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On the risk-return contribution of Hedge Fund investing in a diversified portfolio

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Abstract

Throughout this thesis, I provide two performance analysis. The first one focuses on a comparison between the performance of the Barclay and the Credit Suisse's hedge fund index from 1997 to 2016. From the first performance analysis, we can determinate what indices seem to outperform overall. This lead us to the next step with the second performance analysis that consists in identifying the impact on the risk-return of including a hedge fund index within a diversified portfolio between 2002 and 2016. By mixing a multi-asset portfolios with different weights of the relatively best indices selected in the first analysis, one could conclude on the risk-return contribution of the hedge funds invested in the diversified portfolio.

I would like to extend a special thank you to Professor Petitjean who has always found the time to guide me in the writing of this thesis.

List of abbreviations

- BCAI = Barclay Convertible Arbitrage index
- BEMNI = Barclay Equity Market Neutral Index
- BFIAI = Barclay Fixed Income Arbitrage Index
- BELBI = Barclay Equity Long Bias Index
- BELSI = Barclay Equity Long/Short Index
- BEEI = Barclay European Equities Index
- BDSI = Barclay Distressed Securities Index
- BEDI = Barclay Event Driven Index
- BGMI = Barclay Global Macro Index
- BMSI = Barclay Multi Strategy Index
- BEMI = Barclay Emerging Markets Index
- BFOFI= Barclay Fund of Funds Index
- BHBI = Barclay Healthcare & Biotechnology Index
- BIT = Barclay Technology Index
- CHF = Credit Suisse hedge fund index
- CCA = Credit Suisse convertible arbitrage index
- CDSB = Credit Suisse dedicated short bias index
- CEM = Credit Suisse emerging markets index
- CEMN = Credit Suisse equity market neutral index
- CED = Credit Suisse event driven index
- CEDD = Credit Suisse event driven distressed index
- CEDMS = Credit Suisse event driven multi-strategy index
- CEDRA = Credit Suisse event driven risk arbitrage index
- CFIA = Credit Suisse fixed income arbitrage index
- CGM = Credit Suisse global macro index
- CLSE = Credit Suisse long/short equity index
- CMF = Credit Suisse managed futures index
- CMS = Credit Suisse multi-strategy index
- EO = Equity Oriented
- DS = Directional Strategy
- MS = Multi Strategy
- ED = Event Driven

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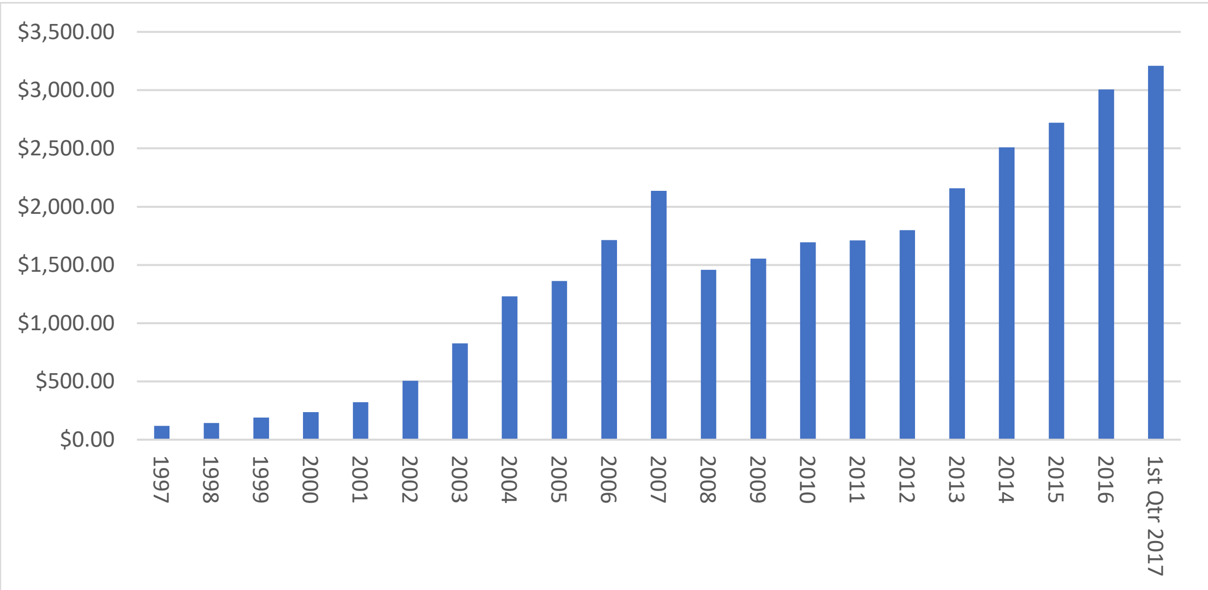
1. Introduction

The hedge funds' industry and all the people who manage them are often associated with huge risk takers and pejorative terms. After 2007, they have even been accused by some people of being one of the causes of the crisis. In a nutshell, most of the time, you will hear that they take too much risk by using risky financial instruments, that their management costs are too high relative to the return or even that on the long run, the hedge funds can't beat passive indices such as S&P500.

In the wake of the last crisis, we may tend to think that professional investors could be reluctant to invest in such funds that seem to be too risky at first sight and that can make huge losses in case of downturn. This tendency is even more emphasized with the increasing instability of the markets, especially in some geographical areas.

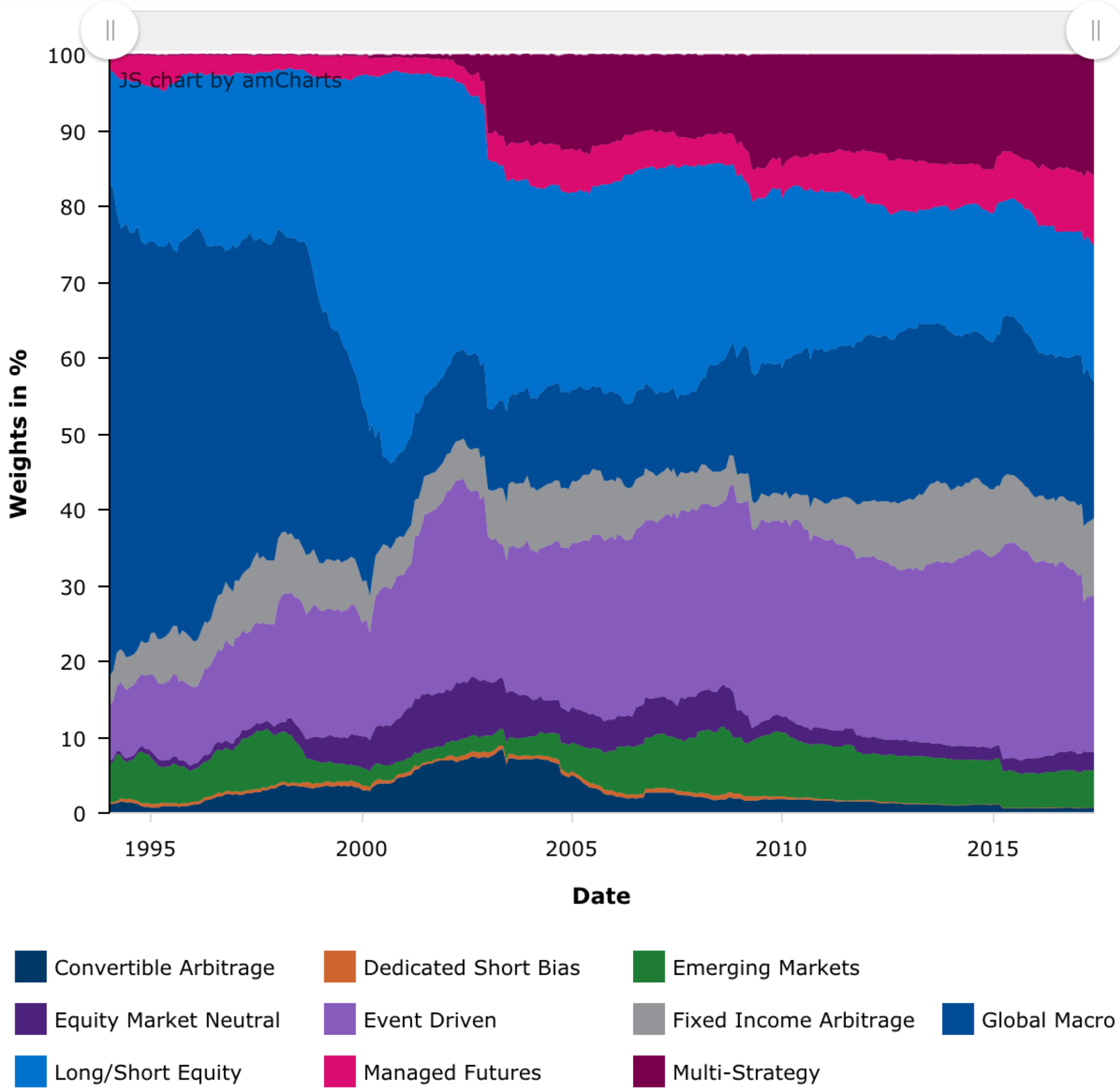
However, we can observe that each year and even since the 2007 crisis, despite a slight decrease in the trend, hedge funds are managing a growing number of assets. As we observe in figure 1, they don't stop breaking their own records in terms of assets under management (AUM) in the last years rising from 2000 billion worldwide in 2007 to over 3000 billion today.

Figure 1: Asset under management (in billion $ USD)



Source: www.barclayhedge.com

Figure 2: Hedge fund's Composition



Source : https://lab.credit-suisse.com

Figure 1 shows that hedge funds seem to be really attractive but why? We could explain this tendency, inter alia, by the fact that if we select an asset class, one will observe that the securities within it will tend to move together with an emphasis in times of extreme market movements. As such, it is interesting to invest in a highly diversified fund as hedge funds. Moreover, past researches, such as Bodie, Kane & Amarucs (2000), show that mutual funds fail to outperform passive indices. Figure 2 represents the asset under management for each strategy. One can see some trends such as the decrease in the global macro asset under management around 1997 and at the same time, the increase of the long/short equity and the event driven AUM.

In contrast, it has been proved that hedge funds are able to provide more diversification than stocks and bonds aside from the fact that they outperform passive indices (Kazemi & Schneeweis, 2002) which makes hedge funds even more attractive.

However, with the current low interest of bonds and the poor performance of equity, are hedge funds the best alternative to invest for wealthy investors?

At the sight of actual bond and equity market (i.e. low returns), it could be interesting to look closer at hedge fund's market on a stand-alone basis with all the strategies it includes but it would be likewise relevant to look at its impact in terms of risk-return when it is included in a portfolio.

The first part of the empirical analysis (see section 5) focuses on the different strategies of the hedge fund in order to make a rank of the best strategies (Credit Suisse VS Barclay). The goal of this section is not only to spot which type of strategy performed the best these last years but also to compare their performances with the benchmarks.

