market. Yet, even though many market neutral funds are not truly neutral, these funds turn out to be less correlated with the market than other styles. Consequently, it can be argued that the hedge fund performance is not only alpha-driven but also driven by the traditional beta components (e.g., Fung and Hsieh, 2004; Géhin and Vaissié, 2006; Bali, Brown and Caglayan, 2012).

Several authors decided then to test individual funds' exposures to various risk factors and decomposed the total risk of each fund into systematic and residual risk components to obtain a comprehensive picture of the hedge fund performance (Fama and French, 1993; Carhart, 1997; Fung and Hsieh, 2001, 2004). In the scientific literature, there are two main approaches to attribute fund's performance to different risks:

- The first one identifies pre-specified risk factors explaining hedge fund performance and can, therefore, be characterized as a « **top-down** » method.

- The second approach, alternatively, can be considered as a « **bottom-up** » approach since it begins with the underlying conventional assets such as stocks or bonds. This method involves replicating the hedge fund portfolios by trading in the underlying securities. Fung and Hsieh (2002) decided to call these constructed factors « Asset-Based Style factors ».

2.4.1. Multifactor models

In 1993, Fama and French developed the famous three-factor model with its two additional factors being size and value. As this model takes into account outperformance tendency, it represented a substantial improvement over the CAPM. As a result, this model has been extensively used in the literature and many papers have been published with modified versions, augmented with additional factors (Wagner and Winter, 2013; Hunter, Kandel, Kandel, and Wermers, 2014).

One of the most famous ones is the one developed by Carhart (1997), who extended this model by including a momentum factor (MOM factor) for asset pricing of stocks. Momentum can be characterised as the trend for a stock price to keep growing if it is going up and to keep falling if it is going down. Afterwards, Fama and French (2015) realised that the three-factor model was inadequate due to the fact that it overlooked a lot of variation coming from profitability and investment and thus, they decided to add two new factors coming from the dividend discount model to obtain a five-factor model.

Viebig (2011) investigated 651 peer-reviewed articles on hedge funds published between 1990 and 2011 and concluded that the Fung and Hsieh's 1997 paper can be considered as the reference with regard to academic research on hedge funds. Fung and Hsieh explained that the level of risk taken by the manager depends on the dynamic trading strategy rather than the asset class in which the manager invests. Following this line of reasoning, they constructed a factor model with trading and location factors to capture the specific risk and return characteristics of hedge funds. The main idea was to discover the style factors which best explain the nonlinear, strategy-specific risk and return characteristics of hedge funds. Later, in 2001, Fung and Hsieh proposed a new model with factors embedding the option-like characteristics of hedge funds. They demonstrated that modelling trend-following strategies with lookback straddles – combinations of a lookback call option and a lookback put option – could better capture the funds' returns than standard asset indices. Consequently, it can be argued that trend-following funds have systematic risk exposures.

In 2004, again, Fung and Hsieh computed an updated model, this time with seven risk factors explaining up to 80 percent of the variation in hedge fund portfolio performance. Their model highlighted the common sources of risk which have an impact on the performance and these seven factors can be divided into three main categories: trend-following risk factors, equity-oriented risk factors, and bond-oriented risk factors. Fung and Hsieh also noticed that extreme market events result in structural breakpoints in return time series and that the exposure to the Standard and Poor's 500 index is considerably reduced after crises such as Long-Term Capital Management (LTCM) collapse in 1998 or the bursting of the dotcom bubble in 2000, showing that managers adjust their exposures according to the market. Nowadays, this seven-factor model can be considered as a reference from an academic perspective when it comes to the evaluation of hedge fund performance. Indeed, over the years, it can be noticed that many authors have made use of it (e.g., Darolles and Mero, 2011; Ammann, Huber, and Schmid, 2011; Joenväärä and Kosowski, 2015).

Agarwal and Naik (2004) also acknowledged that incorporating option-based factors significantly improves the quality of the factor model in order to evaluate hedge fund performance and risk. They confirmed the findings of Fung and Hsieh (2004) and pointed out that hedge funds incur huge losses during market downturns. This observation is due to the fact that a lot of hedge fund indexes are positively correlated with the market in case of down-market conditions. However, no correlation is observed in case of up-market conditions. This betas asymmetry in up- versus down-market circumstances helped them to validate the nonlinear nature of hedge fund payoffs. To replicate them, they opted for highly liquid at-the-money (ATM) and out-of-the-money (OTM) European call and put options on the Standard and Poor's 500 index trading on the Chicago Mercantile Exchange and developed a new model attempting to describe hedge fund returns.

Even though those models seem to be generally accepted and recognized by their peers and as result, will be the main focus of attention for this thesis, it is worth mentioning the other models as well to provide the reader with a complete overview of the current research and studies on this subject.

For instance, the interest of many studies has been to analyse the behaviour of the risk associated with hedge funds in adverse market conditions or crisis situations. Several authors have thus decided to incorporate macroeconomic variables to capture hedge fund performance.

Avramov, Kosowski, Naik, and Teo (2011) showed that conditioning on macroeconomic variables enables to assess managerial skill. They investigated the performance of portfolio strategies investing in hedge funds and taking advantage of predictability based on macroeconomic variables. Their findings suggested that performance could be conditional on these different variables and consequently, the managers who take predictability into account based on the default spread and on the volatility index (VIX)[5] in their strategy outperform the others.

Avramov, Barras, and Kosowski (2013) pursued further research and studied the proportion of future returns that can be explained by macroeconomic variables for individual funds. Simultaneously, Banegas, Gillen, Timmermann, and Wermers (2012) also developed a conditional 4-factor model with state variables for conditioning exposures on macroeconomic information.

In 2011, Bali, Brown, and Caglayan assessed the exposures of hedge funds to diverse macroeconomic and financial factors through substitute measures of factors beta. In their next paper (Bali, Brown, and Caglayan, 2012), they investigated the proportion of the cross-sectional dispersion of hedge fund returns which can be explained by aggregate risk measures such as market risk, residual risk and tail risk.

Afterwards, Bali, Brown, and Caglayan (2014) introduced new measures of macroeconomic risk interpreted as measures of economic uncertainty. They found a significant positive relationship between future hedge fund returns and uncertainty betas.

Sandvik, Frydenberg, Westgaard, and Heitman (2011) also took a closer look at the performance of hedge funds in case of bear and bull markets and observed if hedge funds were able to deliver abnormal risk-adjusted returns. More recently, Racicot and Théoret (2016) adopted the methodology of Beaudry, Caglayan, and Schiantarelli (2001) and analysed the behaviour of hedge fund performance over business cycles and their reaction to macroeconomic risk and uncertainty.

Furthermore, another method consists in considering higher moments to properly model hedge fund performance.

[5] VIX symbolizes the ticker of the Volatility Index, representing the market's expectation of 30-day volatility. This is obtained by using the implied volatilities of a large range of Standard and Poor's 500 index options.

Agarwal, Bakshi, and Huij (2010) designed factors for higher moments (volatility, skewness, and kurtosis) of equity risk using traded put and call options on the Standard & Poor's 500 index. Hübner, Lambert, and Papageorgiou (2015) also focused on higher moments in order to better understand hedge fund performance and the dynamic management style of managers. They developed a conditional multifactor model made of not only asset-based and option-based factors but also the location factor and the trading factor constructed by Fung and Hsieh (1997). They then investigated how changes in the expected levels of US equity volatility, skewness or kurtosis risks have an impact on the risk factor exposure of funds and their allocation.

Additionally, to properly model the non-linearities in time series, various academics developed regime-switching multifactor models.

Spurgin, Martin, and Schneeweis (2001) showed with a high level of confidence that the traditional assets are not constantly correlated with hedge fund returns. Indeed, strategies which do not seem correlated with the market over extended periods of time turn out to be correlated with the market during periods of market downturns. Therefore, academics are tempted to construct regime-switching models to account for the nonlinearity in hedge fund returns (Viebig, 2011). Bollen and Whaley (2009) showed a genuine interest for time-varying properties of hedge fund returns and acknowledged that following the assumption that exposures to risk factors are constant over time, abnormal returns might be wrongly estimated. Bilio, Getmansky, and Pelizzon (2010) also used regime-switching models with four common risk factors: liquidity, credit, equity market, and volatility. They highlighted that the different strategies exhibit common risk factors exposure and that traditional systematic risk factor models drastically underestimate the risk inherent to hedge funds in times of crises.

Finally, multiple authors also developed some procedures employing interesting bottom-up approaches.

Making use of data on convertible bonds and underlying stocks in the United States, Agarwal, Fung, Loon, and Naik (2011) adopted an Asset-Based Style (ABS) approach to investigate the risk-return characteristics of convertible arbitrage funds. Jylha and Suominen (2011) constructed a factor portfolio composed of short positions in currencies with low Sharpe ratios and long position in currencies with high Sharpe ratios. Bhardwaj, Gorton, and Rouwenhorst (2014), for their part, used an Asset-Based Style (ABS) approach to compute benchmarks for Commodity Trading Advisors (CTAs).

More recently, Bussière, Hoerova, and Klaus (2015) focused on the proportion of hedge fund returns which can be explained by common factors. They constructed common factors by using the principal component analysis. Their findings showed that funds exposed to these common risks underperform in difficult market circumstances such as the financial crisis of 2008 due to their great exposure to downside and illiquidity risk. This is coherent with the conclusions of Sadka (2010), who demonstrated that hedge funds having high exposure to liquidity risk significantly outperformed the other hedge funds over the 1994-2008 period but experienced very poor performance during the liquidity crisis.

2.4.2. Influence of hedge fund features on performance

Some authors, to explain the performance from an entirely different angle, dwelled on the intrinsic characteristics of hedge funds such as the size, the age or the cash-flows in order to verify if it could justify performance.

Amenc, Curtis, and Martellini (2003) but also Agarwal, Daniel, and Naik (2007) focused on the age of funds and showed that age is inversely correlated with performance. Liang (2000) analysed hedge funds between 1990 and 1999 and came to the conclusion that young funds outperformed more mature funds. Howell (2001) and Gregoriou (2002) took a stand in this debate by bringing more precise conclusions: 10% of the younger funds would have higher returns than the more mature ones, once the dead funds are removed. This phenomenon can be explained by the fact that during the first years, hedge funds generally have fewer assets under management and are therefore of smaller size. Consequently, managers enjoy a greater flexibility in their decision-making process (Gregoriou and Rouah, 2002).

Other studies focused on hedge funds capital flows to measure their impact on the performance. Agarwal, Daniel, and Naik (2007) and Fung, Hsieh, Naik, and Ramadorai (2008) highlighted the fact that funds receiving capital experience poor performance thereafter.

Finally, the examination of funds' size produced relatively contradictory results. Getmansky (2005) suggested that an optimal size exists for hedge funds and once exceeded, the performance is negatively affected. However, other papers are much more radical in their findings. Harri and Brorsen (2004) detected a negative relationship between the size of some hedge funds and the performance while Boyson and Mooradian (2007) found the opposite result.

2.5. Manager skills versus luck

Managers possessing skills is usually thought to be manifested in the alpha which is the portion of a fund's return that cannot be attributed to systematic risk exposures. Hedge fund managers are often seen as savvy top performers who can exploit their managerial skill without much limitation in their trading strategies. The question is: is it truly the case in practice?

An abundant academic literature has developed contemporaneously to observe whether hedge fund managers actually exhibit superior ability. Researchers have also tried to decompose managerial skill into stock selectivity and timing components.

Barras, Scaillet, and Wermers (2005) focused on false discoveries and computed a new measure called the False Discovery Rate (FDR) to evaluate the fraction of mutual funds with truly positive and negative performance and that way, being able to quantify the impact of luck. Chen and Liang (2007) emphasized the skills of hedge fund managers in timing the market and found that this ability tends to be relatively strong in bear and highly volatile market conditions. The authors showed that market timing funds capture higher returns in favourable market conditions and are able to limit their losses in adverse market conditions.

Kosowski, Naik, and Teo (2006) were the first to take advantage of a bootstrap procedure in order to distinguish skill from luck in hedge fund performance. A relatively similar approach was followed by Cuthbertson, Nitzche and O'Sullivan (2008) on UK equity mutual funds which revealed superior manager skills among the best-performing funds but also value destruction in the left tail of the return distribution. Fama and French (2010) also used a bootstrap approach to differentiate luck from skill in the cross-section of mutual fund alpha estimates. A prime advantage of their simulation approach is that capturing the joint distribution of fund returns is decisive for effective interpretations about the existence of non-zero true α estimates for actual fund returns. Starting from the equilibrium accounting which states that active investment is a zero-sum game, they wanted to detect if they are good funds and consequently, if some managers have superior skills, even though their technique did not enable to precisely know which funds are outperforming.

One year later, Avramov, Kosowski, Naik, and Teo (2011) used a Bayesian framework to compare groups of hypothetical hedge fund investors with varying beliefs about the predictability of managerial skill. Thanks to this framework, they analysed whether hedge fund managers have the ability to deliver alpha in the context of various macroeconomic conditions.

Finally, Chen, Cliff, and Zhao (2012) used the Expectation-Maximization algorithm to deduce managerial skill. Their approach consisted in dividing the managers in a discrete number of skill categories and inferring the percentage of managers in each category by using the observed distribution of alphas. Their findings showed that approximately 50% of hedge fund managers possess skill.

2.6. Performance persistence

Because hedge fund managers have limited access to historical data, it is important for them to assess if outperforming hedge funds remain well-performing or if this trend disappears over time. In other words, managers are particularly interested in the potential performance persistence of their funds (Kat and Menexe, 2002; French, Ko, and Abuaf, 2005; Edwards and Caglayan 2001).

2.6.1. Absolute and relative performance

Among the various studies over persistence, it is of great importance to make a distinction between absolute and relative persistence. The relative persistence allows to determine on a global basis if the collected data from past performance are helpful in order to predict future returns, and this, among a group of funds. Indeed, the relative persistence consists of sorting hedge funds by classifying those that best perform and those that poorly perform and thereafter, investigate if those same funds maintain their position from one period to the next. Because most studies are carried out on the relative performance, the measurement tools used are similar to those used for mutual funds. That way, academics make use of both parametric and non-parametric measures to assess relative performance (Brown, Goetzmann, and Ibbotson, 1999; Liang, 2000; Harri and Brorsen, 2004; Agarwal and Naik, 2000). The limits of relative persistence come from the fact that it does not allow to study a specific fund and its performance over time. In this particular case, the absolute persistence is more helpful to identify funds which consistently generate positive returns. This approach is mostly adapted for hedge funds because managers are supposed to generate great returns in absolute terms which are not compared to any benchmark index. As mentioned earlier, the specific fee structure of hedge funds can be explained by their ability to produce good returns and there have been some studies that have examined this subject (De Souza and Gokcan, 2004; Hassanhodzic and Lo, 2007).

2.6.2. Existence of performance persistence

The literature seems to be mixed with regard to the performance persistence of hedge funds.

The first plausible explanation is the problem of databases. (Fung and Hsieh, 1997; Brown, Goetzmann, and Ibbotson, 1999). Indeed, due to the absence of regulation for hedge funds concerning the provision of public records, many databases of varying quality exist. On top of that, the period under consideration is not always the same, what makes comparisons even more complex. The second reason which could account for these differences is the developed methodology to calculate the different risk measures (Sharp ratio, Jensen's alpha, appraisal ratio, volatility…).

These measures also suffer from the disadvantage of not being computed to evaluate returns which are not normally distributed as it is the case for hedge funds due to both the assets in which managers invest and the dynamic investment strategies undertaken. Indeed, Fung and Hsieh (1997, 2000) proved that hedge funds, contrary to mutual funds, have nonlinear returns which resemble more a function of options payoff. However, Favre and Galeano (2002) attempted to find alternative measures to deal with this dilemma and decided to use a modified Value-at-Risk based on the volatility, but also on the skewness and the kurtosis of the return distribution.

Nevertheless, studies conducted since the year 2000 seem to be less conflicting in their findings and have identified performance persistence among hedge funds. Agarwal and Naik (2000) took advantage of the alpha and the appraisal ratio in order to determine the performance of hedge funds. They found that hedge funds showed short-term little persistence but they do not seem to maintain this level of persistence in the long run.

Edwards and Caglayan (2001) constructed an 8-factor model to evaluate performance. Their results argued that hedge funds are persistent over a relatively short period of time, ranging from one to two years. Capocci and Hübner (2004), for their part, developed a model combining three different models to assess performance persistence: the model of Fama and French (1993), the model of Agarwal and Naik (2000) and a 4-factor model.

A few years later, Kosowski, Naik, and Teo (2007) made use of a bootstrap resampling method to highlight the fact that the outperforming hedge funds are those experiencing persistence. The authors demonstrated the presence of alpha generated by the manager for the best funds. They employed a method previously applied for mutual funds (Busse and Irvine, 2006) but more adapted to hedge funds than former measures. Indeed, they replicated the bootstrap method developed by Kosowski, Timmermann, Wermers, and White (2006) which enables to deal with the lack of data from hedge funds and combined it with a Bayesian approach from Pastor and Stambaugh (2002) because this approach allows to consider data which do not seem related to assets under management, but which brings additional information what balances the lack of data from hedge funds. Their findings demonstrated that the returns from the best funds are not fully explained by luck. Finally, they showed that persistence exists for the best performing hedge funds.

3. DATA

3.1. Database

In order to conduct this analysis, net-of-fees returns on equity long-short hedge funds have been collected from the Morningstar database over the period ranging from January 1998 to May 2017. Morningstar is a Chicago-based leading provider of independent investment research. More specifically, their hedge fund database provides historical data on more than 1200 dead funds and includes information on 7000 actively reporting funds from more than 3700 managers. These reasons explain to a large extent why several authors have made use of it in the past for their research (See Appendix 1).

3.2. Biases

One of the main issues that academics have to handle with when dealing with hedge funds is to interpret empirical results due to the several biases present in all hedge fund databases which can lead to false discoveries (e.g., Bollen and Pool, 2009; Fung and Hsieh, 2001; Getmansky, Lo, and Makarov, 2004; Jiang, Yao, and Yu, 2007; Liang 1999). The source of these biases mainly comes from the fact that hedge fund managers are not compelled to report their performance. Furthermore, hedge fund information is not gathered and centralised since there is no hedge fund industry association that could serve as a global depository. Consequently, the lack of transparency results in the apparition of several identified biases: self-selection bias, survivorship bias, instant history (or backfill) bias and stale price bias. Each single hedge fund database can potentially suffer from one or more of these biases, what can have a non-negligible impact on the inferences involving fund performance and risk. As a matter of fact, the accuracy of commercial hedge fund databases has always been of great concern.

Patton, Ramadorai, and Streatfield (2013) showed that hedge funds often revise their return following their initial reporting to the commercial databases. This practice might mislead the current or potential investors. Aragon and Nanda (2015) documented that timely disclosure is an utmost consideration of hedge fund managers because there are potential benefits to managers from delaying reporting when performance is sufficiently poor. In addition, hedge funds exhibiting important delays in reporting are more inclined to smooth their returns or commit fraud (Ackerman, McEnally, and Ravenscraft, 1999).

Going forward, the different types of biases will be enumerated, described and the treatments applied to limit their harmful impacts will be explained.

3.2.1. Survivorship bias

Survivorship bias appears when a hedge fund database only keeps information on funds that are still operating and reporting information to the database vendor. These funds can be called « surviving » funds (Joenväärä, Kosowski and Tolonen, 2016). A hedge fund company's selection of funds today will therefore include only those that have been successful in the past. In order to hide bad performance, many poor-performing funds are merged into others or even closed (Elton, Gruber, and Blake, 1996). The magnitude of the bias varies with the sample period, the type of database and the fund characteristics. According to Agarwal, Mullaly, and Naik (2015), estimates of this bias range from 2% to 3.6% per year and can be even higher for smaller and younger funds. If it is significant, then, the average historical return of the surviving funds is greater than the average return of all funds over the time period under study (Fung and Hsieh, 2004).

3.2.2. Instant-history bias

The instant-history bias, also called back-fill bias occurs when managers take the decision of not reporting fund performance to a database from the fund's inception (Fung and Hsieh, 2000). When hedge funds are added to a certain database, they are frequently allowed to backfill their historical returns after an incubation period, once they have established and accumulated a track record of success with a fund (Kosowski, Timmerman, Wermers, and White, 2006). The mean return is therefore upwardly biased in the hedge fund database (Fung and Hsieh, 2004).

3.2.3. Stale price bias

Hedge funds are differentiated from other investment vehicles due to their ability to invest in illiquid assets (Asness, Krail, and Liew, 2001). Valuing these assets is particularly challenging since a current market price is not always available. As a result, hedge funds use stale prices to give an appropriate value to their holdings, reflecting the market reality. This way, managers smooth their returns and can manipulate Sharpe ratios (Sharpe, 1994) by artificially reducing estimates of volatility and correlation with traditional indices.

3.2.4. Self-selection bias

Hedge fund data are usually gathered by data seller and sold, with the approval of the hedge fund manager to qualified investors (Joenväärä, Kosowski, and Tolonen, 2016). Due to the fact that hedge funds are prohibited from public solicitation, word of mouth is the only way through which the fund can be marketed. Logically, by belonging to a particular database, information about the fund is conveyed. To the extent that the performance of funds seeking investors is different from the performance of funds not seeking investors, the database will be plagued by selection bias.

Agarwal, Fos, and Jiang (2013) reported that two different self-selection biases named « timing bias » and « delisting bias » take place because of the competing motivations. On the one hand, when their returns have been strong, hedge funds exploit this opportunity and report it to databases. On the other hand, when their performance has been weak, they logically cease reporting to databases (Liang, 1999).

3.3. Treatment

To ensure that the findings are robust to the multiple above-mentioned biases, dummy variables were created (in SAS) to make the necessary treatments and obtain an appropriate database in order to properly apply the different statistical techniques thereafter. A procedure recommended by Kosowski, Naik, and Teo (2007), Teo (2009), Avramov, Kosowski, Naik, and Teo (2011) and Joenväärä and Kosowski (2015) was thus applied.

This method consists, in a first instance, in only keeping the funds that report monthly returns and excluding the first twelve months of data to hedge the obtained results against backfill and incubation biases. However, this approach gives rise to survivorship bias because some hedge funds are deleted. Also, since the majority of database vendors started making their data available in 1994, information concerning funds which disappeared before December 1993 was rejected. That way, there are fewer data issues and the results delivered by the analysis will be more reliable (Elton, Gruber, and Blake, 2001). Furthermore, by truncating returns between the limits of -90% and 300%, a possible source of error is deleted due to the fact that keeping outliers would have had a significant impact on the mean, on the standard deviation and on the distribution. Indeed, rejecting returns below -90% reduces the probability that data providers replace missing observations by large negative returns (Joenväärä, Kosowski, and Tolonen, 2016).

To avoid survivorship bias, dead funds will be incorporated in the data sample. As Morningstar gives the opportunity to observe the characteristics of the dead funds as well, this step can be easily performed. Finally, returns and assets under management (AuM) observations denominated in other currencies were converted to USD using end-of-month spot rates downloaded from Bloomberg[6] in order to make the comparisons more meaningful.

Once the initial dataset cleaned, the funds were classified by primary strategy as defined by Joenväärä, Kosowski, and Tolonen (2016) and then filtered to only keep the funds exhibiting a long/short equity strategy. The emphasis was placed on long-short equity funds because, as demonstrated by Fung and Hsieh (2001), long-short equity funds face risks similar to equity mutual funds and are not highly exposed to option-like factors. As a matter of fact, long-short equity strategies exhibit strong exposure to the three factors originating from the Fama and French model (the excess return on the market, the firm size and value stock). Conversely, conducting the analysis on other strategies would have led to confusing results coming from the higher probability of including irrelevant risk factors.

[6] The data were retrieved from the Bloomberg’s website: https://www.bloomberg.com/

4. METHODOLOGY

The idea is to control if the performance assessed by the different models used to measure hedge fund performance is biased by false discoveries. The difference between the actual performance and the performance found with the benchmark models is called bias in the evaluation process. However, the actual performance of hedge funds is not known because the perfect model has not been discovered yet. As a result, it is not possible to compute neither the theoretical bias of these models nor the proportion captured by the bootstrap because the abnormal return will be composed of luck and manager skills at the same time.

To solve this issue, the analysis will be conducted on different theoretical models, with some being composed of optional factors which will enable to adequately benchmark the performance of hedge funds exhibiting option-like features. The impact of the bootstrap will be isolated by comparing the performance captured by a model with the performance captured by the other models.

As explained above, the purpose of this paper is to highlight the impact of bootstrapping on performance inference. To this end, performing a bootstrap procedure on models which are not adapted to hedge funds makes no sense. On the contrary, it is worth comparing the findings obtained with different appropriate models to assess hedge fund performance, according to the academic literature. This explains why the four most relevant models to evaluate hedge funds were selected and will be described in detail in the next section.

The first step consists therefore in using an Ordinary Least Squares (OLS) regression to evaluate each fund's three-factor, five-factor, seven-factor and eight-factor α and their related t-statistic $t(\alpha)$ over the period under study, ranging from January 1998 to May 2017.

The regression intercept can be interpreted as the return of the fund in excess of the return generated by a comparable passive portfolio and the slopes on the explanatory returns describe the exposure of the fund to common factors in returns. Based on the fifth theorem of Dybvig and Ross (1985), a positive intercept is construed as good performance and a negative one as bad performance.

These regressions will be coupled with the comparison between the results from the 1000 bootstrap simulations and the actual cross-section of fund α estimates as applied to mutual funds by Fama and French (2010). Indeed, the returns resulting from the simulation runs exhibit similar characteristics to those of the actual returns, except that α is set equal to zero in the returns on which the simulations are based. Consequently, the bootstrap simulations provide the distribution in the case where the managers do not have superior skills. That way, the potential existence of managers possessing superior skills leading to outperformance can be revealed.