For the second part of the empirical analysis, I will construct a multi-asset portfolio by using the same structure than El-Erian (2008), structure that will be explained later.

This analysis will cover the introduction of the (relative) best hedge fund, selected in the later section, in a diversified portfolio. The goal here is to observe the effect on the risk-return of the inclusion of an HF in a portfolio. In point of fact, thanks to the Modern Portfolio Theory (MPT), we know that building portfolios with instruments that are imperfectly correlated reduces portfolio's risk without reducing expected return. Table 1 shows us basic statistics on hedge funds (total returns of Barclay hedge fund index and Credit Suisse hedge fund) and S&P500.

Table 1 Hedge fund indices and S&P500 - Descriptive statistic

	Annualized Return	*Annualized SD*	*Credit Suisse HFI*	*Barclay HFI*	*S&P500*
CS HFI	6.28%	0.0657	1		
Barclay HFI	8.48%	0.0706	0.8555	1	
S&P500	7.11%	0.1530	-0.0003	0.0768	1

At first sight, the Barclay Hedge Fund Index seems to be a good investment as it performs better than the S&P 500 on a return basis and he displays a lower risk with a standard deviation of 0.07 against 0.15 for the S&P. Table 1 shows us that the correlation between hedge funds and the market is very low and both can even be negatively correlated.

Throughout this work, I'll try to answer, or at least give an element of answer, to this question:

What happens, in terms of returns and volatility, when you include a hedge fund in a diversified portfolio?

As it will be explained later, it exists several types of strategies in the hedge funds' industry. Before answering the main question of this thesis, it would be interesting to know what strategies perform the best and what impact would have the index using this strategy on my investment if I include it in a diversified portfolio?

The rest of this thesis will be organized as followed: in the next section, I will give an overview of the hedge fund's industry and about the literature related to it, in section 3 the data used will be described, section 4 develops some of the tools available to measure the performance of a fund, section 5 makes an analysis of the hedge funds performance and the impact it has on the portfolio's performance when it is included into it and finally section 6 reports what we can conclude from this thesis.

2. A primer on Hedge Funds

2.1. Definition of a Hedge Fund

Although there isn't one and unique definition concerning the hedge funds, we can find the source of its name in the first hedge fund established by Alfred Winslow Jones in the late 1940s (Mallaby, 2010). This hedge fund, as its name indicates it, consisted in a simple hedging strategy: being equally long and short. But today, the term "hedge fund" regroup a multitude of funds with several strategies which are more elaborate as each other. Nonetheless, they all have some characteristics in common that can help to make the difference between them and the other type of funds (e.g. mutual funds).

First, we can define the hedge funds as a private alternative investment using pooled funds managed by professional investment managers and whose access is restricted to institutional investors or at least to institutions with substantial resources, according to Fung & Hsieh (1999); Capocci & Hübner (2004) and Amin & Kat (2002).

Another particular characteristic is the fact that the general partners who are also the fund's managers will invest a fraction of their personal wealth in the fund in order to have the same economic interests as the investors. Furthermore, these fund's managers will be paid partly by a performance fee named "incentive fee" what, according to some literature, has an impact on the hedge fund returns (see section 2.3.2 inventive fee).

On the legal aspect, hedge funds have the particularity to not be as regulated as the other type of investment vehicles such as mutual funds. Indeed, some academics tend to think that it is one of the main reasons why they are able to outperform mutual funds (Ackermann and Ravenscraft, 1998). Thanks to this lack of regulation, hedge funds employ dynamic trading strategies making use of derivatives (whereas mutual funds deploy static buy-and-hold strategy), but they also exploit the leverage (Fung and Hsieh, 1999). Their legal environment allows them to not provide semi-annual and annual reports to their supervisor (Fung and Hsieh, 1999).

"Hedge Funds have also been described as absolute return strategies, as these managers attempt to maximize long term returns independently of a traditional stock and bond indices (Schneeweis, Kazemi and Martin, 2002). That is why we could describe them as skill-based investment strategies.

While some sources give a definition for hedge fund, it is less relevant to describe "what is a hedge fund" as a whole (except for the few common characteristics on which they are established) as each hedge fund is built "to take advantage of certain identifiable market opportunities"[1]. Indeed, within each hedge fund lies different investment strategies and that is why it would be more useful to explain what it represents by splitting its definition by investment style: equity oriented, relative value, event driven, directional and multi-strategy. These strategies are explained in detail in the next together with some relevant facts about each strategy.

2.2. Strategies in Hedge Funds

Fung and Hsieh (1999) give us a general framework regarding hedge funds strategies.

First, the investor must choose a target. To do so, he has two possibilities, either he will set a "relative return" target or an "absolute return" target. The first one, as indicated by its name, will be set **relative** to a benchmark. The investor chooses an index that represents the target he hopes to reach (e.g. the S&P 500 for a US equity portfolio or Eurostoxx 50 for an EU equity portfolio) and will assess his performances based on it. The "absolute return" doesn't depend on a benchmark but rather is a figure settled before the investment period. The hedge fund's model is closer from the second type as they are supposed to perform well even in times of recession.

When they decide to set an absolute return target, they will reach it by using one of these approaches: Market Timing Approach (MT) and Non-Directional Approach (ND) (Fung and Hsieh, 1999).

MT approach attempts to predict what could happen in the market by using technical indicators or economic data for instance. As the manager has built its predictions, he will be long or short on the market or he will invest only in certain asset classes at that point, trying to anticipate the stock's movements. This approach is mainly used by Global, Global/Macro, Short-Sellers, Long-only managers. However, few investors get significant performance using this approach. Indeed, according to the estimation of Morningstar, portfolio managers using the MT approach got 1.5% return below the managers of passive portfolio[2].

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[1] www.investopedia.com
[2]www.Investopedia.com

The investor using the ND approach tries to track anomalies of markets such as mispriced securities to exploit the underlying arbitrage opportunity and generate higher returns. Typically, he will be long and short on comparable securities in order to capture the value and at the same time cancel the non-diversifiable risk of the market. Later, we will talk about the A.W. Jones hedge fund strategy which is a classic example of Non-Directional strategy.

By having classified strategies in this way, we can already give some of their characteristics such as the correlation between their returns and market indices. For example, Fung and Hsieh (1999) observed that overall both approaches (ND and MT) have correlations close to zero with market indices except in the case of continuous upward trend where MT strategies will show a negative correlation with market indices in certain periods. Likewise, we will see a difference in terms of risk (i.e. standard deviation) between the two approaches like in extreme market conditions, the MT strategies could demonstrate higher performance volatility.

Finally, though there are two main approaches, it exists a strategy in between that is a mix of both. This hybrid style, principally used by Event-driven funds, is named “hybrid” because after having eliminated the main part of the systematic risk, the portfolio still contains some risk and is thus more volatile than a typical ND style portfolio.

Although each hedge funds have its own strategies, Travers (2012) have listed the classical approaches that we can find in every hedge funds.

2.2.1. Equity-oriented Strategies

In this strategy, the manager will use, as its name indicates, equities but likewise equity-like securities. It consists in three “sub-strategies” which are **Variable Equity Long/Short Strategies, Long Biased Strategies and Short Biased Strategies**.

The logic behind the first strategy is that the manager anticipates that he can earn value from the lack of efficiency on the market.

The manager will play on several parameters, such as the market capitalization and the regions or countries to construct its strategies. For example, depending on the opportunities he detects, a manager can choose to invest either in small, in mid or in large cap’s stocks or alternatively he can choose to be specialized in one market cap.

The short portfolio has two goals; either it will be used as a hedging tool for the long portfolio or the manager will use it to generate an additional potential alpha.

The Long-Biased strategies consist simply in investing in equities massively. The investor can go further by using leverage what will have as consequences to increase the beta and the correlation with the equity market.

The Short-Biased Strategies is essentially the opposite of the latter. It is specifically useful when market volatility increases or in case of downturns as it will have positive impact on the overall portfolio in that case.

Schneeweis, Kazemi and Martin (2002) give us an insight on the signs that this strategy will outperform. The first sign is that the yield curve must be “upward sloping” but with small increases or decreases in its slope. Then we must see a decline in the credit risk premium with no significant variation in the short-term interest rate. Finally, when looking at the intra-month volatility of the S&P500 and the VIX, their levels must be “moderate” and large cap and small cap stocks display high returns.

2.2.2. Relative Value

The key words for these strategies are “arbitrage opportunities”. The goal of the manager will be to find a mispricing in an investment (or a combination of investments) and to use it to make profits. We can find three types of relative value strategies: **Convertible bond arbitrage, equity market neutral funds and fixed income arbitrage.**

In the first one, the managers will try to find arbitrage opportunities within the market of the convertible bonds and hybrid securities.

As defined by Travers (2012), “the equity market neutral strategy employs long and short portfolios of equity securities that are dollar neutral, beta neutral and/or factor neutral” (e.g. neutrality in market cap or in a sector). The equity market neutral manager’s purpose is to reduce his exposure to the stock market by being short and long on it. It is the “basic” hedge fund strategy as it was the one being used by the first hedge fund, the A.W. Jones hedge fund.

The third sub-strategy is the exploitation of arbitrage opportunities between related fixed income securities.

2.2.3. Event Driven

These strategies are directly linked with corporate events such as a merger or a bankruptcy. It consists in three sub-strategies that are the **distressed and high-yield strategies, the merger arbitrage and the activist strategy.**

In the distressed and high-yield strategies, the manager will focus on "the credit securities of companies with below-investment-grade ratings" (Travers, 2012). Their purposes are either to get non-investment-grade securities for their high yield or because they foresee that it will be paid down.

The merger arbitrage strategy has for purpose to make profit on the difference of security's value now and when the merger will take place. The manager behind this strategy will typically buy stocks of the targeted company and short the acquirer's ones (but can also do the opposite if he thinks the deal may fail).

The last strategy, the activist strategy, is, according to Travers (2012), "one where the hedge fund's manager believes that some kind of corporate change would benefit the company". In order to apply it, he must be active within the company thus he would have to get enough shares to be on the board and have his say. But he can also take a passive role by just writing a letter to company stakeholders (management or board) to share his recommendations.

2.2.4. Directional Strategies

This type of strategies is separated in two kinds of sub-strategies.

The first one is **the global macro strategy** where the manager will seize opportunities in global markets by performing a macroeconomic analysis and using tools such leverage as well as short sales in order to magnify its exposure. This type of manager will typically use top-down economic and market analysis to justify his choices.

The commodity trading advisor (CTA), which is the second directional strategy, will use more quantitative tools to justify its investments. For example, he can use quantitative models to identify undervalued securities.

2.2.5. Multi-Strategy

Finally, the manager here will combine all or a part of the strategies described hereinbefore in order to construct his own strategy.

2.3. Literature Review

In this section, I will mention literature relative to hedge funds' performance.