In this section, the different multifactor models selected and the regression framework will be described before explaining in detail the bootstrap approach. Furthermore, an explanation of how inferences can be drawn on hedge fund performance by comparing the simulated and actual returns will be given.

4.1. Model specification and regression framework

The various traditional multifactor models used to analyse the performance of hedge funds have the following form:

$$\mathrm{R_{i,t}} = \alpha_{\mathrm{i}} + \sum_{\mathrm{k=0}}^{\mathrm{K}} \beta_{\mathrm{i,k}} * \mathrm{F_{k,t}} + \varepsilon_{\mathrm{i,t}}$$

where $R_{i,t}$ is the return on a given hedge fund i at time t (in excess of the risk-free rate);

α_i is the intercept of the regression representing the Jensen's alpha, which is the abnormal performance of the hedge fund i;

$\beta_{i,k}$ is the exposure of the hedge fund i to the factor k;

$F_{k,t}$ is the return on factor k at time t;

$\varepsilon_{i,t}$ is the regression error.

After a thorough review of the existing academic literature, the decision was taken that the benchmarks for assessing hedge fund performance are the 3-factor model of Fama and French (1993), the 5-factor model of Fama and French (2015) and the 7-factor model of Fung and Hsieh (2004) and the 8-factor model of Agarwal and Naik (2004).

4.1.1. Fama and French 3-factor model

The Fama and French 3-factor model was established in 1993 with its three well-known factors being market, size and value (See Appendix 3). This model represented a unique improvement over the CAPM because it adjusted for outperformance tendency by taking into account two admitted anomalies (size and value factors). Subsequently, it has been extensively used in the literature and many papers came up with modified versions augmented with additional factors (Carhart, 1997; Wagner and Winter, 2013; Hunter, Kandel, Kandel, and Wermers, 2014).

$$\mathrm{R_{it}} - \mathrm{R_{ft}} = \alpha_\mathrm{i} + \mathrm{b_i} * (\mathrm{R_{Mt}} - \mathrm{R_{ft}}) + \mathrm{s_i} * \mathrm{SMB_t} + \mathrm{h_i} * \mathrm{HML_t} + \varepsilon_\mathrm{it}$$

where R_{it} is the return on fund i for month t;

R_{ft} is the return on the risk-free asset for month t (the one-month U.S. Treasury bill rate);

R_{Mt} is the return on the market portfolio for month t (the return on a value-weight portfolio of NYSE, Amex, and NASDAQ stocks);

SMB_t is the return on the mimicking portfolio for the size factor (the size return of Fama and French (1993));

HML_t is the return on the mimicking portfolio for the book-to-market factor (the value-growth returns of Fama and French (1993));

α_i is the average return left unexplained by the benchmark model (the estimate of α_i);

ε_{it} is the regression residual.

4.1.2. Fama and French 5-factor model

As the 3-factor model appeared to be inadequate due to the fact that it overlooked a lot of variation coming from profitability and investment, Fama and French (2015) incorporated two new factors to rectify that breach: investment and profitability (See Appendix 4). The authors, to came up with this new model, started initially from the dividend discount model. Indeed, this model states that the current value of a stock is dependent upon future dividends (Musarurwa, 2015).

The fourth factor, « Robust Minus Weak » (RMW) is based on the profitability anomaly described by Novy-Marx (2013), stating that profitable firms tend to outperform companies with lower profitability ratios. The fifth factor, « Conservative Minus Aggressive » (CMA) is the return spread between firms investing in a conservative way minus companies tending to drastically invest (Fama and French, 2015). All the Fama and French factors are available on their website[7]. With these two complementary factors, the five-factor model time series regression has the following form:

$$\mathrm{R_{it}} - \mathrm{R_{ft}} = \alpha_\mathrm{i} + \mathrm{b_i} * (\mathrm{R_{Mt}} - \mathrm{R_{ft}}) + \mathrm{s_i} * \mathrm{SMB_t} + \mathrm{h_i} * \mathrm{HML_t} + \mathrm{r_i} * \mathrm{RMW_t} + \mathrm{c_i} * \mathrm{CMA_t} + \varepsilon_\mathrm{it}$$

where R_{it} is the return on fund i for month t;

R_{ft} is the return on the risk-free asset for month t (the one-month U.S. Treasury bill rate);

R_{Mt} is the return on the market portfolio for month t (the return on a value-weight portfolio of NYSE, Amex, and NASDAQ stocks);

SMB_t is the return on the mimicking portfolio for the size factor (the size return of Fama and French (1993));

HML_t is the return on the mimicking portfolio for the book-to-market factor (the value-growth returns of Fama and French (1993));

RMW_t is the return spread of the most profitable firms minus the least profitable ones;

CMA_t is the return spread of the firms that invest conservatively minus those investing aggressively (AQR, 2014);

α_i is the average return left unexplained by the benchmark model (the estimate of α_i);

ε_{it} is the regression residual.

Since the factors created by Fama and French are not optimal for picturing the non-normality of the return distribution as they do not take into account the optional payoffs generated by hedge funds, it is necessary to complement these existing models with optional variables (Amin and Kat, 2003; Agarwal and Naik, 2004; Fung and Hsieh, 2004).

[7]The factors were retrieved from the Fama and French's website: http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/Data_Library/f-f_5_factors_2x3.html

4.1.3. Fung and Hsieh 7-factor model

The 7-factor model developed by Fung and Hsieh (2004) can be considered as a reference from an academic perspective when it comes to the evaluation of hedge fund performance. Over the years, it is crystal clear that many authors have made use of it to conduct their own research (e.g., Darolles and Mero, 2011; Ammann, Huber and Schmid, 2011; Joenväärä and Kosowski, 2015).

They demonstrated that hedge fund returns can be better explained through the use of lookback straddles than standard asset indices. A lookback straddle is the combination of a lookback call option and a lookback put option, providing a payoff equal to the difference between the highest and lowest levels achieved by the underlying asset during the life of the option. Their study helped to spot that trend-following funds exhibit systematic risk exposures. These seven factors include three trend-following risk factors, two equity-oriented risk factors and two bond-oriented risk factors:

- The trend-following risk factors are constructed by combining lookback straddles on bonds (PTFSBD), commodities (PTFSCOM) and currencies (PTFSFX) to obtain respectively a bond trend-following factor, a commodity trend-following factor and a currency trend-following factor. These three risk factors are available on their website[8].

- The two equity-oriented risk factors are the Standard and Poor's 500 index monthly total return and a size spread factor, being the difference between the Russell 2000 index monthly total return and the Standard and Poor's 500 index monthly total return.

- The two bond-oriented risk factors are the monthly change in the 10-year Treasury constant maturity yield[9] and a credit spread factor, being the difference between the monthly change in the Moody's Baa yield and the 10-year Treasury constant maturity yield[10].

[8] These three trend-following factors are available and updated each month on the Fung and Hsieh's website: https://faculty.fuqua.duke.edu/~dah7/HFRFData.htm

[9] The bond market factor was retrieved from the Federal Reserve Bank of St. Louis: https://fred.stlouisfed.org/series/DGS10

[10] The credit spread factor is was retrieved from the Federal Reserve Bank of St. Louis: https://fred.stlouisfed.org/series/DGS10

4.1.4. Agarwal and Naik 8-factor model

The last model will be constructed as follows. To begin, to consider the fact that hedge funds usually invest in a large set of asset classes, « buy-and-hold » factors are included in the model. As equity factors, the Russell 3000 (RUS) index monthly total return, the Fama and French (1993) size (SMB) and value (HML) factors as well as the momentum factor of Carhart (1997) were selected in the model. On top of that, four option-based factors artificially-replicated were added to the model. Agarwal (2004) emphasized the nonlinear payoffs delivered by hedge funds and as a result, they computed four new risk factors coming from the options market to explain hedge fund performance. Indeed, they realised that hedge funds generally face large losses during adverse market conditions due to a positive correlation with the market in case of market downturns while there is no correlation in favourable market conditions. As a matter of fact, ignoring the tail risk could have a substantial harmful impact (huge losses) during unfavourable market conditions (Amin and Kat, 2003; Fung and Hsieh, 2004).

To capture this exposure, they used highly liquid at-the-money (ATM) and out-of-the-money (OTM) European call and put options on the Standard and Poor's 500 composite index trading on the Chicago Mercantile Exchange. These four option-based risk factors can be easily synthetically computed by using the Black-Scholes formula which allows to correctly price options (See Appendix 5). The strike price is the current price of the index for at-the-money options and is five percentage points away from the current value of the index for out-of-the-money options. The maturity considered for these options is precisely one month. Based on these inputs, the mechanism to obtain the returns is really simple. On the first trading day of the month, say t, the decision is taken to buy an at-the-money call option on the Standard and Poor's 500 index with an expiration date exactly one month later. On the first trading day of the month t+1, the at-the-money call option bought one month earlier is sold and once again, a new at-the-money call option is bought on the Standard and Poor's 500 index. By repeating this simple process every month for the whole period under study, the time series of returns on buying an at-the-money call option is obtained. This procedure is replicated to obtain the times series of returns on buying an out-of-the-money call option, buying an at-the-money put option and buying an out-of-the-money put option.

4.2. Bootstrap procedure

4.2.1. Legitimacy of the statistical approach

The basic intuition underlying the bootstrap implementation is simple. The purpose is to compare the observed fund performance with the performance of funds in artificially generated data samples in which variation is entirely due to sampling variability or luck. That way, it can be easily observed if managers possess true skills.

Due to their elaborated dynamic investment strategies, it can be argued that hedge funds are more likely to experience return non-normality, model misspecification and short sample problems as compared to mutual funds (Eling, 2006; Malkiel and Saha, 2005). The bootstrap procedure should thus be even more relevant for hedge funds as explained in detail by Kosowski, Naik, and Teo (2007). Indeed, it is especially relevant to the study of hedge fund performance for three main reasons.

First, the bootstrap procedure allows the researcher to avoid having to make a priori assumption about the shape of the distribution from which hedge fund alphas (and their corresponding t-statistics) are drawn. It is believed that the empirical return distribution of residuals from multifactor regressions is not Gaussian for many hedge funds. Consequently, the distribution of α may be poorly approximated by the normal distribution, with its statistical significance better evaluated using a nonparametric approach such as the bootstrap one.

Secondly, the bootstrap simulation frees the researcher from being compelled to calculate the whole covariance matrix describing the joint distribution of individual hedge funds, which is usually impossible to assess accurately.

Last but not least, a bootstrap procedure provides a simple approach for handling unknown time-series dependencies which come from, for instance, heteroskedasticity or serial correlation in the residuals from performance regressions (Horowitz, Härdle, and Kreiss, 2003). Indeed, the bootstrap enables to relax the assumptions of independence and zero serial correlation (Fung, Hsieh, Naik, and Ramadorai, 2008).

4.2.2. Main steps of the procedure

The cross-sectional bootstrap that will be applied in this paper can be decomposed in five main steps. These steps will be detailed for the case of the Fama and French 3-factor model but there are identical for the three other models. The procedure followed is in line with the one of Fama and French (2010) which is itself an improvement over the methodology implemented by Kosowski, Naik, and Teo (2006) who were the first to use this statistical tool to distinguish luck from skill in the performance of hedge funds. The enhancement consists in simultaneously simulating factor returns and residuals for all hedge funds instead of doing that one at a time. This change enables to prevent cross-correlation of hedge fund returns (Fama and French, 2010).

- First, using Ordinary Least Squares Regression, the 3-factor alpha (t-alpha) and residuals for each return time series will be computed:

  $$\mathrm{r(i,t)} = \alpha(\mathrm{i}) + \{\beta_1(\mathrm{i}) * \mathrm{MKT(t)} + \beta_2(\mathrm{i}) * \mathrm{SMB(t)} + \beta_1(\mathrm{i}) * \mathrm{HML(t)} + \varepsilon(\mathrm{i,t})\}$$

  The observed historical returns of each individual fund are therefore regressed against the returns of a specified list of risk factors over the period of time under study (January 1998 - May 2017). At this stage, the estimates of actual alpha, $\alpha(\mathrm{i})$, and its related t-statistic, $\mathrm{t}(\alpha(\mathrm{i}))$ are recorded.

- The second step is the creation of a pseudo time series of excess returns, with the alpha set to zero by construction, by taking a random sample of months b(t) (with replacement):

  $$\mathrm{r^z(i,t)} = \{\beta_1(\mathrm{i}) * \mathrm{MKT(t)} + \beta_2(\mathrm{i}) * \mathrm{SMB(t)} + \beta_1(\mathrm{i}) * \mathrm{HML(t)} + \varepsilon(\mathrm{i,b(t)})\}$$

  It is important to note at this stage that the majority of hedge funds will not have return history for the whole period. Indeed, it is the case for all the funds which started reporting returns after the first observation of the period and for the funds which died before the last one.