2.3.1. Returns characteristics of hedge funds

William Fung and David Hsieh (1999) give us an insight of the hedge fund industry in their paper « A primer on hedge funds ». Using the « MARHedge »[3] database and by relying on other researches (in particular their own paper published in 1997(a)), Fung and Hsieh were able to identify some return characteristics for certain strategies.

Given that the **Global/Macro funds** are based on major global events expectations allied with fundamental economic concepts, we are able to approximately predict that their returns' distribution will be impacted by "the random arrival of major economic events and the accuracy of their judgments" (Fung and Hsieh, 1999). Because of this, we expect the return patterns to be not or barely correlated with standard asset classes. This affirmation will be verified later, in section 3. Description of data as we will compare hedge funds and market indices basic statistics.

2.3.2. Incentive fees and funds' age

The way the fees are structured in hedge funds make them attractive for the managers. Some researchers have shown a clear positive relationship between incentive fees and managers' performances. The fees are separated in two parts: management fees (comparable to a fixed wage for the manager and amounted generally to 1% to 3%) and the incentive fee (more like a variable salary directly proportional to the manager's performances and usually situated between 15% and 30%). The latter is effective only when the manager has reached the hurdle rate in terms of cumulative returns what incites him to recover his losses. However, it could also encourage him to take more risk as it is the end of a period that the hurdle rate must be met. Furthermore, the manager being a partner in the hedge fund has interests to increase his performances in order to protect its own investments placed in the fund.

In a paper released in 1998, Bing Liang attempts to demonstrate what the main determinants of hedge funds returns are. To do so, he relies on a cross sectional regression with multiple factors: incentive fees, management fees, fund assets, lockup periods, funds' age. The

[3] MARHedge was a financial newsletter about hedge funds from 1994 to 2006 (*Wikipedia*)

incentive fee obtained a significantly positive coefficient exhibiting a clear relationship between returns and incentive. More accurately, using his dataset, he found that “a 1% increase in the incentive fee will increase the average monthly return by 1.3%”. The same conclusion has been made by Ackermann, McEnally and Ravenscraft (1999) who tried to explain the same relation (i.e. between performance and incentive fee). They concluded by putting different assumptions on it (e.g. higher incentive fees attract superior managerial talent, superior performances may allow a manager to negotiate a higher incentive fee, …).

Another factor that has been indicated as determinant for the hedge funds’ returns is the age of the fund. Indeed, past researches have proved that the age of a hedge fund has a negative impact on its returns. An explanation given by Liang (1998) is that « the older funds become too big to manage for the managers ». However, Ackemann, McEnally and Revnscraft (1999) obtained as result for their regression that the age’s coefficient is never significant.

The same way researchers tried to find a link between age and returns, they did so for the size of the hedge fund in terms of assets managed. Amenc, Curtis and Martellini (2003) reported a significant difference between large and small funds returns on 4 models out of 10. Though, Schneeweis, Kazemi and Martin (2002) shows different results as they conclude that, overall, “larger funds tend to underperform smaller funds on a pure return basis”. But they also clarify the fact that this conclusion is simplistic since the result changes depending on whether we analyze a strategy (see section 2.2) or another. Liang (1998), with his regression, found a positive coefficient for the size of the hedge funds and explains that large funds realize economies of scales and therefore larger funds outperform smaller.

2.3.3. Performance persistence

Most of the time, when an investor wants to evaluate an investment, he will use historical data to get a sense of it and uses the outcome of the historical data’s analysis as a predictor for future performances. In the case of hedge funds, this way to do is subject to controversy because a manager who wins his bet today might not do it tomorrow. Consequently, one won’t find a lot of literature investigated the performance persistence of hedge funds such as Malkiel and Saha (2005) who show that, by posing the assumption that funds that stopped reporting were just dropped from the database, it exists some persistence with a lot of variation in the result. In their 2004 research, Hübner and Capocci split their analysis into different timeframes and sub-strategies. They conclude that it exists “significant evidence of superior performance over long periods of time for most of the individual strategies and sub-strategies” but that significance was not present regarding shorter periods of time. Agarwal and Naik (2000) used the same analysis structure as Hübner and Capocci and obtained opposite results. Indeed, they notice a strong persistence over a short-horizon (quarters) but a weak level of persistence on longer horizon.

2.3.4. Offshore VS Onshore hedge funds

Offshore hedge funds differ from onshore hedge funds in the fact they are located in tax-favorable jurisdictions.

Brown, Goetzmann and Ibbotson have devoted a research on the offshore hedge funds (1997). In this paper, they assess the performance of such funds between 1989 and 1995. They came to a positive conclusion as they found that "offshore funds as a group have positive risk-adjusted performance". Plus, they mention the fact that every style (except one) showed positive risk-adjusted returns. However, they assign these hedge funds' performance to the style and not to the managers' skills.

2.3.5. Performance of hedge VS the market as well as within a portfolio

Several researches cover the topic of such an impact.

Fung and Hsieh (1997) published an article about the "empirical characteristics of dynamic trading strategies". After a deep analysis, they reach the conclusion that a traditional stock-bond portfolio can be improved in terms of return by adding hedge fund. That improvement will be associated with a low risk increasing.

Amin and Kat (2002) analyzed hedge funds performance between 1990 and 2000. At the end of their research, they explain that, as a stand-alone investment, investing in hedge funds may be a bad deal. Then, they go further by assessing the impact of the hedge fund's inclusion in a portfolio. They come to a totally different conclusion by developing the fact that hedge funds "score much better when seen as part of an investment portfolio".

In an article published in 1999, Ackermann, McEnally and Ravenscraft show us how hedge funds performed from 1988 until 1995. Their conclusion is that, at that time, hedge funds can't beat the market in terms of risk-adjusted returns as well as in terms of absolute returns.

In a research published in 2006 (update version of the 2002' version), the research department of the Center for International Securities and Derivatives Markets (CISDM) shows firstly an overview on the risk return performance of hedge funds and then the effect of adding hedge fund in a classic portfolio (stock-bond). They show that, between 1990 and 2005, their hedge funds' portfolio is able to beat the market in terms of return as well as in terms of risk-adjusted return. They also conclude that adding hedge funds in a traditional portfolio can improve its performance.

3. Description of Data

3.1. Hedge funds' data

As Capocci and Hübner (2004) explain, one of the issues when analyzing hedge funds is that they are not legally obliged to release any report or data. When they do so, it is only on a voluntary basis, often with the purpose to attract new investors. Relative to that, it exists a problem in the data's reliability as they would probably release their best years' data which in turn doesn't allow us to make a reliable performance analysis.

Moreover, the problem of survivorship bias (see section 3.1.3), which is capital in hedge funds' analysis, will have an impact their performance's evaluations what can lead us to inaccurate conclusions.

Concerning the hedge funds index data, I used the data, from 1997 to 2016, of two collectors for the analysis: Credit Suisse[4] and Barclay Hedge[5] (which is not associated with Barclays bank).

3.1.1. Credit Suisse

The first set of data has been collected on credit Suisse website and tracks around 9000 funds that have a minimum threshold of $50 million (USD) under management. This database is updated on a monthly basis and is net of all performance fees and expenses. Their funds are all asset-weighted which gives a better insight of an investment in the asset class.

One can find nine types of strategy in their database, most of which have already been described in section 1.3. (strategies in hedge funds):

- *Convertible arbitrage*

[4] https://lab.credit-suisse.com/#/en/index/HEDG/
[5] https://www.barclayhedge.com/

- *Emerging markets*
- *Equity market neutral*
- *Event driven,*
- *fixed income arbitrage,*
- *global macro,*
- *long/short equity,*
- *managed futures*
- *multi-strategy*

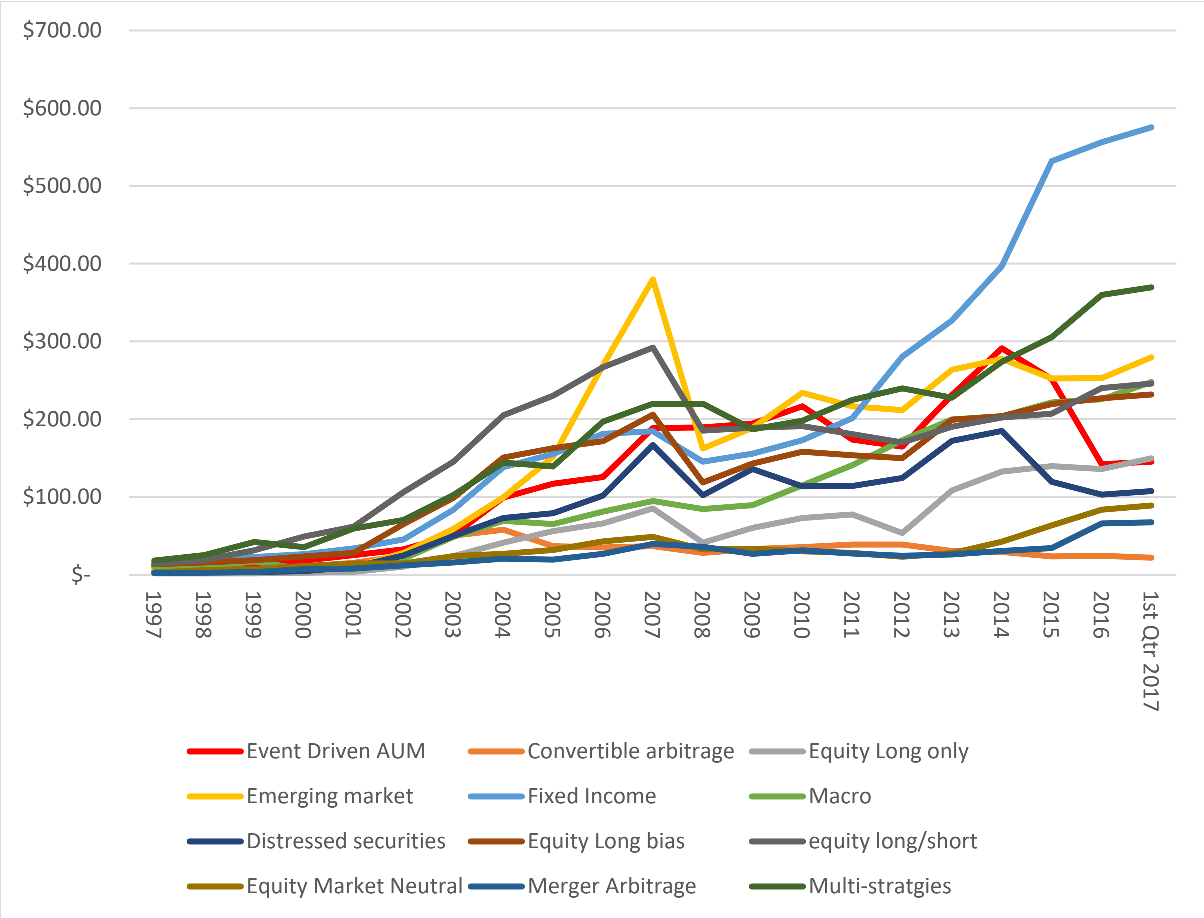
3.1.2. Barclay Hedge

The second set of hedge fund data used to evaluate the performance of hedge funds was collected from the Barclay Hedge's database. It includes approximately 5589 funds currently that are updated in real-time as soon as the monthly data for each fund are available. The strategies reported in their database are the following:

- *Convertible Arbitrage Index*
- *Distressed Securities Index*
- *Emerging Markets Index*
- *Equity Long Bias Index*
- *Equity Long/short Index*
- *Equity Market Neutral Index*
- *European Equities Index*
- *Event Driven Index*
- *Fixed Income Arbitrage Index*
- *Global Macro Index*
- *Healthcare & Biotechnology Index*
- *Merger Arbitrage Index*
- *Multi Strategy Index*
- *Technology Index*

However, Barclay Hedge gives also other relevant data beside the returns such as the assets under management (AUM) evolution by strategies (Figure 3).