- The third step is the estimation of the 3-factor alpha (t-alpha) for the zero-alpha adjusted $r^z(i,t)$ using Ordinary Least Squares Regression:

  $$\mathrm{r^z(i,t)} = \alpha^{\mathrm{z}}(\mathrm{i}) + \{\beta_1^{\mathrm{z}}(\mathrm{i}) * \mathrm{MKT(t)} + \beta_2^{\mathrm{z}}(\mathrm{i}) * \mathrm{SMB(t)} + \beta_3^{\mathrm{z}}(\mathrm{i}) * \mathrm{HML(t)} + \varepsilon^{\mathrm{z}}(\mathrm{i,b(t)})\}$$

As a result, new series of zero-alpha hedge fund returns and new series of risk factor returns are obtained. The returns are in fact picked from the sample according to the drawn time indices of the simulation run. Because sufficient return data are required to properly evaluate factor loadings, only hedge funds exhibiting at least 36 months of return data will be considered in the bootstrap sample (as advised by several authors such as Liang (1999)). The regression can then be run, in the same manner as it was performed for actual hedge fund returns in the first step. The only difference is that now, the constructed excess fund returns of the simulation are used as dependent variables and the corresponding set of risk factor returns are considered as explanatory variables.

- The fourth step consists of creating a bootstrap cross-sectional zero-alpha distribution by iterating the second and third steps 1000 times. A set of 1000 simulation runs is created and this set is the same for each fund, independently of the chosen model specification. That way, the cross-correlation of hedge fund returns is preserved.

- Finally, the fifth step is the comparison between the actual alphas (t-alphas) of the initial return time series from the first step and the bootstrap zero-alphas (t-alphas) from the fourth step. In accordance with previous research, the conclusions will be drawn from the t(α) estimates to have everything on equal terms and include the precision measurement as advised by Fama and French (2010).

4.2.3. Comparison between actual and bootstrap returns

When estimating a benchmark model based on the actual returns of each individual funds, a cross-section of t(α) estimates is obtained, that can be further ordered into a cumulative distribution function of t(α) estimates for actual returns. At the same time, a simulation run for the identical combination of benchmark model delivers a cross-section of t(α) estimates, ordered into a cumulative distribution function for a world where true alpha (α) is set to zero.

A comparison is then made between the t(α) estimates from actual fund returns at different percentiles or ranks of the cumlative distribution function and the average across 1000 bootstrap simulations of the t(α) estimates at the same percentiles giving hints about the influence of manager skills on the delivered returns. For instance, the t(α) estimates of hedge funds that best performed in the benchmark regression can be compared with the best t(α) estimates of each of the 1000 simulations, where alpha is completely due to luck.

The comparison method is very intuitive. Indeed, the actual estimates for the different percentiles will be confronted with the average over all the 1000 simulations of t(α) estimates for the same percentile. The average of all the simulations represents therefore a measure of how well the given rank is supposed to perform in the absence of manager skill, when all the performance is attributable to chance.

The column « % < Actual Return » provides, for its part, likelihoods and specifically, the proportion of the 1000 simulations resulting in lower values of t(α) at selected percentiles than actual fund returns. More specifically, in the case where low fractions of the simulation runs deliver left tail percentiles of t(α) estimates below those from actual returns, it can be inferred that the majority of managers does not have enough skill to cover the fees and trading costs involved. In the same way, it can be inferred that managers exhibit sufficient skill to cover fees and trading costs if large fractions of the simulations runs produce right tail percentile t(α) estimates below those from actual return, or equivalently, if low proportion of the simulation runs outperform the right tail t(α) estimates from actual hedge fund returns. The lower or symmetrically the higher the fractions are, the more obvious is the existence or absence of superior manager skills.

5. EMPIRICAL RESULTS

5.1. Hedge fund returns

The idea behind this section is to analyse how hedge funds following the well-known strategy called « Long/Short Equity » have performed over the period under study and assess if the findings from the academic literature concerning the hedge fund return distribution and the failure of the mean/variance framework in picturing the included risk are true in this case as well.

First, a mean/variance framework coupled with the basic descriptive statistics are used to give a general overview of the performance during the period ranging from January 1998 to May 2017. Then, the normality assumption is controlled by applying a Jarque-Bera test on the series of returns. Finally, higher moments and alternative extreme risks are scrutinized to observe the behaviour of the returns in various market circumstances. The ultimate goal is to verify the legitimacy of using a bootstrap procedure and including optional factors in the benchmark models.

5.1.1. Descriptive statistics

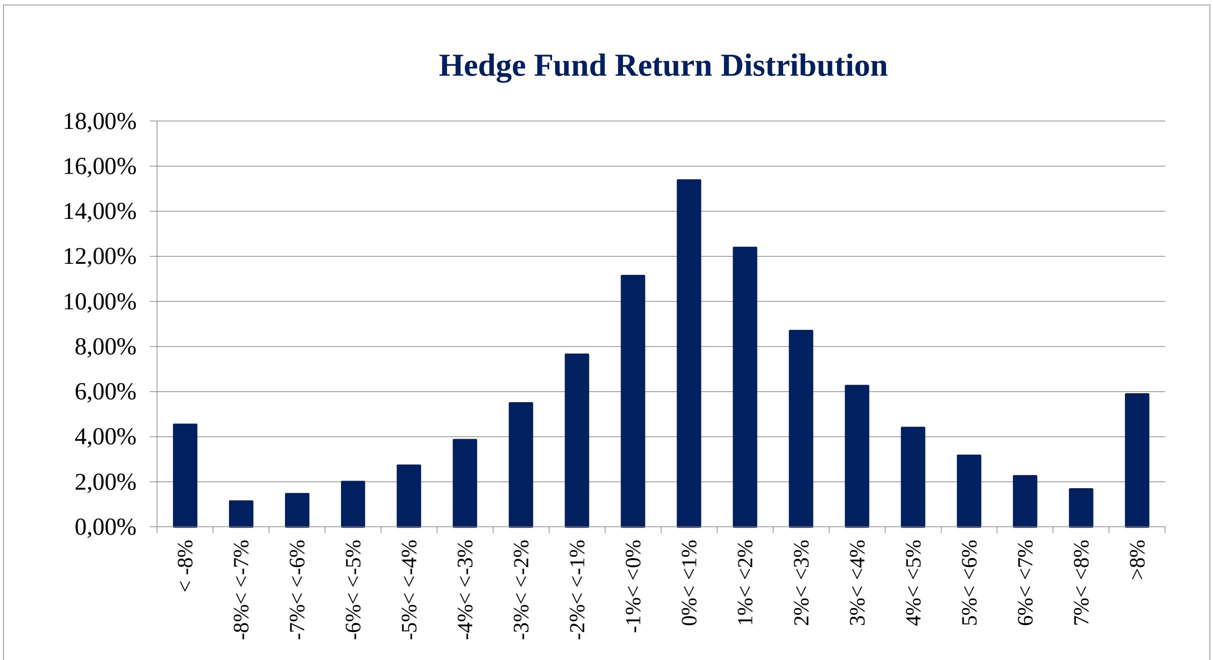
To begin, the mean return was simply computed by summing every individual monthly return and dividing the total by the number of observations. That way, the mean is susceptible to be biased by the outliers. This is the reason why the median was also calculated as an alternative to have a more precise measure of the central tendency. Indeed, if the median of the return distribution is substantially different from the mean, it signals an asymmetry in the distribution. As a result, when the right tail of a distribution is lighter than the left tail, the median will be greater than the mean (Bali, Brown, and Demirtas, 2013).

Summary Statistics					
Mean	Median	Monthly Vol	Annualized Vol	Min	Max
0.6414	0.6435	5.6599	19.6063	-89.8612	233.3912

In the table above, it can be noticed that the median is slightly higher than the mean, due to the fact that the right tail of the distribution is lighter than the left tail. This situation is highlighted by a minimum return in absolute value which is lower to a large extent than the maximum return. An annual volatility of 19.6% can also be observed by multiplying the monthly volatility by the square root of 12. This high level of volatility is characteristic of hedge funds whose return can potentially be spread out over a large range of values (as shown by the spread between the minimum and the maximum values) and whose Net Asset Value (NAV) can change dramatically over a short time period in either direction. In fact, the larger the dispersion of returns around their arithmetic mean, the greater the potential risk (Lhabitant, 2004).

5.1.2. Jarque-Bera test for normality

When considering the normality assumption, it can be easily noticed that the monthly returns of hedge funds do not seem to follow a normal distribution as depicted on the graph below:



If hedge fund returns do follow a normal distribution, volatility is sufficient to evaluate risk due to the fact that a normal distribution is completely characterized by its mean and its variance. Nevertheless, it has been proved by several authors in the academic literature that hedge fund returns are not normally distributed (Bali, Brown, and Caglayan, 2012; Eling, 2006; Malkiel and Saha, 2005).

Even though many empirical studies have already been conducted, a normality test is applied to verify this finding thanks to the Jarque-Bera Statistic:

$$JB = \frac{N}{6} * (S^2 + \frac{(K-3)^2}{4})$$

where N is the number of observations (or degrees of freedom in general);

S is the sample skewness;

K is the sample kurtosis.

Jarque-Bera Normality Test	
N	314923
JB STAT	12516794.92
P-VALUE	< 0.0001

This statistic follows a Chi-Square distribution with two degrees of freedom (Jarque and Bera, 1987):

$$JB \sim \chi^2_{(2)}$$

Once the test run, it can be remarked that the null hypothesis of a normal distribution is strongly rejected as the p-value is equal to zero with a very high confidence level (Lo, Thiam, and Haidara, 2015). As a matter of fact, as the mean-variance framework involves normality of asset returns and the Jarque-Bera test proved their non-normality, using these risk measures would not adequately evaluate the risk supported by this investment vehicle. More specifically, it would substantially underestimate the lower tail risk for assets with negatively skewed payoffs, as observed during important market downturns such as the financial crisis of 2008.

5.1.3. Higher order moments and extreme risks

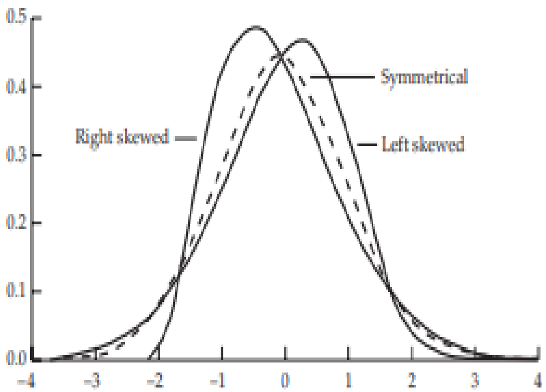
As hedge fund returns are not normally distributed, other tools will be required to have a deeper understanding of the actual distribution. Evidence was shown in the previous section that conducting analyses only based on the mean/variance framework is often insufficient due to the fact that it will not picture the whole risk included in hedge funds. As a result, the higher order moments of the distribution are meaningful statistics to better model risk. Indeed, the impact of outliers is logically amplified in skewness and kurtosis measures because they are raised to the third and fourth power (Kim and White, 2004).

The skewness (3^{rd} order moment) represents the distribution asymmetry, showing if the curve is skewed or distorted to the left or to the right. This indicator defines the extent to which a distribution differs from a normal distribution in a particular direction. In other words, skewness reflects the presence of too many large positive or negative observations in a distribution.

The kurtosis (4th order moment), for its part, measures the tails of a frequency distribution when compared with a normal distribution. When a large number of observations are away from the mean, the excess kurtosis is positive and the distribution is called leptokurtic. This distribution exhibits a distinct peak around its mean and heavy tails.

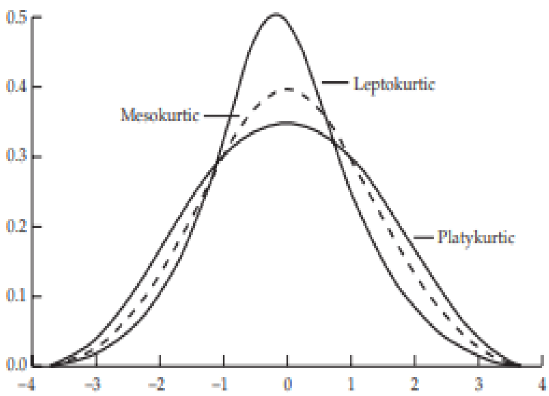
Theoretically, investors should prefer stocks with high positive skewness coefficients that provide opportunities for very large returns and they should prefer stocks with low kurtosis that provide little risk of extreme movements. However, Brooks and Kat (2002) found that hedge funds tend to exhibit third and fourth moment attributes that are, in general, opposite to those that investors desire to have.

$$S(R) = \frac{E[(R-E(R))^3]}{[Var(R)]^{3/2}} = 0.4912$$



Typical Skewness curve. Source: Gujarati (2004)

$$K(R) = \frac{E[(R-E(R))^4]}{[Var(R)]^2} = 30.8695$$



Typical Kurtosis curve. Source: Gujarati (2004)

Over the sample period under study, hedge funds have a positive skewness (0.4912) and a very high kurtosis (30.8695). A very high kurtosis is dangerous as it signals more frequent extreme returns, as can be observed on the return distribution graph above. This situation is generally feared.

These findings about higher moments are confirmed by Brooks and Kat (2002) and Anson (2002) who demonstrated that hedge funds tend to produce positive kurtosis and by Kouwenberg (2003) who reported positive skewness for hedge funds following long/short equity strategies.