Figure 3 : Asset Under Management's evolution by strategies (1997 – 2016)



First, one can observe that the equity long/short and the Emerging market are the two strategies with the greatest growth to reach their first peak of $ 379.9 billion for the Emerging market and $ 292.1 billion for the equity long/short during the crisis in 2007 following by a decline (a brutal one for the emerging market funds).

Despite the crisis, we notice that three strategies, the merger arbitrage, macro and the event driven, don't seem to be impacted as their AUM continue to increase.

Finally, since 2010, the three strategies with the highest growth in terms of asset under management are the fixed income strategy with $ 575.40 billion in the first quarter of 2017, the multi-strategies that amounts to $ 369.6 billion in 2017 and the emerging market strategy with its $ 279.9 billion which could be a consequence of a good performance after the crisis.

3.2. Models and ratios' Data

To use all the models and ratios described in section 4. Theoretical Framework, other data was required. To perform the CAPM, alongside with other ratios, a market benchmark was needed to mimick the market portfolio. As it is one of the most widely used in past research with the Russell 3000 (which is composed of a wide range of small and large companies "represents over 95% of investable US equity market" (Capocci and Hübner, 2004)), the S&P 500 has been selected as a proxy for the market. This index includes 500 leading publicly traded U.S. companies. These data have been downloaded on yahoo finance.

Used in several ratios as well as in the CAPM, I chose as proxy for the risk free rate the one published by Kenneth French in his database. This rate is based on the returns for a one month T-Bill rate from Ibbotson Associates.

For the next analysis, I included the "best" hedge fund index in a portfolio. This portfolio is constructed based on El-Erian Multi-asset Portfolio (El-Erian, 2008) and inspired from the process used by Laly and Petitjean (2016). It consists in seven indices and funds:

1. S&P 500 Index (SP500 Index)
2. IShares MSCI EAFE Index (EFA)
3. Vanguard Emerging Markets Stock Index Fund (VEIEX)
4. Vanguard Long-Term Treasury Fund (VUSTX)
5. Vanguard Inflation-Protected Securities Fund (VIPSX)
6. PIMCO Global Bond Fund (PIGLX)
7. Real Estate Investment Trust (REIT Index)

All of these data have been collected on the Bloomberg terminal.

Finally, The MSCI World Index has been selected as another benchmark to compare the hedge funds' performance. As defined by its website[6], it is "a broad global equity benchmark that represents large and mid-cap equity performance across 23 developed market countries".

[6] https://www.msci.com/world

3.3. Survivorship bias

When analyzing hedge funds' past performances, survivorship bias is an important issue to consider. Indeed, the data available on hedge funds' returns won't reflect the returns of all of them but only from the one that are currently actives. By not taking into account the "dead" funds that had probably in most of the cases poor performances, our analysis will be upwardly biased by overestimating the past returns of funds. Many researches on hedge funds' performance focused on this issue and have estimated the bias. Malkiel and Saha (2005) showed that it exists a substantial difference in terms of return between the "defunct funds" and the funds that are still alive. They estimate the survivorship bias at 442 basis points which is higher than what we can find in academic literature generally. Though it depends on the strategy analyzed, one can typically estimate this bias between 1.5% to 3% (Brown, William and Goeztman. (1997); Fung and Hsieh (1999)).

4. Theoritical Framework

4.1. CAPM

The Capital Asset Pricing Model is a single factor model set up by William Sharpe (1964), John Lintner (1965) and Jan Mossin(1966) between 1964 and 1996 (cited by Bodie et al. 2014), based on the modern portfolio theory (MPT) of Harry Markowitz (1952). This model describes the link between the expected return of a portfolio P and the systematic risk this portfolio bears (i.e. the only risk that should be rewarded) following this equation:

$$E(R_P) - R_F = \beta_P(E(R_M) - R_F)$$

Where $E(R_P)$ = Return of portfolio P; R_F= Risk-free rate ; β_P= Beta of portfolio P (=systematic risk) ; R_M = return of the market portfolio.

The result we obtain applying this model can be useful for two reasons; first of all, we could be able to compute the fair price of an investment and compare it to the rate of return it should have in order to determine if former is currently cheap or expensive. Secondly, we can use it as a forecasting tool, to know what an investment could worth in the future.

As every model, the CAPM is based on several assumptions. Here, we first assume that all investors' portfolios are optimized « a la Markowitz ». Practically, this means that all agents in the market use a set of expected returns and a covariance matrix to build an efficient frontier. Then they will identify the efficient portfolio by drawing the « Capital Market Line » (CML) which is the tangent line to the efficient frontier. By doing this, they have maximized their utility. Then, the CAPM assumes that all investors can solely invest in the same set of securities and therefore, use the same data to draw the efficient frontier. This last assumption will have as consequence that all investors would choose the same portfolio (i.e. the market portfolio). As explained by Bodie et al. (2010), because the **market portfolio** is the aggregation of all of these identical portfolios, each asset will have the same weights within each portfolio. We can conclude, by this affirmation, that every investor will choose the same risky portfolio, **the market portfolio**, no matter their risk aversion.

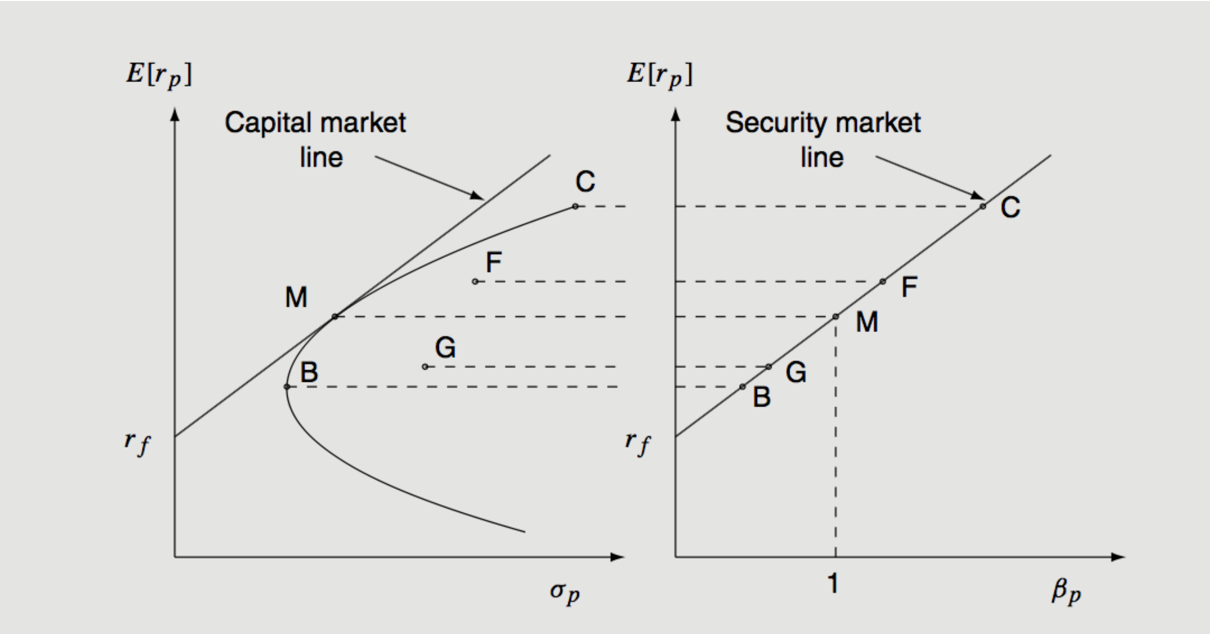
Since all investors hold a diversified portfolio, they will only be rewarded for the systematic risk, i.e. « Beta » (β). The Beta describes how an asset or a portfolio varies when the market as whole moves and is calculated as:

$$\beta_P = \frac{cov(r_P, r_m)}{\sigma_m^2}$$

Where $\boldsymbol{\sigma_m^2}$= Variance of the market portfolio return and $cov(r_P, r_m)$= the covariance between our portfolio and the market portfolio.

Given that the same risk-free rate is available for all investors, they will face a trade-off between invest a fraction of their wealth in a risk-free asset or in a risky portfolio. This trade-off, that reflects the risk aversion of the investor, gives the weight invested in each of the alternatives. By drawing all the possible combination risk-free/ risky investments, we can draw the « Capital Market Line ».

Figure 4 CML and SML



source: Van Der Wijst, 2013

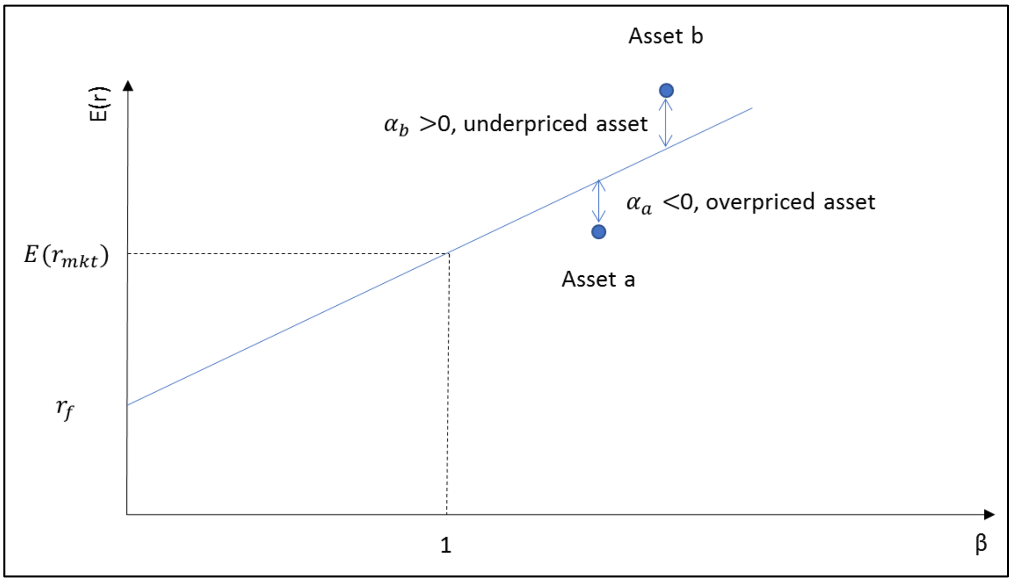
However, though it is a very popular model, some academic literature (inter alia Fama & French, 1993; Kothari & Warner, 2001) have demonstrated that the CAPM is not accurate enough to describe the return of an investment. Indeed, a factor alone is not appropriate to explain the returns of a security.