5.1.4. Value-at-Risk and Conditional Value-at-Risk

Two statistics used to measure extreme losses and risks turned out to be insightful as well: the Value-at-Risk (VaR) and the Expected Shortfall (ES) (or Conditional Value-at-Risk). The Value-at-Risk indicates the loss faced in the x% worst scenarios (depending on the selected confidence interval) and the Expected Shortfall, or Conditional Value-at-Risk (CVaR), is an average of all the returns below the Value-at-Risk value.

By considering R the return on a portfolio through a given time period, f_R the probability density function (PDF) of R, F_R the cumulative distribution function (CDF) and p the probability level, the Value-at-Risk can be expressed as follows:

$$\mathrm{VaR}(F_R, p) = -F_R^{-1} * (1 - p)$$

The Conditional Value-at-Risk, or Expected Shortfall, is given by:

$$\mathrm{CVaR}(F_R, p) = -E(R|R \leq -\mathrm{VaR}) = -\frac{\int_{-\infty}^{-\mathrm{VaR}} x * f_R(x)dx}{F_R(-\mathrm{VaR})}$$

Three different Value-at-Risk were computed: the Historical Value-at-Risk, the Gaussian Value-at-Risk and the Adjusted Cornish-Fisher Value-at-Risk. While the Gaussian Value-at-Risk assumes a normal distribution, the Adjusted Cornish-Fisher Value-at-Risk is a semi-parametric approach that does not pre-assume a specific distribution but accounts for non-trivial higher moments (Cornish and Fisher, 1937). This last measure is therefore the most relevant in our particular case due to the non-normality of the return distribution. Favre and Galeano (2002) also developed this modified Value-at-Risk to better capture the risk incurred when investing in hedge funds. This risk measure is obtained by following these computations:

$$z_{\alpha_{adjusted}} = z_\alpha + \frac{1}{6} * (z_\alpha^2 - 1) * S + \frac{1}{24} * (z_\alpha^3 - 3z_\alpha) - \frac{1}{36} * (2z_\alpha^3 - 5z_\alpha) * S^2$$

$$\mathrm{MVaR} = \mu + z_{\alpha_{adjusted}} * \sigma$$

where z_α is the quantile of the distribution at the significance level α (normality is assumed);

$z_{\alpha_{adjusted}}$ is the Cornish-Fisher asymptotic expansion for the quantile of a non-gaussian distribution;

S is the skewness calculated from the observed returns;

K is the kurtosis calculated from the observed returns;

σ is the standard deviation calculated from the observed returns;

μ is the mean return calculated from the observed returns;

$MVaR$ is the so-called Modified Value-at-Risk.

As highlighted previously, assuming a parametric distribution may not be sufficiently satisfactory to entirely capture the risk involved, due to their specific left tail characteristics. To address this issue, the Conditional Value-at-Risk seems to be the best risk measure to give a more faithful picture of the actual situation. The table below reports Value-at-Risk and Conditional Value-at-Risk at the 95% and 99% confidence levels:

Value-at-Risk and Expected Shortfall						
Confidence Level	Historical		Gaussian		Cornish-Fisher	
	VaR	CVaR/ES	VaR	CVaR/ES	VaR	CVaR/ES
95%	-7.56	-14.42	-8.66	-13.10	-4.32	-9.10
99%	-16.17	-19.05	-12.52	-23.38	-50.81	-60.51

Globally, as expected, the Conditional Value-at-Risk increases with the volatility and confidence level, meaning going further in the left tail and/or at higher confidence level. At both thresholds, it can be noticed that the Adjusted Cornish-Fisher Value-at-Risk is less negative (has a higher value) than its Historical and Gaussian counterparts thanks to the positive impact when accounting for skewness. Also, the values at the 99% level are all lower than at the 95% level. The Historical Expected Shortfall is logically lower in comparison with its corresponding Value-at-Risk with a value of -14.4% at the 95% confidence level against -7.56% for its Value-at-Risk. This observation turns out to be true for the Gaussian and Cornish-Fisher ones as well.

That being said, what directly stands out when looking at these numbers is the impressive losses obtained when computing the Cornish-Fisher modified Value-at-Risk at the 99% confidence level, with respect not only to the Historical and Gaussian ones but also to the Cornish-Fisher one at the 95% confidence interval. Indeed, a Value-at-Risk of -50.81% and an Expected Shortfall of -60.51% are obtained while the other values are all settled into a range between -4 and -19%. This remark is in line with the large losses faced by hedge funds when dramatic market circumstances take place (Agarwal and Naik, 2004; Fung and Hsieh, 2004, Amin and Kat, 2003; Lambert, 2012).

To sum up, the study of these risk measures shows evidence that the tail risk is substantially underestimated when applying the mean-variance framework and the return distribution cannot be characterised as Gaussian. As a result, a bootstrap procedure would be particularly appropriate as this statistical tool will not be affected by the non-normality of the return distribution. On top of that, it seems important to incorporate optional factors in the benchmark models to capture the extreme behaviour of hedge funds returns in adverse market conditions (Barras, Scaillet, and Wermers, 2009).

5.2. Regression results

To assess the goodness-of-it of the 4 models, the traditional « Least Squares Method » is used. In this method, each point of data is representative of the relationship between known independent variables and a dependent variable (the hedge fund performance here). This approach is based on the general relation:

$$\text{Total Sum of Squares } (\mathrm{SS_{total}}) = \frac{\text{Sum of Squares Error } (\mathrm{SS_{Error}})}{\text{Sum of Squares Model } (\mathrm{SS_{Model}})}$$

To properly estimate the proportion of total variation of the dependent variable explained by independent variables, the R^2 is computed applying the following formula:

$$\mathrm{R}^2 = \frac{\mathrm{SS_{Model}}}{\mathrm{SS_{total}}}$$

The more this indicator is approaching 1, the better is the adequacy between the model and the dataset. When a new variable is introduced in a model, the Sum of Squares of the Model (SS_{Model}) increases with the same amount as the quantity of the Sum of Squares of the Error (SS_{Error}) decreases. That way, each time a model is complemented by a variable, the R^2 logically increases. However, this growth in R^2 is coupled with a higher risk of multicollinearity. This explains why an « Adjusted R^2 » is computed, taking into account the number of parameters used in the model.

	Fama and French 3-factor model	Fama and French 5-factor model	Fung and Hsieh 7-factor model	Agarwal and Naik 8-factor model
R^2	0.3180	0.3711	0.4718	0.5106
Adjusted R^2	0.2571	0.2606	0.2986	0.2820

It can be logically observed that the R^2 is always increasing when new factors are added to the model with 31.8% of the hedge fund performance explained by the three factors of the Fama and French 3-factor model, 37.11% by the five factors of the Fama and French 5-factor model, 47.18% by the seven factors of the Fung and Hsieh 7-factor model and 51.06% by the eight factors of the Agarwal and Naik 8-factor model. Nevertheless, when accounting for the impact of additional variables through the computation of « Adjusted R^2 » for the different models, very small differences between the different models are noticed, with a proportion of variation explained ranging from 25.71% for the Fama and French 3-factor model to 29.86% for the Fung and Hsieh 7-factor model.

It is therefore interesting to check the significance of the added factors to ensure their relevance in the model. At this point, evidence is shown that incorporating optional factors enhance the efficiency of the model but it can be observed that the improvement is not critical when focusing on the Adjusted R^2 values.

Now that the explanatory power of each model has been revealed, it is time to delve into the four models to obtain more details. After reviewing the summary statistics in order to have a first general description of the different factors, the correlation matrix will be inspected and an extensive multicollinearity analysis will be conducted. Finally, through the comparison of the p-values with the confidence threshold, the significance of the variables incorporated in the models will be assessed.

5.2.1. Fama and French 3-factor model

It can be observed in the Summary statistics table (See Appendix 6, Table 1) that the MKT factor is characterized by a monthly mean return of 0.57% which is higher than the SMB and HML factors. The performance of the market factor is in line with the intuitive expectation. Indeed, the market portfolio performance is higher than the one of the risk-free asset. Besides, the MKT factor is more volatile with a standard deviation of 4.47% against respectively 3.39% and 3.21% for the size and value factors. On top of that, the MKT factor is the only one to have a negative skewness, which indicates that when surprises happen for this factor, there are more often bad. If the attention is now focused on the median, which is less impacted by outliers, the MKT factor has a monthly median return of 1.09% which highlights the presence of negative outliers for this factor.

According to the Correlation matrix (See Appendix 6, Table 2), the correlation between the different factors is relatively low. The correlation between the size and value factors is slightly negative (-0.05), which corroborates the findings of Fama and French (1993) while the correlation between the value and market factors is slightly positive (0.128). Between the market and size factors, a correlation of 0.317 is noticed, which contradicts what Fama and French found in the past (-0.38).

That being said, it is important to bear in mind that the period under study in their paper does not coincide at all with the analysis conducted here, which can explain the variation. An important correlation between different factors could be a symptom revealing a collinearity problem which does not seem to be the case with this model.

To quantify the severity of multicollinearity, different measures were computed. Indeed, multicollinearity can have many harmful impacts on multiple linear regression, both in the interpretation of the results and in how they are obtained. On top of that, the use of several variables as predictors makes the determination of multiple correlation between the independent variables necessary to identify multicollinearity.

First, to measure how much of the variance of an estimated regression coefficient is increased because of the collinearity, the Variance Inflation Factor (VIF) is calculated as follows:

$$\mathrm{VIF_j} = \frac{1}{1 - \mathrm{R_j^2}}$$

where $\mathrm{R_j^2}$ is the proportion of total variation of the dependent variable j explained by independent variables.

Tomassone, Audrin, Lesquoy de Turckheim, and Millier (1992), starting from the VIF indicator, introduced a Global Multicollinearity Index defined as the sum of the VIF from all the factors of the model. The generally accepted threshold for this indicator is 10, above which a collinearity problem is spotted.

In this model, the 3 factors are far below this level and the Global Multicollinearity Index is also really low with a value of 1.095 (See Appendix 6, Table 3). The tolerance (See Appendix 6, Table 3), for its part, is specified as the inverse of the VIF and has therefore to be above 0.1 which is the case here for the MKT factor (0.879), the SMB factor (0.891) and the HML factor (0.975).

Another method consists in computing the condition index (CI) which represents the collinearity of variables' combinations in the dataset (actually the relative size of the eigenvalues of the matrix) and evaluating the regression coefficient variance-decomposition matrix which shows the proportion of variance for each regression coefficient attributable to each condition index (eigenvalue). The first step is therefore the identification of all the condition indices above a threshold value of 30 according to Besley, Kuh, and Welsh (1980). These authors also defined a multicollinearity index by computing the mean of the inverses of the eigenvalues. Then, for all the condition indices exceeding the threshold, the variables with variance proportions above 50% need to be highlighted as they are the source of the collinearity problems. In Table 4 « Collinearity Diagnostics » of Appendix 6, it can be observed that the highest condition index has a value of 1.4410 which is far below the threshold. With a multicollinearity index of 1.0953, this model has definitely no problem of collinearity.

Finally, the t-statistic, which is obtained by dividing the beta of the factor by its standard error has to be high enough so that the associated p-value is lower than the confidence threshold of 5%. Concerning the significance of the variables highlighted in Table 5 « Model Parameters » of Appendix 6, they are all significant at a confidence level of 95% (but also at the 99% level). As the p-values are all lower than the threshold, the null hypothesis of a factor coefficient equal to zero can be clearly rejected.

5.2.2. Fama and French 5-factor model

The conclusions drawn from the Fama and French 5-factor model are very similar to those of the Fama and French 3-factor model. As the three first factors (MKT, SMB and HML) are the same, the emphasis will be put on the two added variables: RMW and CMA. The monthly mean return for the RMW factor is 0.3112% and the median is almost equal (0.3%), with a variance around 9% close to the one of the SMB factor and HML factor. This factor also has a slightly negative skewness (-0.3709%) coupled with the highest kurtosis (8.6511%). On the other hand, the CMA factor is relatively less volatile and exhibits a monthly median return being almost equal to zero with a value of -0.04% (See Appendix 7, Table 1).

Concerning the Correlation matrix (See Appendix 7, Table 2), the attention is directed to the two new factors and their correlation with the rest of the model. The RMW factor, picturing the profitability, demonstrates a relatively high negative correlation with the market (-0.504), in much the same way as the CMA factor, representing the investment strategy, with the HML factor (0.544), apart from their sign.

At the first glance, no collinearity issue seems obvious. The additional variables in the Fama and French 5-factor model present tolerance and VIF values in the same range as the three first factors, leading to a very low Global Multicollinearity of 1.521 (See Appendix 7, Table 3). This finding is corroborated when looking at the eigenvalues and the condition indexes. Indeed, with a multicollinearity index of 1.2860, a potential problem of collinearity can be totally discarded (See Appendix 5, Table 4).

As was the case for the previous model, the market, size and value factors are all significant at the 95% confidence level with all the p-values lower than 0.05 thanks to high t-statistics derived from low standard errors (See Appendix 5, Table 5). On top of that, while the CMA factor is significant at both confidence levels, the RMW factor is not significant (0.4680) and consequently, does not improve the goodness-of-fit of the model

5.2.3. Fung and Hsieh 7-factor model

What directly stands out when looking at the « Summary statistics » Table (See Appendix 8, Table 1) of the Fung and Hsieh 7-factor model is the huge variance of the different lookback straddles (PTFSBD, PTFSCOM, PTFSFX) with values ranging from 208.75 to 342.63 accompanied by negative monthly median returns (around -4%) which are lower than the mean values due to huge losses faced during adverse market conditions. This remark is not overwhelmingly surprising regarding the high volatility of this kind of options. Concerning the other factors, the SP and SIZE factors have monthly mean returns of respectively 0.3569% and 0.1359% which is similar to the MKT and SMB factor of Fama and French (1993).

All the correlation coefficients of this model are relatively low (See Appendix 8, Table 2), with the highest values being the correlation between BOND and CRED (-0.4507) and between PTFSFX and PTFSBD (0.4136). Once again, all the VIF are in the same value range (between 1.2 and 2.1), resulting in a Global Multicollinearity Index of 1.5575 and no suspicion of multicollinearity (See Appendix 6, Table 3). This is confirmed by the other collinearity test, delivering a multicollinearity index of 1.2035 with all the individual condition indexes being lower than 2.5 (See Appendix 6, Table 4).

The factor parameters are also all significantly different from zero at a 95% confidence interval except the PTFSCOM factor representing the monthly return of the PTFS Commodity Lookback Straddle. As the p-value of the PTFSCOM factor is significantly higher than the threshold (0.1719), the null hypothesis stating that the factor coefficient is equal to zero cannot be rejected.

5.2.4. Agarwal and Naik 8-factor model

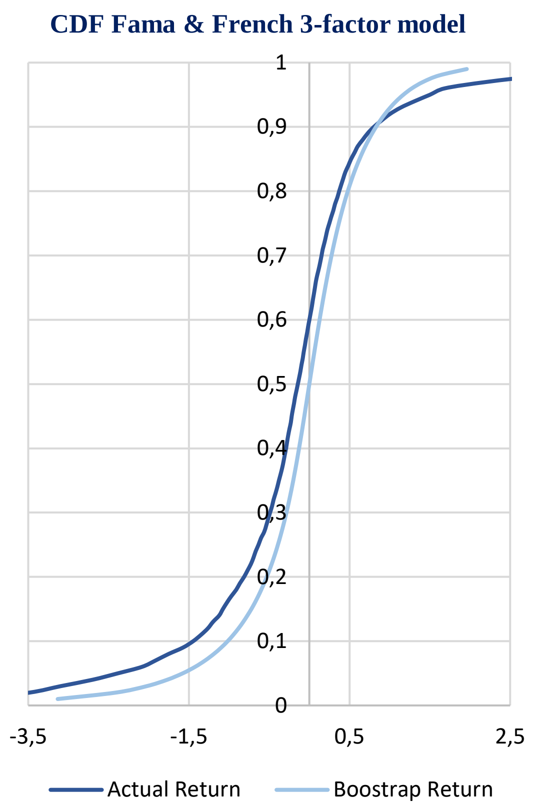
The four optional factors have very high variance and also large kurtosis. This behaviour is even more pronounced for the two out-of-the-money options. A substantial difference between the median and the mean monthly return for the optional factors can also be highlighted (See Appendix 8, Table 1), which is consistent with the observations of the Fung and Hsieh 7-factor model for the option-based factors. These comments are on purpose since these factors have been constructed to reflect market downturns and unusual or extreme circumstances. The RUS and MOM factors have a monthly mean return of respectively 0.85% and 0.36%.

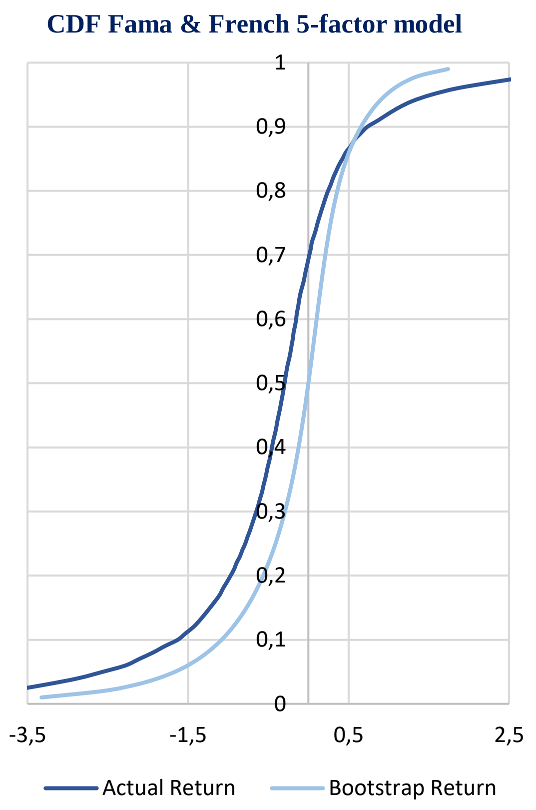
As a reminder, the optional factors of Agarwal and Naik were synthetically computed. As a result, by construction, these factors are deeply correlated with one another (correlation of 0.88 between the ATMP and OTMP factors and of 0.89 between the ATMC and OTMC factors). As far as the rest of the factors are concerned, the VIF and tolerance values do not exceed the required threshold, inducing a Global Multicollinearity Index of 1.01 if we only take these 4 factors into account but which increases to achieve a value of 130.10 when we include the optional factors as well (See Appendix 8, Table 3). Regarding the other method (See Appendix 8, Table 4), only the last eigenvalue is subject to collinearity trouble with a condition index of 65.11 which is far higher than the threshold of 30. The variables having a variance proportion above 0.5 need therefore to be highlighted to understand where the problem lies. Looking at the table more carefully, it can be noticed that it comes from the four optional factors exhibiting proportion of variation above 0.8. However, as Agarwal and Naik (2006) decided not to take this multicollinearity issue into account, the same procedure will be followed in this paper and the 8 factors will be incorporated.

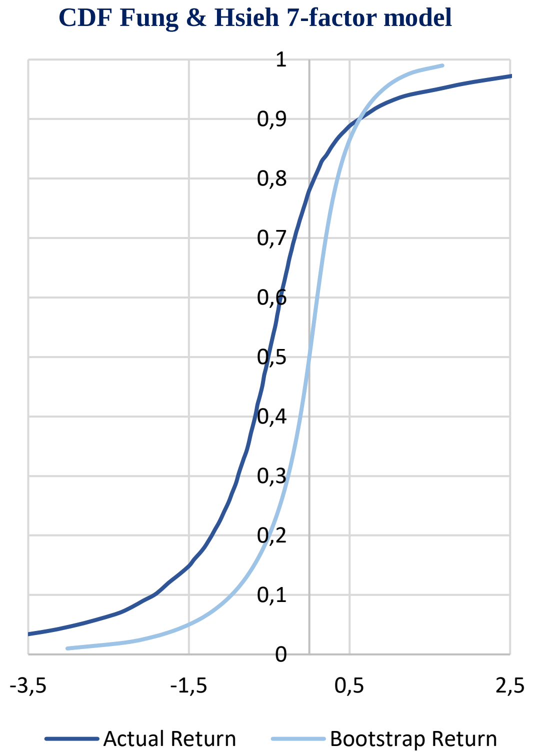
A solution to this problem would have been to perform a Stepwise regression instead of an OLS regression to be able to identify which are the most important factors among a predetermined set of risk factors for hedge funds (the different optional factors in this particular case). Once this specific regression conducted, the Akaike’s and Schwarz’s Bayesian information criteria would enable to assess the goodness-of-fit of the statistical model for the given dataset. Indeed, this method was adopted by several authors due to its parsimonious selection of significant risk factors (e.g., Liang, 1999; Titman and Tiu, 2011; Schaub and Schmid, 2013; Jawadi and Khanniche, 2012; Bussière, Hoerova and Klaus, 2015)

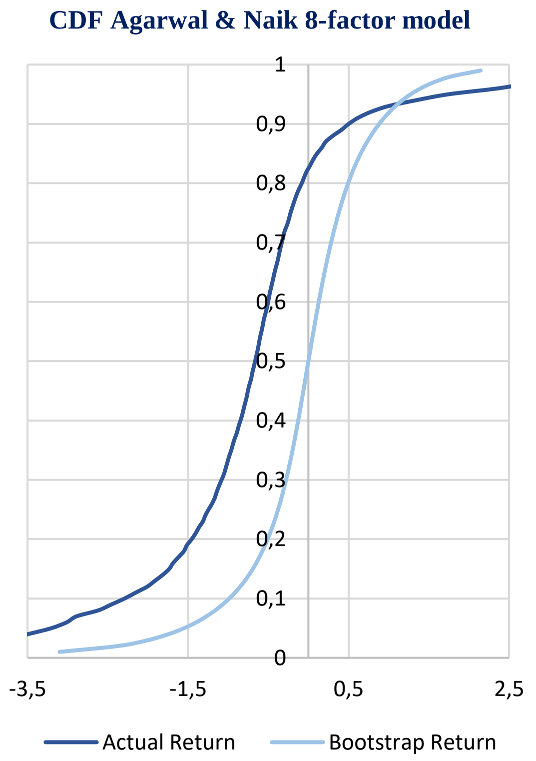
Finally, all the p-values are below 0.05, and thus significant at the 1 percent level in a one-tailed test, except for the HML factor with a p-value of 0.86 (See Appendix 8, Table 5).

5.3. Bootstrap results









	Fama & French 3-factor model			Fama & French 5-factor model			Fung & Hsieh 7-factor model			Agarwal & Naik 8-factor model		
Pct	Simulated	Actual	%<Actual	Simulated	Actual	%<Actual	Simulated	Actual	%<Actual	Simulated	Actual	%<Actual
1	-3.1334	-4.1622	4.8	-3.3264	-4.3982	0.8	-3.0120	-4.8636	0.48	-3.1005	-4.9763	0.2
2	-2.4091	-3.4841	2.7	-2.5593	-3.7555	0.2	-2.2900	-4.2931	0.03	-2.3657	-4.2900	0.1
3	-2.0256	-3.0964	1.8	-2.1466	-3.2772	0.1	-1.9294	-3.7046	0.2	-1.9924	-3.7989	0.1
4	-1.7689	-2.6977	2.3	-1.8682	-2.8639	0.4	-1.6857	-3.2288	0.25	-1.7392	-3.4914	0.45
5	-1.5759	-2.3829	2.6	-1.6624	-2.5608	0.5	-1.5021	-2.8839	0.06	-1.5482	-3.2018	0.06
10	-1.0166	-1.4458	7.4	-1.0804	-1.6261	2.1	-0.9684	-1.9305	0.2	-0.9863	-2.2900	0.5
20	-0.5296	-0.8123	9.5	-0.5626	-0.9687	1.8	-0.5015	-1.2145	0.1	-0.5075	-1.4535	0.2
30	-0.2853	-0.4891	10.2	-0.2921	-0.6490	2.1	-0.2635	-0.8877	0.38	-0.2783	-1.0814	0.91
40	-0.1279	-0.2898	11.6	-0.1221	-0.4533	3.2	-0.1119	-0.6742	0.9	-0.1269	-0.8463	1.12
50	< **0.0001**	-0.1597	14.4	< **0.0001**	-0.2973	4	< **0.0001**	-0.5115	1.56	< **0.0001**	-0.6635	3.82
60	0.1276	-0.0144	21.9	0.1027	-0.1528	7.2	0.0980	-0.3573	3.28	0.1294	-0.5014	5.2
70	0.2762	0.1522	26.1	0.2111	0.0114	17	0.2048	-0.1825	5.12	0.2828	-0.3311	7.12
80	0.4786	0.3485	32.9	0.3601	0.2452	30.4	0.3504	0.0609	11.41	0.4954	-0.0819	11.26
90	0.8306	0.7264	50.2	0.6568	0.7366	72.4	0.6256	0.6212	57.4	0.8818	0.5022	27.5
95	1.1706	1.3115	83.6	0.9698	1.5341	92.2	0.9214	1.5897	95.3	0.2752	1.7473	89.8
96	1.2768	1.5012	87	1.0705	1.8565	95	1.0161	1.9435	97.3	1.4011	2.3685	97.7
97	1.4167	2.2105	95.5	1.2031	2.3260	97.7	1.1418	2.4043	99	1.5595	2.8249	99.1
98	1.6148	2.6189	99.1	1.3952	2.8538	99.1	1.3252	2.9042	99.4	1.7802	3.4233	99.8
99	1.9604	3.1993	99.9	1.7412	3.4657	98.9	1.6564	3.5844	99.6	2.1465	3.9695	99.8

5.3.1. Structure

The three-factor, five-factor, seven-factor and eight-factor regressions were performed and the distributions of the alpha t-statistics were tabulated to put all the funds on an even footing and to base the related interpretations on a more accurate measure since it incorporates the measurement precision (Fama and French, 2010). That way, it removes the influence of funds lasting a very short time period and funds taking on a lot of idiosyncratic risk and which are thus more likely to be lucky.