An alternative to this model is, for example, the Three Factor Model (Fama &French, 1992) or the Four Factor Model (Carhart, 1997).

4.1.1. Jensen's Measure (α)

The Jensen's Measure, or Jensen's Alpha from its creator (Jensen, 1968) is a risk-adjusted performance measure, as the beta, based on the CAPM. The alpha indicates if a portfolio is overpriced or underpriced relative to its fair price given by the CAPM. Theoretically, in the risk-return universe, all the portfolios should lie on the Capital Allocation Line (CAL) according to the CAPM. If the portfolio we are actually analyzing is above the CAL, we'll say it is underpriced.

Figure 5: Jensen's alpha



Source: Petitjean (2013)

Put another way, being underpriced indicates the portfolio generates positive abnormal returns. To obtain this measure, we need to resolve the CAPM equation in alpha:

$$\propto_t = [R_{Pt} - R_{Ft}] - \beta_P[R_{Mt} - R_{Ft}]$$

In this thesis, I will use it (if it is relevant what depends on its p-value) as a mean to evaluate the performance of an investment manager by assessing if his portfolio earns the proper return for the level of risk taking. Thereby, we'll be able to say if he beats the market or not.

4.1.2. Beta (β)

Based upon the CAPM, beta is a measure of the systematic risk of a portfolio relative to the market portfolio (Jensen, 1969). Unlike the standard deviation (σ), the beta will only consider the risk that is not diversifiable thus the one the investor will be rewarded for. It indicates how our portfolio varies as the market moves as a whole. A portfolio's beta is calculated as follows:

$$\beta_P = \frac{Cov(R_P, R_M)}{Var(R_M)}$$

4.2. Multi-Factor model

As defined by the website Investopedia[7], « a multi-factor model is a financial model that employs multiple factors in its computation to explain market phenomena and/or equilibrium asset prices ». The purpose of such a model is, inter alia, to find the factors that drive an investment's returns (e.g. an assets' portfolio). The difficulties here is to decide how many and which factors include in the model in order to be the most accurate.

Though it exists several multi-factor models, one of them that is widely used to assess hedge funds' performance is the Three Factor Model often describes as an extension of the CAPM. Indeed, it is based on the CAPM model in which we add two factors, in addition to the excess return on the market portfolio [E(Rm)-Rf], the size risk [E(SMB)] and the value risk [E(HML)]. This model rests on the fact that, according to their research, Fama and French found that small cap stocks tend to outperform large cap stocks because of liquidity issues and low price-to-book (P/B) stocks tend to outperform high book-to-market stocks because of their riskiness. Its equation to estimate the returns is the follows:

$$R_{Pt} - R_{Ft} = \alpha_P + \beta_{P1}(R_{Mt} - R_{Ft}) + \beta_{P2}SMB_t + \beta_{P3}HML_t + \varepsilon_{Pt} \qquad t=1,2,\ldots,T$$

Where SMB_t= the size risk factor (Small Minus Big) ; HML_t = the value risk factor (High Minus Low).

By adding these factors, the model aims to isolate « the firm-specific component of returns » (Capocci and Hübner, 2004).

[7] www.investopedia.com

As explained on the Kenneth French website and detailed in the Fama and French's paper "Common Risk Factors in the Returns on Stocks and Bonds" (1993), "SMB is the average return on the three small portfolios minus the average return on the three big portfolios". These six portfolios are derived from six value-weight portfolios formed on size and book-to-market.

$$SMB = \frac{1}{3}(Small\,Value + Small\,Neutral + Small\,Growth) - \frac{1}{3}\,(Big\,Value + Big\,NEutral + Big\,Growth)$$

"HML is the average return on the two value portfolios minus the average return on the two growth portfolios":

$$HML = \frac{1}{2}\,(Small\,Value + Big\,Value) - \frac{1}{2}\,(Small\,Growth + Big\,Growth)$$

The second multi-factor often cited in the academic literature is the Asset Class Factor Model. This model has been explained for the first by Fung and Hsieh in a paper they published in 1997. This model is, as the Fama French Three Factor Model, an extension of the Sharpe's model but includes the five dominant investment styles in hedge funds.

This model is expressed as follows:

$$R_t = \propto + \sum_k \beta_k F_{kt} + \varepsilon_t \qquad \text{with k= 1,2,..,8 and t= 1,2,…,T}$$

The eight factors being; The S&P 500 index; the MSCI world equity index, the MSCI emerging market index for equity markets; the Salomon Brothers world government bond index; the Salomon brothers government and corporate bond index for bond markets; the Federal Reserve Bank trade-weighted dollar index for currency; the gold price for commodities; and one month eurodollar deposit for cash.

4.3. Risk Measures

4.3.1. Standard Deviation, Downside Deviation & semideviation

The standard deviation of a portfolio, which is one of the most basic statistics used to measure the risk, is defined by Investopedia as “a measure of the dispersion of a set of returns from its mean”. The lower the standard deviation the better as it reduces the risk of the portfolio by indicating that its volatility has been historically low. We obtain it by calculating first the variance and then by taking the square root of the variance:

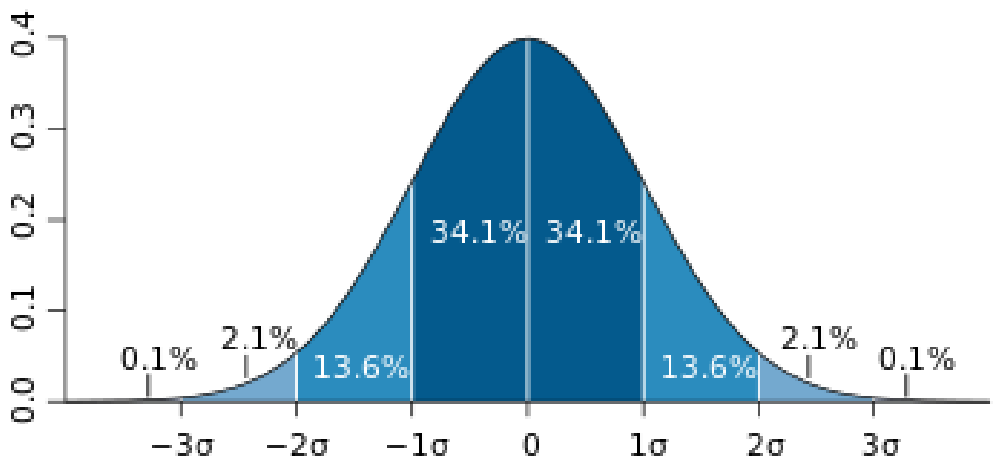
$$S.D. = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(x_i - \bar{x})^2}$$

Where x_i = monthly returns; n = number of months; $\bar{x}$ = average return.

The Downside Deviation is based on the same philosophy as the standard deviation with the particularity that, as its name indicates, it only takes into account the returns being under a specified threshold that we call “MAR” for Minimum Acceptable Return.

Based on the same concept, the semideviation is the standard deviation of returns that fall below the mean return.

Figure 6: Standard Deviation

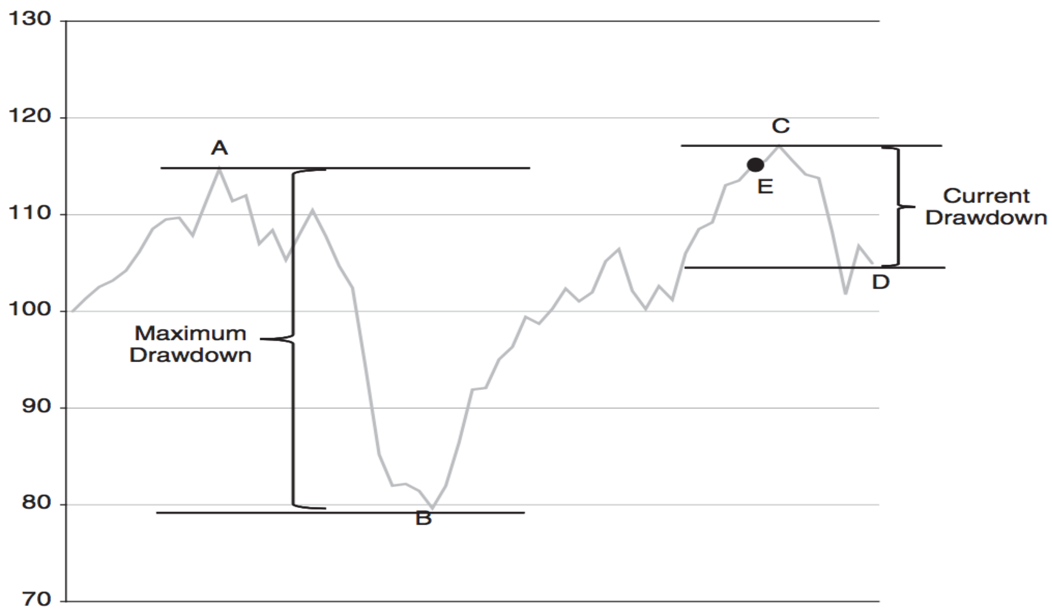


Source: www.wikipedia.org

4.3.2. Drawdown Analysis

As defined by Investopedia, “a drawdown is the peak-to-trough decline during a specific recorded period of an investment, fund or commodity”. Although it exists several types of drawdown (e.g. average, maximum, duration, deviation, largest), I will only use the maximum drawdown in the performance evaluation.