The graphs above picture the four empirical cumulative distribution functions for simulated and actual values of t(α) estimates, coming from the four different multifactor models. These charts can be understood as graphical representations of the values from the actual and simulated columns of the table above.

On all the charts, it can be noticed that the line based on actual values lies everywhere to the left when compared with the line based on simulated values until around the 90th percentile. This remark is consistent with the observation that between 5% and 10% of the best-performing hedge funds do exhibit some outperformance with respect to the average of the 1000 simulation runs.

By plotting, at the same time, the true distribution and the simulated distribution where all true alphas are in fact zero, the underlying distribution of true alpha can be deduced (See Appendix 10). Even though it will not show precisely who are the best ones, it will highlight the actual proportion of good and bad funds. The idea behind the bootstrap procedure is simply simulating how many alpha t-statistics will be seen if there is no true alpha and then, observing the world distribution of alpha t-statistics.

The first column named « Simulated » details the average of the 1000 bootstrap simulations at different percentiles. The second column, « Actual » includes the corresponding results from the benchmark regressions. That way, the cross-sectional distribution from the four different multifactor benchmark models can be easily compared with the mean values of the analogous percentiles of simulated t(α) estimates, resulting from the 1000 bootstrap simulations.

5.3.2. Analysis and interpretation

Based on the Fama and French 3-factor model, it can be noticed on the table in the simulation column that 3% of the funds should have a t-statistic greater than 1.4167 if there were no skill at all. In the real world, approximately 4.5% can actually be observed which is more than the expected proportion only due to luck. However, the results in the lower tail are contrasting. Indeed, for the Fama and French 3-factor model, 5% of the funds should have a t-statistic less than -1.5759 but in reality, around 9% of the funds have a t-statistic less than that which means that they are not enough funds to reach the amount corresponding to the threshold only due to chance. In comparison with the Fama 3-factor model, the 5-factor model results are similar. The median has also a negative t-statistic (-0.30 instead of -0.16) and in the lower tail, 5% of the funds should have a t-statistic lower than -1.6624 while there are actually approximately 10%, as can be spotted in the actual return column.

This observation is confirmed when including option-based factors through the application of the two remaining benchmark models. By focusing on the Fung and Hsieh 7-factor model column (incorporating lookback straddles), 3% of the hedge funds should have a t-statistic less than -1.9294, considering a world where managers do not have any skill. In reality, it can be highlighted that around 10% of hedge funds are actually observed, meaning that the expected fraction obtained only due to chance is substantially underestimated. Surprising as it may seem, the number of hedge funds with managers possessing inferior skills is higher than the proportion suggested by the bootstrap procedure.

Concerning the Agarwal and Naik 8-factor model, the findings from the Fung and Hsieh 7-factor model are amplified and it can be observed that the average percentile values of the $t(\alpha)$ estimates from the simulations of net returns (where skill is sufficient to cover costs by construction) always beat the corresponding percentile values of the $t(\alpha)$ estimates for actual net returns until percentile 93.

Generally speaking, there are less good funds than the number of funds that should be observed only due to chance in the left tail while the situation is the opposite in the right tail. The upper tail of the three-factor $t(\alpha)$ estimates suggests the existence of managers with hot hands generating superior performance relative to passive benchmarks. For instance, the 5^{th} best and worst percentiles of actual $t(\alpha)$ estimates for the Fung and Hsieh 7-factor model are 1.5897 and -2.8839, whereas the mean values of the corresponding ranks from simulations are 0.9214 and -1.5021. The situation is analogous for the three other models.

On the contrary, for most of the left side of the distribution – from worst percentile to above the 85th percentile – the simulated t(α) estimates are greater than the actual values in more than 90% of the draws. This finding leaves little evidence for misfortune as the most likely explanation for poor hedge fund performance, meaning that bad results are probably not only due to bad luck.

On top of that, the inferior performance in the left tail of t(α) estimates is clearly more obvious than the outperformance in the right tail. For instance, the 5th percentile of the 3-factor t(α) estimates for the actual returns is 0.807 standard errors below the mean from the simulations, but the 95th percentile for actual return is only 0.1409 below the average. For the 8-factor t(α) estimates from the model of Agarwal and Naik, the 95th percentile for the actual returns is 1.4721 below the average simulated value while the 5th percentile is bigger with 1.6536 standard errors below the mean. That being said, the fund returns are all net of fees and an adjustment for trading costs would probably result in a superior performance of the actual returns far before the 95th percentile.

Regarding the median fund, negative t-statistics are obtained for the four multifactor models considered, highlighting that the median fund underperforms the market and that there are thus more bad funds than there should be just due to chance if funds had zero alpha.

Furthermore, when focussing carefully on the two models containing option-based factors, it can be argued that adding option-based factors implies a shift of the whole actual return cumulative distribution function to the left, with higher standard errors between the two curves capturing therefore different patterns in returns.

For example, the 40th percentile of the Fama and French 3-factor t(α) estimates for the actual returns of hedge funds is only 0.1619 standard errors below the average from the 1000 bootstrap simulations while the 40th percentiles of the Fung and Hsieh 7-factor model and the Agarwal and Naik 8-factor model are respectively 0.5623 and 0.7194 standard errors below the simulation average.

This situation is identical in the right tail with a 70th percentile of the Fama and French 3-factor t(α) estimates for the actual returns 0.124 standard errors lower than the simulated mean whereas the 70th percentile of the 7 and 8-factor model are respectively 0.3873 and 0.6139 standard errors below the average from the simulation runs.

Finally, the last column called « % < Actual » gives the proportion of simulation runs providing a lower result than the actual observations. For example, considering the 5th percentile, only 2.6% of the observations from the simulated runs are lower than the actual values based on the 3-factor regression of Fama and French. This finding is magnified for the three other models applied where the fraction of simulated values lower than the actual ones is almost zero at the same rank. This emphasizes « bad skill » or value destruction. For all the benchmark models, the majority of the left side of the distribution has simulated values greater than the actual $t(\alpha)$ estimates in 85% or more of the draws.

Moreover, when incorporating optional factors, for most of the distribution, ranging from the worst rank to above the 90th percentile, the actual values are higher than the simulated $t(\alpha)$ estimates in more than 90% of the draws. Once again, this situation gives little evidence for misfortune as the principal reason explaining the poor performance of hedge funds, meaning that it would not be only due to bad luck.

At the same time, it can be noticed that the hedge funds among the best performing of the distribution have an important fraction of actual values greater than the simulated ones. For example, at the 98th percentile, the simulated values are below the actual ones in more than 99% of the cases for all the models taken into account in this paper.

However, it is of paramount importance to keep in mind that the performance produced by a hedge fund is contingent on the results of all the other hedge funds when comparing with the numbers found thanks to the simulation runs. As a result, conclusions cannot be drawn for individual funds and it is therefore not possible to observe the main characteristics (R^2, factor loadings, etc.) of the best-performing and worse-performing funds.

Overall, the bootstrap procedure results in evidence of both inferior and superior hedge fund performance, meaning that the returns produced cannot be explained by luck alone. Also, the thresholds vary from one benchmark model to the other, meaning that false discoveries can influence the conclusions drawn and the reader has to keep in mind that the abnormal performance generated can actually come from a multifactor model which is not able the capture the whole risk involved (this finding will be emphasized with the CAPM model in the next section). Also, including optional factors leads to a shift of the whole actual return curve to the left, capturing therefore an additional pattern in returns in comparison with the two first models.

5.3.3. CAPM bootstrap simulations

A similar bootstrap procedure is conducted but this time, using the CAPM as benchmark. The excess market return is therefore the only independent (or explanatory) variable. This benchmark model was used to assess the impact of not taking into account patterns in average returns during the sample period. This also emphasizes how failing to account for trends in returns can lead to false discoveries.

By analysing the graph and the table in Appendix 11, strong evidence is found that some fund managers have hot hands and are able to produce enough superior performance to cover the costs and fees that the investors have to bear. As expected, the CAPM test brings more cogent evidence that managers possess skills leading to positive true alpha (α) than the four other benchmark models previously used. For instance, in the upper tail, 5% of the hedge funds should have a t-statistic greater than 0.9034 if the managers did not possess any skill. In reality, around 10% of hedge funds can be observed, meaning that there are many more hedge funds reaching the performance level than the fixed threshold only due to chance. In the lower tail, the results are a bit more depressing: 5% of the funds are supposed to have a t-statistic lower than -1.69 but in the world, approximately 8% hedge funds having a t-statistic lower than -1.69 are noticed. Also, once again, the median hedge fund underperforms the market (-0.12).

To sum up, all the benchmark models demonstrates the presence of managers possessing skills in the upper tail of the return distribution. That being said, the threshold at which the actual return is above the average bootstrap return depends on the benchmark model used, ranging from the percentile 74 for the CAPM to the percentile 93 for the 8-factor model developed by Agarwal and Naik which emphasizes the importance of false discoveries.

5.3.4. Robustness check

The applied methodology relies on different factor models to estimate the performance of a fund. An option that has already been exposed in the academic literature (as detailed in the literature review section) in order to improve the goodness-of-fit of the multifactor model consists in implementing conditional factor models which allow for time-varying coefficients. Indeed, by using unconditional models, it is implicitly assumed that the factor loadings are constant throughout its whole lifetime of the hedge fund which is not realistic. It is therefore important to test if the results found previously with the unconditional models will remain the same when adding conditional factors.

Many authors decided then to introduce diverse financial indicators to adjust hedge fund exposures to risks given the fact that hedge funds frequently use dynamic trading strategies (Amenc, El Bied, and Martellini, 2003; Fung and Hsieh, 2004; Kat and Miffre, 2006; Chen and Liang, 2007). The common point between all these studies is that the hedge fund return at time t can be to a certain extent forecasted by public information including not only market returns $R_{M,t}$ but also a larger range of economic variables z that need to be specified.

In order to perform this robustness check, the procedure of Ferson and Schadt (1996) and Becker, Ferson, Myers and Schill (1999) who considered the products of the market return with lagged instruments to monitor the use of public information by hedge funds will be replicated. The idea behind this procedure is that managers simply using publicly available information should not be credited with superior manager skills.

The Fung and Hsieh 7-factor model will be reused (as it gave the highest R^2 adjusted in the previous section) and augmented by 4 lagged instruments to represent public information as advised by Chen and Liang (1999): the three-month T-bill rate, the quality spread between Moody’s BAA- and AAA-rated corporate bonds, the dividend yield of the Standard and Poor’s 500 index and the term spread between 10-year and three-month Treasury bonds. The instruments’ data are available on the website of the Federal Reserve Bank of St. Louis[11] and their summary statistics are provided in Appendix 12.

The overall idea is to include the impact of public information on hedge fund beta as it is believed that it has predictability to the market funds in order to properly assess the conditional performance. The conditional abnormal return is therefore obtained by using the subsequent regression:

$$R_{p,t+1} = \alpha + \sum_{j=1}^{K} \beta_j * r_{j,t+1} + \sum_{l=1}^{L} \delta_l * z_{l,t} * R_{m,t+1} + \varepsilon_{t+1}$$

where z’s are lagged series of the four (i.e., L=4) chosen instruments, including the three-month T-bill rate, the quality spread, the dividend yield on the Standard and Poor’s 500 index and the term spread.

[11] The instruments’ data are retrieved from the website of the Federal Reserve Bank of Saint Louis: https://fred.stlouisfed.org/

When observing the graph and table depicted in Appendix 13, it can be argued that the results produced by the conditional multifactor models corroborates those obtained with the previous models. Indeed, the threshold at which the actual return curve crosses the simulation one is the 92nd percentile which is slightly higher than what was noticed with the Fung and Hsieh 7-factor model. For example, when looking at the upper tail, 5% of the hedge funds should have a t-statistic greater than 1.1379 if the managers did not possess any skill. In reality, around 8% of hedge funds can be observed, which means that there are more hedge funds achieving the performance level than the fixed threshold only due to chance. These results confirm therefore those found previously as the model highlights the existence of managers possessing superior skills leading to outperformance. To sum up, including time-varying coefficients does not call into questions the interpretations made previously and the findings are thus robust to conditional multifactor models.

6. CONCLUSION

6.1. Concluding remarks

Since the database used for this study only includes net returns, it is challenging to draw any conclusion about whether hedge fund managers as a group can actually be considered as skilled or unskilled. Indeed, there is a chance that there exist many skilled managers being able to deliver significantly positive alphas measured on gross returns but not anymore on net returns. A bootstrap procedure based on net returns has the weakness that superior skills may be concealed by high fees charged.

For the period under study (January 1998-May 2017), after treating the Morningstar database to obtain a dataset relatively free of biases, it can be observed that some hedge fund managers have superior skills and abnormal performance cannot be attributed only to chance, regardless of the benchmark multifactor model used.