Figure 7: Maximum Drawdown



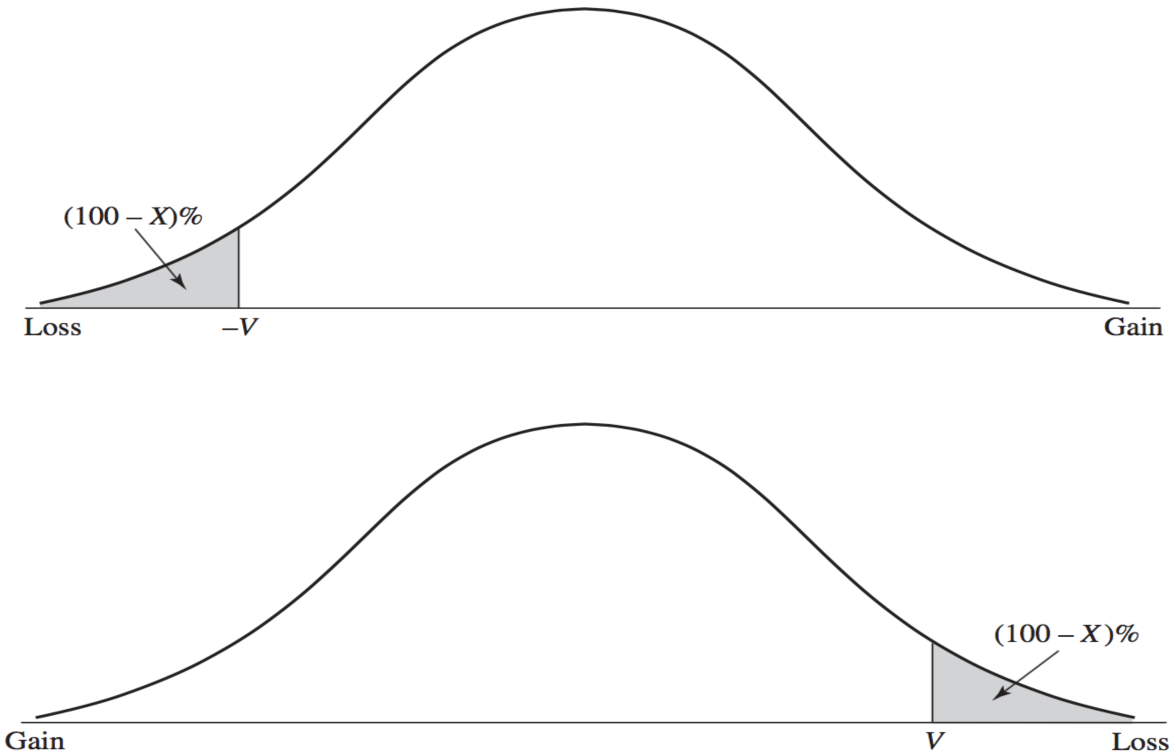
Source: Travers, 2012

The maximum drawdown is a measure of the largest loss reached during a defined timeframe (typically 3 years). Being an investor, I can interpret it as the loss I will face by buying a security at its most expensive price for a certain period and sell it at its bottom during the same period.

4.3.3. Value-at-Risk

According to Benninga (2014), « The Value at Risk is a statistical tool that measures the worst expected loss under normal market conditions over a specific time interval at a given confidence level ». In other words, through the VaR, we want to know what is the maximum loss we can expect within a time horizon (generally 1 to 10 days in risk management's practices) and given a confidence level (e.g. 99%). Therefore, the VaR, which is a quantile of the potential losses, is based on a probability distribution and is a function of two parameters, the time horizon and the confidence level that will both vary depending on how the risk is managed. We can use it from two opposite perspectives: the gain and the loss:

Figure 8: Gain and loss of the distribution



Source: Hull (2015)

This tool is widely used, among other, because it gives a concrete and useful value of the risk in terms of currency.

The VaR can be calculated by means of three methods: (a) the analytical method (also named Gaussian method), (b) the historical data method and (c) the Monte Carlo simulation. One of the latter will be more appropriate depending on what case we face.

a. Delta-normal Method

We can separate the Gaussian methodology to obtain the VaR in four steps:

1. ***Find the relevant random variable***

The object of this step is to gather the relevant historical data to be able to build the variance-covariance matrix.

The historical data are considered as relevant if they reflect well the portfolio yield. Therefore, the challenge will be to find what random variable to choose that will explain our portfolio behave (Saita, 2007).

To do so, we have three approaches available to us:

- The “delta-normal” approach where the « delta » is the slope of the equation describing the portfolio value relative to the assets being in the former (the relation between both should be linear). The term « normal » indicates that the risk factors’ returns are normally distributed.
- The approach of the « normal asset » where the underlying variables will be the benchmark’s returns.
- The « normal portfolio » approach where the underlying variable is the portfolio return.

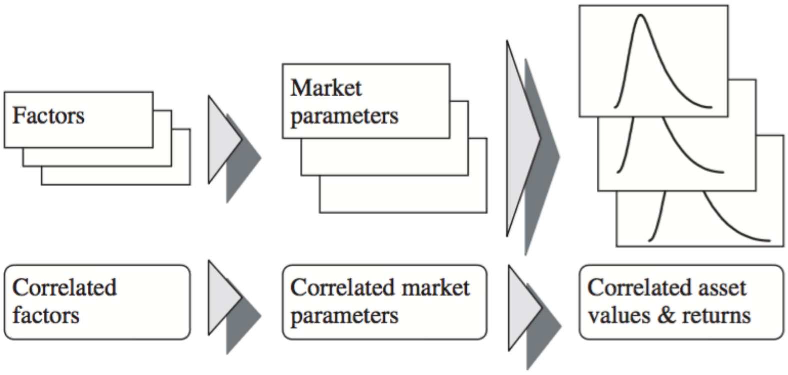
2. ***Mapping***

«*The portfolio mapping is a process through which a trading portfolio is transformed and decomposed into a vector of exposition to a number of random variables*» (Saita, 2007).

Put another way, we will use our analysis relative to the relevant random variables to construct a new portfolio that is solely composed of risk factors.

Each factor has its own probability distribution. That distribution will be the base for the next step, the individual VaR computation.

Figure 9: Analytical method's mapping



Source: Bessis (2007)

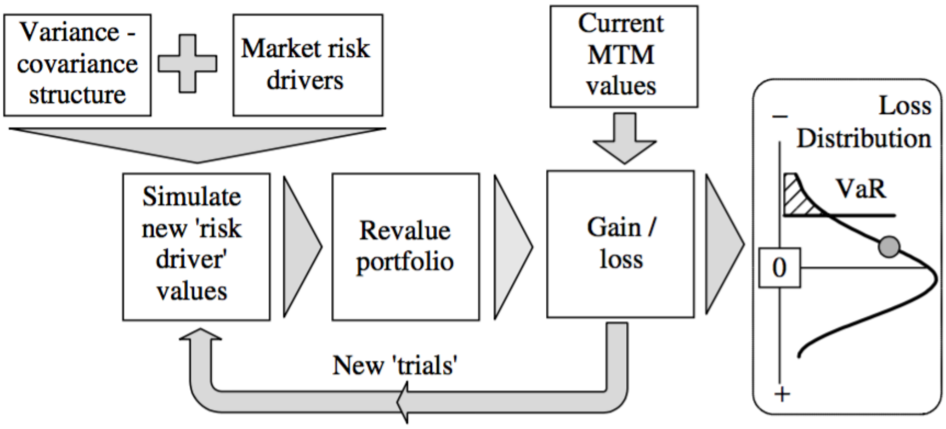
3. Individual VaR

Based on the new risk factors portfolio, we can calculate the VaR for each risk factors separately.

4. Variance-Covariance Matrix and Portfolio VaR

Given that we obtained a portfolio composed of different types of risk, we know that they are probably correlated to different degrees. To take advantage from the diversification impact on our VaR, one must compute the variance-covariance matrix of the risk factors. From the latter, we will be able to calculate the portfolio VaR.

Figure 10: Analytical method's process



Source: Bessis (2007)

b. Historical Data Method[8]

The historical simulation uses the historical data as well as the current data to construct a new portfolio. This portfolio will be the basis to calculate the VaR.

We name it « simulation » because it will generate a scenario by multiplying the weight of each asset currently in the portfolio by the past returns what will create the new portfolio.

The next step aims to find the loss straightly on the new portfolio returns' distribution by setting a confidence level that would allow us to read the percentile on the distribution.

The central assumption of this method is that the future returns' distribution can be approximated by the past returns' distribution.

This method has advantages as well as drawbacks. Indeed, it is easy to implement and to explain. Plus, the absence of assumption on the returns' distribution makes it more reliable. On the drawbacks' side, one can notice that assuming past returns approximate future returns is not always a good idea. Inter alia, the number of past periods used has a substantial impact on the results. Particularly, we can mention the "echo effect" that is defined as followed: by giving the same weight to all the data that are in our sample, if extreme values exist, they will have an impact on our forecasts not only as they enter in the sample but likewise when they go out of it what will bias our estimations. Solutions have been found to mitigate this impact. One of these solutions is the « exponential weight of observations » that gives a higher weight to most recent observations.

c. Monte Carlo Simulation

Though this method is much more complex, I will attempt to summarize it in a relatively simple way with these four steps:

1) Set up assumption on the returns' distribution for each asset and on the dependency structure among the different assets returns (Saita, 2007).
2) Evaluate the parameters of the distribution determined in step 1 with the help of historical data.
3) Simulate several returns scenarios based on the results of step 1 and 2. Then, one must sort the results obtained in ascending order to create a distribution.
4) Read the VaR directly on the loss distribution that has been created in step 3.

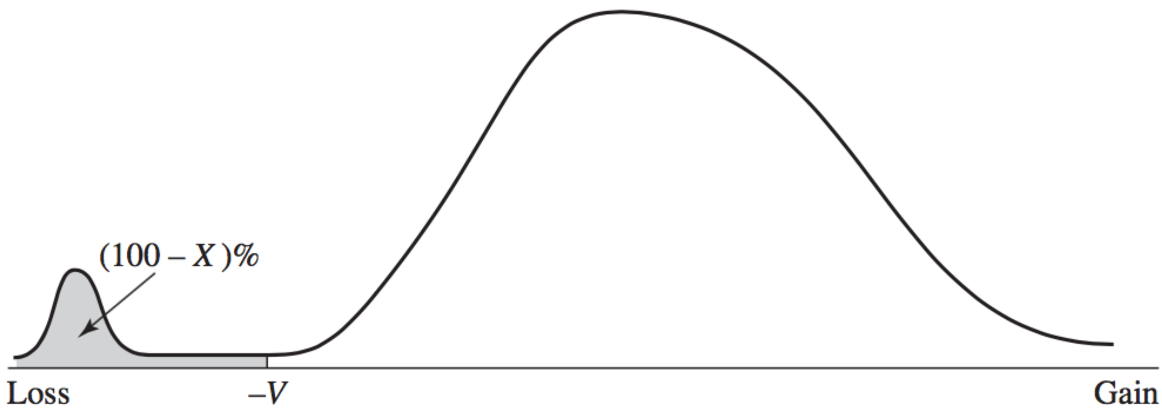
[8] Saita (2007)

I won't go further explaining this method as it is relatively complex. As each method, it has likewise its pros and cons. Among other, we can assert that it is very useful for the options, unlike the Gaussian approach that can't reflect a non-linear relation between the portfolio and the underlying assets. Unfortunately, this method is difficult to implement as it required powerful computers, plus it is relatively complicated to understand it.

One probably wonders what methodology is better? Choudhry (2015) gives us a lead by stating that it depends on the portfolio composition. If the latter doesn't contain option-like asset, we can use the analytical method (the first one) because as there is no need of pricing model, the linear relationship's assumption is plausible. In case we meet a portfolio with option-like assets, the two other models (historical simulation and Monte Carlo simulation) are more appropriated. However, in 2002, Favre and Galeano introduced the modified VaR that seems to be a good measure as it takes into account the skewness and kurtosis using a Cornish-Fisher expansion (Favre and Galeano, 2002 cited by Bacon, 2008).

However, no matter the method used, the concept of VaR in itself counts many drawbacks. First of all, use solely the VaR to calculate the risk of a portfolio would be incomplete. Indeed, it gives us an idea of what happens in the X % of confidence level but beyond this threshold, we don't know what could happen.

Figure 11: VaR Drawback



Source: Hull (2015)

However, to address that drawback, we can use the CVaR, that will be discussed in the next part of this section.

Then Artzner, Delbaen, Eber and Eath (1999) give us an insight of what should be a coherent risk measure. Among the properties that make a risk measure coherent, there is the sub-additivity. The sub-additivity is a concept that explains that the risk measure of two portfolios summed should be lower than the addition of the risk measures of the two portfolios separated. This property is based on the concept of diversification. But by computing the VaR of a portfolio composed of two "sub-portfolios", one can obtain a VaR bigger than the sum of the "sub-portfolios" VaR.

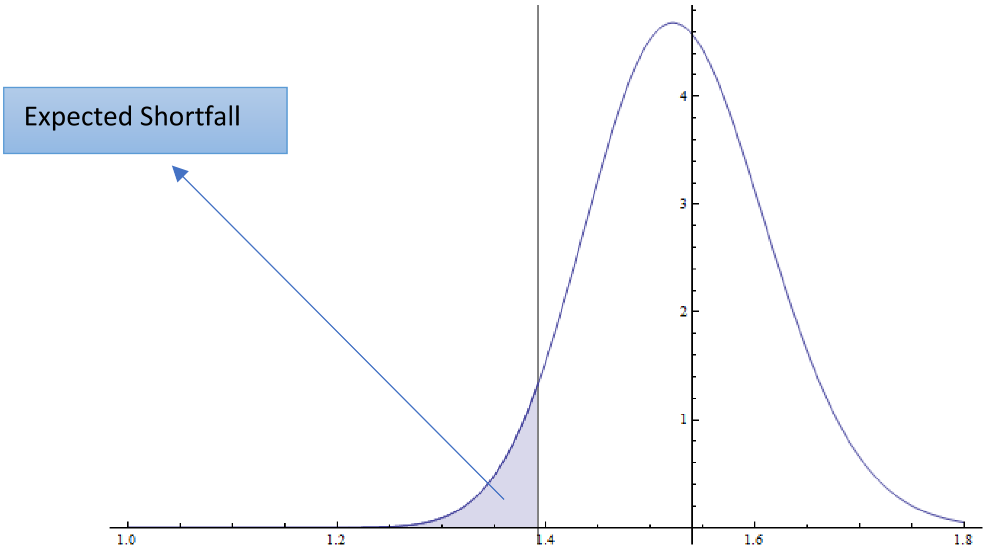
d. Backtesting

Generally, the backtesting methods are means to define if a model is robust or not by using the model on historical data and compare it to what effectively happened. It can be defined as "a statistical "ex-post" procedure consisting of verifying the adequacy of losses with the level of losses actually forecasted by risk measures" (Henrard, 2016). For example, in the case of VaR, we can use a portfolio historical data and apply the VaR on it. Once we have the result, we compare it to the portfolio's actual losses and then gauge the accuracy of the model. If we come to the conclusion that the model is not good enough, we'll have to adjust it and then retest it.

4.3.4. CVar (Expected Shortfall)

The Conditional VaR or the Expected Shortfall is defined by Investopedia as "a risk assessment technique that assesses the likelihood at a specific confidence level that a specific loss will exceed the value at risk". Mathematically speaking, it is the weighted average between the VaR and losses exceeding the VaR. Put another way, it is the expected value of the loss beyond the VaR. We name it Conditional VaR because « it is the expected loss during time T conditional on the loss being greater than the Xth percentile of the loss distribution » (Hull, 2015). Whereas the VaR answers the question "how high could be our maximum portfolio's loss in T days with X% of confidence, the ES will answer "If I'm beyond these X% of confidence, what could happen in terms of loss?". Plus, the fact that it gives us a larger insight of the risk our portfolio bears, another reason to use the ES instead of the VaR is for its properties. Indeed, it takes into account the diversification from the risks aggregation as it incorporates the sub-additivity property. Plus, unlike the VaR, it makes no assumptions on the data's distribution what makes him applicable to a larger range of data.

Figure 12: Expected Shortfall



4.4. Return distributions

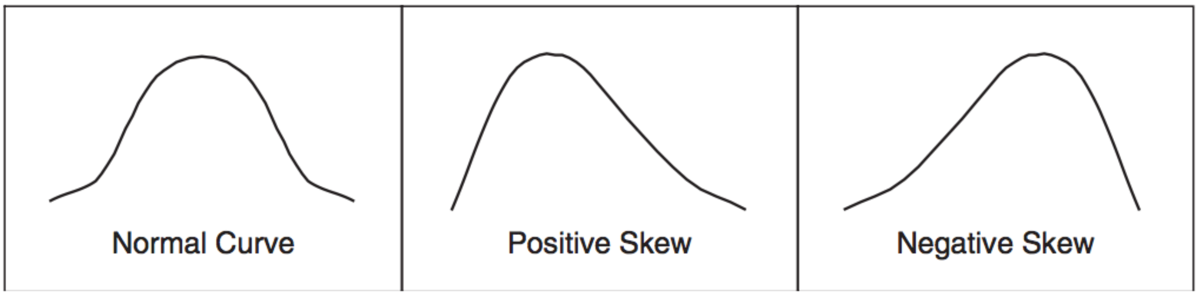
4.4.1. Skewness

The skewness of a distribution gives us information about its lack of symmetry from the normal distribution. As we can notice on Figure 13, a set of data can be either positive if it skewed to the right (S>0) or negative if it is skewed to the left (S<0). Therefore, the normal distribution is characterized by a skewness of zero. The skewness is calculated as:

$$S = \sum \left(\frac{r_i - \bar{r}}{\sigma_P}\right)^3 * \frac{1}{n}$$

Skewness allows the investor to understand the shape of the portfolio return distribution and to get, for example, a better estimation of his portfolio future value.

Figure 13: Skewness



Source: Travers (2012)

Brooks and kat (2002) found that hedge fund indices generally have low skewness.

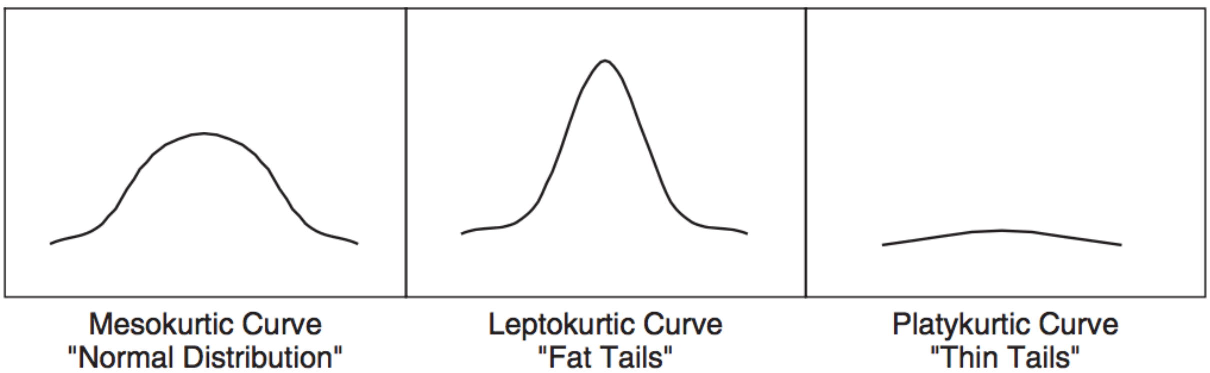
4.4.2. Kurtosis

Pearson's Kurtosis gives information in order to assess the shape of the data distribution in terms of "fat" or "skinny" tails with a distribution concentrated or not toward the mean (Pearson, 1905 cited by Bacon, 2008).

$$K = \sum \left(\frac{r_i - \bar{r}}{\sigma_P}\right)^4 * \frac{1}{n}$$

Analyzing data, we can find three types of kurtosis compared against a normal distribution that has a kurtosis of 3 and is named "mesokurtic". In the case we meet a K lower than 3, it would indicate we face a "leptokurtic" distribution. Here, we notice extremely thick tails while the peak is tall and thin. An example of leptokurtic distribution is the Student distribution. When K is greater than 3, we are standing in the case of a "platykurtic" distribution. The shape of its distribution is characterized by thin tails and a peak smaller than a normal distribution with return points clustering around the mean.

Figure 14: Kurtosis



Source: Travers (2012)

One can expect to get high kurtosis in our analysis as showed by Brooks and Kat (2002).

4.4.3. Jarcque-Bera

Since it is relevant to know if the returns' distribution is normally distributed or not, we can use de Jarque-Bera test (Jarcque & Bera, 1987) to verify this hypothesis. This statistic is computed as:

$$JB = \frac{n}{6} * \left(S^2 + \frac{K_E^2}{4}\right)$$

Where K_E is the Excess Kurtosis that is simply obtained by subtracting 3 from the kurtosis. The BJ statistic is distributed Chi-Square and has two degrees of freedom.

In this test, the H_0 Hypothesis is "the returns follow a normal distribution" and will be rejected with 5% of confidence if the JB statistic goes beyond 5.99, and with a confidence level of 1% if it exceeds 9.21. In the case the JB equal zero, we know that we face returns that are perfectly normally distributed.

4.5. Correlation (ρ)

"The correlation coefficient is a measure that determines the degree to which two variables' movements are associated" (Investopedia). In this thesis context, it is a very important measure as when building a portfolio, we try to put together assets that are highly uncorrelated in order to maximize the diversification effect (i.e. remove the unsystematic risk). The formula to obtain the correlation coefficient between a portfolio P and an asset A is:

$$\rho_{P,A} = \frac{Cov(R_P, R_A)}{\sigma_P \sigma_A}$$

4.6. Sharpe Ratio

The Sharpe Ratio named after William Sharpe (1966) or the rearward-to-variability (cited by Bodie et al., 2014) is defined as the ratio of the average excess fund returns over the standard deviation. Given that agents are assumed to be risk averse, they would prefer to receive a higher return for each additional unit of risk they take, therefore the higher the ratio the better. It is computed as follows:

$$\text{S.R.} = \frac{(R_P - R_F)}{\sigma_P}$$

Where R_P = portfolio return; R_F= risk-free rate; σ_P= portfolio standard deviation

However, in the field of this thesis, this ratio has a consequent drawback given that we analyze the hedge funds performance. Since we know from some researches (Malkiel & Saha, 2005; Brooks & Kat, 2002) that the hedge funds' returns are not normally distributed, the results obtained by using the Sharpe ratio would be inaccurate as the latter assumes the returns are normally distributed. However, it will be confirmed, later, with the help of the Jarque-Bera Test of normality that hedge funds in the database do effectively not follow a normal distribution (see appendix 5 and 6). To address this problem, I will use, besides the original Sharpe ratio, alternative tools that have been set up over years. Though, it could be interesting to use the "classic" Sharpe ratio to evaluate the performance evolution of a fund over years. Pézier and White (2006) offers a way to adjust the Sharpe ratio for skewness and kurtosis by embedding a penalty factor for negative skewness and excess kurtosis with their "ASR". This ratio is defined as:

$$ASR = SR * \left[1 + \left(\frac{S}{6}\right) * SR - \left(\frac{K-3}{24}\right) * SR^2\right]$$

Where SR is the Sharpe ratio, S is the skewness and K the kurtosis.