The analysis also shows the interest of including optional factors in the multifactor models in order to assess performance and avoid false discoveries. Some optional factors considered are significant and are therefore adequate to characterize the non-linear risks of the long/short equity strategy, as illustrated by the use of a Conditional Value-at-Risk framework. Indeed, as demonstrated by Agarwal and Naik (2002), when compared with a mean-conditional Value-at-Risk framework, it is crystal clear that a traditional mean-variance framework is inefficient since it largely underestimates the left tail risk and the large losses which can happen with hedge funds. Also, the Jarque-Bera test enabled to prove the non-normality of the hedge fund return distribution and the appropriateness of a bootstrap procedure to conduct this analysis.

Even though some savvy managers have been able to outperform the market, it could not be proved that managers, in general, have enough skills to produce persistent performance. This result is in accordance with the equilibrium accounting theory stating that active investment must be a zero-sum game, some active hedge fund managers have been able, over the years, to beat the market but they have achieved these good results at the expense of other active managers.

The bootstrapping analysis gives evidence of significant superior manager skills among the top performing hedge funds and of inferior manager skills among the worst performing ones. In the upper tail of the distribution, hot hands among the best managers can be highlighted. Indeed, those managers are able to produce better returns than what would be expected purely by luck. The bootstrap procedure shows that approximately the 97th and higher percentiles of the different multifactor models $t(\alpha)$ estimates for net returns are higher than the mean value from the 1000 bootstrap simulations for the corresponding percentile in more than 99% of the simulation runs. Nevertheless, in the lower tail of the distribution, the results are disheartening. There is some evidence of poor returns which are not coming from bad luck and which are therefore a sign of value destruction. These findings corroborate the ones of Kosowski, Naik and Teo (2006), except that they took the decision to do the simulations independently for each fund whereas the hedge fund returns are jointly sampled in this paper, as advised by Fama and French (2010) in order to take into account the correlation between the $t(\alpha)$ estimates of the different funds.

On top of that, by using different multifactor models whose quality has been proved in the academic literature, it must also be kept in mind that the perfect model to capture the hedge fund risk has not been discovered yet and therefore, the results are biased by false discoveries to a certain extent that cannot be determined with precision. It has been shown here that the threshold at which the actual returns become higher than the simulated ones significantly varies between the different multifactor models used, ranging from the 74^{th} percentile to the 93^{rd}. That being said, managers possessing skills can always be found in the right tail even though the proportion is not fixed and this finding remained robust when applying a conditional multifactor model.

6.2. Avenue for future research

The first thing that comes to mind when examining some avenues for further research is the improvement of the existing dataset by including gross returns. In fact, this could potentially provide powerful contribution such as a more robust interpretation of the existence of hedge fund managers possessing superior skills. Assessing performance before expense allows one to disentangle the stock-picking skills of the managers from the fund’s expense policy, which sometimes is not under the control of the fund manager. This integration could also reveal a potential correlation between skills and the fees charged.

Furthermore, investigation regarding the persistence of the superior performance found in the right tail of the distribution would bring valuable insights to assess if outperforming hedge funds remain well-performing over time or if this trend disappears.

Finally, it would be really interesting to take a closer look at the hedge funds in the right tail and left tail of the distribution and detect their characteristics (R^2, factor loadings, etc.) in order to find out what sets them apart from other hedge funds. To reach this goal, instead of performing a bootstrap procedure to assess performance in the cross-sectional distribution of hedge funds alpha (α) estimates, time series regressions should thus be conducted on net returns of each individual hedge fund present in the sample.

PROJECT MANAGEMENT

When talking about project management, a first distinction has to be made between a project thesis, which takes place within the company itself and a research thesis, whose drafting may be more related to the management of a project during one entire academic year.

Lester (2017) simply defined a project as a unique process consisting of a series of monitored actions, with a start date and an end date. This process is undertaken to achieve a precise objective which is subject to specific requirements such as time, money or resource constraints. Aside from budgetary constraints, a research thesis might therefore be considered as part of a project according to the stated definition and a good understanding of the project management concepts is of paramount importance to ease the project completion.

The required main steps to undertake were the following: a deep understanding of the research question, a good summary of the academic literature, an efficient collection of the raw data, a thoughtful transformation of the data into concrete results and a meaningful interpretation of the findings. Good communication skills were also essential in order to properly interact with the designated academic contact persons whose help and wise pieces of advice were crucial factors to ensure that the project becomes a success.

Newton (2015) specified four constraints to overcome in order to reach a satisfactory outcome:

- Time;
- Quality;
- Scope;
- Cost.

The **time** constraint was undoubtedly the most complex one in my particular case. Indeed, the first semester was dedicated to theoretical classes which were obviously followed by an examination session, carried out in December and January. At the same time, the Master in « Financial Engineering » requires a strong involvement and a steady work to successfully complete the various group assignments. On top of that, I took part in the CFA Institute Research Challenge which is an annual global competition between many universities where students work in teams to analyse and value a publicly traded company. Even though this experience was extremely enriching on many levels, the magnitude of the task made it extensively time-consuming.

Furthermore, concurrently with the January session, I had to deal with an internship at Gambit Financial Solutions. This traineeship played as well a prominent role for at least two reasons. On the one hand, an internship represented a great opportunity to discover a professional area which seemed to correspond to my aspirations for the future. On the other hand, I also had to write an internship report to detail my daily tasks within the company, directly followed by an oral examination. Once again, I made things a bit more difficult for myself by choosing an internship of sixteen weeks instead of the ten required. My goal was to learn everything I could and to accumulate as much field experience as possible as I am deeply convinced that this knowledge will be highly valuable in the future. In addition, responsibilities taken within a student association, the ESN (Erasmus Student Network) have to be added. These activities also play a key role in the life of an involved student, especially in the final year of the master. All these constraints made a good time management a crucial prerequisite for the realization of my research thesis.

This leads us to the second constraint enumerated by Newton (2015): the **quality**. Averous and Averous (2004) identified four different perceptions of the customer-oriented quality:

- The expected quality, which is the level of quality that the customer wishes to obtain. In this particular case, the customer is embodied by the research promoter;
- The desired quality, which is the level of quality intended by the student;
- The delivered quality, which is the difference between the obtained and stated outcomes, evaluated by indicators measuring the progress of the mission;
- The perceived quality, which is the assessment of the provided quality.

The quality of service expected by the promoter has the effect of compelling the student to set himself ambitious targets. This procedure is thus a virtuous circle in which it is necessary to adapt and match the work in research with the expectations and requirements of the promoter and readers. The quality of service will therefore be optimal when the quality delivered by the student is the same as the quality perceived by the assessors.

Throughout the course of my studies, I have learned that submitting a report hastily drafted, at the last minute, resulted in unnecessary stress and caused stupid mistakes leading to frustration. Consequently, I thought it wiser to pay close attention to the different papers read while taking care of properly understand the logic of the authors and summarize it before the concretization when writing my final report.

The third constraint is the **scope** given to the assignment. The Associate Professor Marie Lambert, academic director of research at HEC-Management School of the University of Liège and promotor of this thesis as well as the PhD Candidate in Finance, Boris Fays, helped me to a large extent to identify the various theoretical and practical dimensions. Through multiple meetings over the year, they gave me precious pieces of advice which have been of valuable help when I faced difficulties.

Bodiglio (2016) made it clear that structuring the work remains an important task to be performed. A poor start in such a project has a full chance to end badly. Indeed, once started, the research has a certain inertia and it becomes harder to lead it back on the right track. At best, it is still possible to achieve the initial goal but with a substantial loss of precious time. At worst, the research cannot be delivered according to the high standards requested. Establishing the scope consisted in:

- Determining the objectives in terms of expected results;
- Detailing the work in terms of products, functionalities, organization, process, etc.;
- Determining the major steps, key dates, main targets, etc.;
- Defining the required means and resources;
- Identifying the risks and potential dependencies;
- Defining the key figures and indicators.

Finally, the **cost** constraint is covered not from a budgetary point of view, as described above, but from an opportunity cost perspective. Before being entirely committed to this work, it was required to give the highest priority to other assignments such as the internship, the theoretical courses, the various group projects, etc. In the execution phase of this research project, though choices had to be made. Some aspects were voluntarily set aside. Indeed, studying the performance of hedge funds is a very broad topic and it was impossible to extend the study of the subject as far as I would have wished. The scope had therefore to be narrowed to principally focus on false discoveries and manager skills.

On top of that, Newton (2015) raised three important questions that need to be answered for a project to be properly defined:

1. How does the project fits into the organizational framework?
2. What are the required skills for carrying out this mission?
3. How is the project going to evolve over time?

The first question consisted in knowing if the research project would be accepted within the framework laid down by the University of Liège. This proved to be no problem at all as the research proposal « Manager skills of Long/Short Equity Hedge Funds: The Factor Model Dependency » was part of the suggested topics by Mrs. Lambert.

Then, the second question to address was the one related to the functional part. The courses followed throughout these five years and more specifically, the master, substantially facilitated the completion of this dissertation. All these classes developed my critical thinking, sharpened my analytical skills and gave me the motivation to deepen my financial knowledge. In addition to the theoretical knowledge, Polonovski (2016) highlighted that in project management, the soft skills related to the reality on the ground tend to be more important that the hard skills which can be learned by reading the academic literature.

Last but not least, in order to address the time issue, the multiple steps composing the completion of this work will be detailed in chronological order. It goes without saying that even though these steps were clearly defined, a series of unforeseen events involving reconsiderations and modifications of the previously implemented strategies had to be taken into account. For that reason, the realisation of this project required a high degree of flexibility and a strong capacity to quickly and efficiently adapt to various circumstances. That being said, distinctly identifying the tasks and risks linked to the accomplishment of this project allowed me to prevent potential unexpected events and to closely follow the completion stages.

- **May 2017**

As previously explained, choosing a subject was really short and easy thanks to the list of proposed subjects at my disposal. The choice of this topic was driven by the fact that I did not learn a lot about alternative investments such as hedge funds during my academic years and I was willing to get deeper insights in this financial area to further my education.

- **September 2017**

In order to set out the theoretical framework and a general methodology, a first meeting with B. Fays was organized. As my research thesis included a statistical technique called bootstrap procedure requiring a software to properly conduct it, we agreed on the use of SAS Enterprise Guide as the appropriate tool in my particular case. This software was chosen because I got the SAS certification one year earlier as part of the portfolio « Become a Certified Business Analyst: SAS Certified Young Potentials program » given by S. Aerts.

Also, we discussed the database that could be used and the various treatments required to end up with a workable outcome and Morningstar was chosen due to the free access provided by the university.

The following months were dedicated to the reading, analysis and understanding of the various papers dealing with the subject to achieve a thoughtful review of the existing scientific literature at the end. The next step was then to test the software and translate the theory I learned to obtain my SAS certification into the practical case of a performance analysis of hedge funds. It is true that this task took more time than expected due to my very busy school program of the first semester (classes, group assignments, CFA Institute Research Challenge, etc.).

- **February 2018**

Once the exam session completed, an interview was organized with my promotor, M. Lambert, and my reader, M. Fays to readdress the methodology to follow and clarify the way to go forward. In the meantime, my laptop was stolen which represents one of the unforeseen events I had to face. Even though most of the work already accomplished was saved on an external hard drive, my SAS code developed so far was not, implying a substantial waste of time.

- **March – May 2018**

These last three months were dedicated to the actual materialization of the research: the writing. However, as my internship lasted sixteen weeks instead of ten, good organisational skills were required for carrying out this mission. I also met G. Hübner, second reader of this thesis, because I wanted to have his opinion on my methodology and analyses. Even though the timing was very tight, I tried my best and managed to produce a work which I hope will meet expectations.

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EXECUTIVE SUMMARY

Can top-performing hedge funds such as George Soros' one be considered as just lucky or, on the contrary, can the generated abnormal performance be regarded as persistent and directly coming from superior skills of the managers through efficient dynamic trading strategies? Over the years, this question has often made headlines and a diverse array of experts have discussed this problematic.

Assessing the return-generating process of hedge funds has always been a genuine challenge due to the opaqueness of this industry and the multiple investment strategies at the disposal of the managers.

First. the several multifactor models that are supposed to explain hedge fund returns will be highlighted in a comprehensive review of the literature. The development of the hedge fund industry will be detailed, the features of this alternative investment vehicle will be highlighted, the different trading strategies will be explained, the current knowledge over manager skills (versus luck) will be described and the performance persistence will be discussed.

Afterwards, the data and methodology used will be clarified and the most adapted models to hedge funds will be selected and then regressed to obtain the intercepts for each fund, representing the abnormal performance. Once this step completed, 1000 bootstrap simulations will be performed with the aim of comparing the observed top hedge fund performance to the performance of top funds in artificially generated data samples for which variation in fund performance is fully due to sample variability or luck. Indeed, using bootstrap procedures. academics were able to quantify the percentage of hedge funds exhibiting persistent performance.

The goal is to demonstrate the potential bias and/or outperformance brought by some multifactor models applied when estimating hedge fund manager skills.

Key words: hedge fund, performance, risk/return, dynamic investment strategies, bootstrap procedure, multifactor model, regression, manager skills, luck, false discoveries.

Key tools: SAS Enterprise Guide, Multiple Linear Regression, Bootstrap Simulations.