Lo (2002) provides an adjusted Sharpe Ratio that doesn't rely on any assumption related to the returns' distribution. Plus, it takes into account the existence of positive autocorrelation[9] in a fund's returns which artificially increases the Sharpe ratio. The Lo's adjusted Sharpe ratio is defined as followed:

$$SR_q = SR * \sqrt{12} * \left[1 + \frac{2 * \rho}{1 - \rho} * \left(1 - \frac{1 - \rho^{12}}{12 * (1 - \rho)}\right)\right]^{-1/2}$$

Where ρ is the first order autocorrelation.

Finally, I will employ the Modified Sharpe Ratio which is a variant of the original one with the VaR or the CVaR instead of the Standard Deviation in the denominator.

[9] Autocorrelation = the correlation between a time series (here returns from 1997 to 2016) and the lagged version of itself (the same time series lagged of one month)

4.7. Information Ratio

This ratio is calculated as the Sharpe ratio except that we compare the excess return relative to a specific benchmark (which will be the S&P 500 in the performance evaluation's section). The denominator, the tracking error, is the standard deviation of excess return relative to that benchmark. The information ratio is calculated as:

$$Information\ Ratio = \frac{Premium}{Tracking\ Error}$$

Where *the premium* is the benchmark return removed from the portfolio return:

$$Premium = \bar{r}_p - \bar{r}_b$$

and *the tracking error* is the standard deviation of the difference between the returns of the portfolio and the returns of the benchmark:

$$Tracking\ error = \sqrt{\frac{\sum_t (\Delta_{p,t} - \bar{\Delta}_p)^2}{T - 1}}$$

The information ratio is often seen as a measure of a portfolio manager's skill. Although the question of what is a good information ratio remains unanswered, according to Goodwin (1998) "an information ratio of 0.5 is good, 0.75 is very good and 1.0 is exceptional" but generally a positive one is enough to determinate an outperformance. A relevant way to assess manager skills is to analyze its information ratio through time. Indeed, as he's able to maintain an information ratio above 0.5 for several periods, we can conclude that he's highly skilled.

4.8. MAR and Calmar Ratios

Created in 1991 by Terry Young, the Calmar Ratio is a risk-adjusted performance measurement. As in the previous ratios, the calculation of the CALMAR and MAR ratios are both based on the Sharpe ratio. As the latter, the lower the Calmar ratio the worse the fund has performed. Here, we will compare the portfolio return with the maximum drawdown as following:

$$CR = \frac{Portfolio\ Return}{Maximum\ Drawdown}$$

The difference between MAR and CALMAR reside in the timeframe we take into account in the computation of the ratio; for the MAR, we will use the whole life of the fund, for the CALMAR, only the three last year data will be considered.

4.9. Sterling Ratio

The Sterling ratio, as it is used here to evaluate funds' performance (since it exists several variations of this ratio), is the exact same ratio as the Calmar ratio with the difference that, as we work with past data, we assume that the situation in the future could be worse than it has been until today. Under this assumption, we will deduct 10% (this figure is arbitrary) from the maximum drawdown that is the denominator of the Calmar ratio. Therefore, we compute it as follows:

$$Sterling\ Ratio = \frac{Portfolio\ Return}{Maximum\ Drawdown - 10\%}$$

As stated earlier, it exists different versions of the Sterling ratio. To avoid confusion, Bacon (2008) suggest using the "Sterling-Calmar" ratio which is computed as:

$$SCR = \frac{r_P - r_f}{\overline{D}_{max}}$$

Where r_P= the portfolio return; r_f= the risk-free rate; $\overline{D}_{max}$ = the average maximum drawdown

4.10. Sortino Ratio

Named after its creator (Sortino and Price, 1994), the Sortino ratio is also similar to the Sharpe ratio. The agent who invests in a fund will probably be more concerned about the losses he can face rather than the gains. Consequently, this ratio takes into account only the downside volatility, unlike the Sharpe ratio that considers the whole volatility. The downside volatility or the downside deviation is calculated as the standard deviation but considers only returns that fall below a defined minimum that we will name "MAR", minimum that is defined by the investor. It is calculated as follows:

$$Sortino\ ratio = \frac{r_P - r_T}{\sigma_D}$$

Where r_P= the portfolio return; r_T = MAR = the minimum acceptable return defined by the investor; σ_D = downside deviation.

In the analysis performed at section 5, we will use the risk-free rate for the relevant period as MAR.

4.11. Omega ratio (Ω)

This ratio, set up by Shadwick and Keating (2002), is particularly relevant for the hedge funds' analysis as it considers skewness. It aims to calculate the probability for the fund to reach a defined threshold in terms of return. The higher the ratio the better as it means the probability to meet the threshold is actually high. It is interesting to use it as a ranking.

To compute it, we first need to find the "upside potential" and the "downside potential" that are calculated as:

$$Up_p = \frac{1}{n}\sum_{i=1}^{i=n} \max(r_i - r_T\,, 0) \text{ and } Down_p = \frac{1}{n}\sum_{i=1}^{i=n} \max(r_T - r_i\,, 0)$$

Then we divide the upside potential (Up_p) by the downside potential ($Down_p$) to obtain the Omega:

$$\Omega = \frac{\frac{1}{n}\sum_{i=1}^{i=n} \max(r_i - r_T\,, 0)}{\frac{1}{n}\sum_{i=1}^{i=n} \max(r_T - r_i\,, 0)}$$

4.12. UPR (Upside Potential Ratio)

Mentioned for the first time by Sortino, Van de Meer & Plantinga (1999), the UPR is used, as the omega, as a ranking statistic measure. It is obtained as follows:

$$UPR = \frac{\sum_{i=1}^{i=n} \max(r_i - r_T, 0)}{\sigma_D}$$

Where the denominator, σ_D, is the downside deviation.

4.13. M-Squared ($\boldsymbol{M^2}$)

Named after its creators, Franco and Leah Modigliani, in 1997, the M^2 or the Modigliani risk-adjusted performance measure is a metric similar to the Sharpe ratio, from which it is inspired. As the outcome of this metric is in unit of returns, that makes it more intuitive and allows us to give him a simpler interpretation. It is computed as followed:

$$M^2 = SR * \sigma_{ER} + \overline{R_F}$$

Where σ_{ER} = the standard deviation of the excess return.

As explained earlier, it will be more useful than the Sharpe ratio as it allows to use it on a stand-alone basis and not in a ranking.

5. Empirical Analysis

5.1. Introduction

Initially demonstrated by Markowitz and then deepened by other economists, the diversification is one of the key concepts in the Modern Portfolio Theory (MPT). It states that by holding a diversified portfolio, an investor can reduce his exposure to risk. Put another way, by adding assets that are not perfectly positively correlated in my portfolio, I can get the same return as before but my portfolio will bear less risk. Mathematically speaking, we can demonstrate the concept of diversification taking the return's and standard deviation's (i.e. risk) formulas:

$$E(R_P) = \sum_i w_i E(R_i)$$

$$\sigma_P = \sqrt{\sum_i w_i^2\,\sigma_i^2 + \sum_i \sum_{j \neq i} w_i w_j \sigma_i \sigma_j \rho_{ij}}$$

Where $E(R_P)$ = Expected return of portfolio P, w_i = weight of asset i in portfolio P, σ_P= Standard deviation of portfolio P, ρ_{ij} = Correlation between asset i and j.

First, looking at the expected return formula, we see that by adding assets to my portfolio, my return will increase depending on how the new asset performs and the weight it has in the portfolio. Then, bearing in mind that the correlation can take values between -1 and 1, one can state that when adding an asset to a portfolio, the standard deviation of the portfolio will reach its maximum in case of perfectly positively correlated assets ($\rho_{ij} = 1$). In the latter case, the standard deviation will be the sum of the individual standard deviations. Consequently, by including an asset which is not perfectly positively correlated in my portfolio, I can reduce my risk. The perfect deal would be to include a perfectly negatively correlated asset.

By considering the hedge funds as an asset class, I can insert it in a diversified portfolio (El-Erian derived Portfolio) and observe what impact it has on the performance of the portfolio.

In table 2, we can already have an idea of the correlation between the hedge fund index[10] (BHFI)[11], the hedge fund chose and the assets within the portfolio.

Table 2: Diversified portfolio's assets and the Barclay HFI – Correlation matrix

	SPX_Index	*EFA_US*	*VEIEX_US*	*VUSTX_US*	*VIPSX_US*	*PIGLX_US*	*REIT_Index*	*BHFI*
SPX_Index	1							
EFA_US	0.8835	1						
VEIEX_US	0.7957	0.8728	1					
VUSTX_US	-0.3064	-0.2055	-0.1931	1				
VIPSX_US	0.0726	0.1914	0.2426	0.6071	1			
PIGLX_US	0.1264	0.2981	0.3028	0.3898	0.6525	1		
REIT_Index	0.6924	0.6862	0.6019	0.0040	0.2740	0.2772	1	
BHFI	0.1420	0.1923	0.1833	-0.2063	0.0682	0.1059	0.1856	1

One can observe that the portfolio is well diversified since the correlations remain relatively low especially regarding the hedge fund index' (BHFI) correlation with other assets. From this analysis, we expect to get good results in terms of risk reduction.

But before the "inclusion phase", I will first analyze the performance of the different strategies present in my database (see section 3.1 hedge funds') using all the tools developed in section 4. Theoretical framework. This evaluation is made in order to select the" best" hedge fund's strategy and insert it in the portfolio.

The remaining of this section will be organized as follow: the next section has for purpose to determinate which strategy is the best in terms of risk-return, the section 5.4. analyzes the impact of including a hedge fund index in a diversified portfolio and finally, I will conclude by explaining the results I get in section 5.5. Conclusion.

[10] Has been chose because of its superior performance (see table 1 in section 1. Introduction)
[11] BarclayHedge :BHFI= Average of the hedge funds in the BarclayHedge database

5.2. Hedge Funds' strategies: Performance Analysis (1997-2016)

Though it exists plenty of performance measurements, only a few of them will be used throughout this section. Indeed, since the hedge funds' managers use different investment styles than other investors, some measurements could not be appropriate here, thus I will focus on the most relevant one.

Earlier, the fact that hedge funds' returns was normally distributed was mentioned

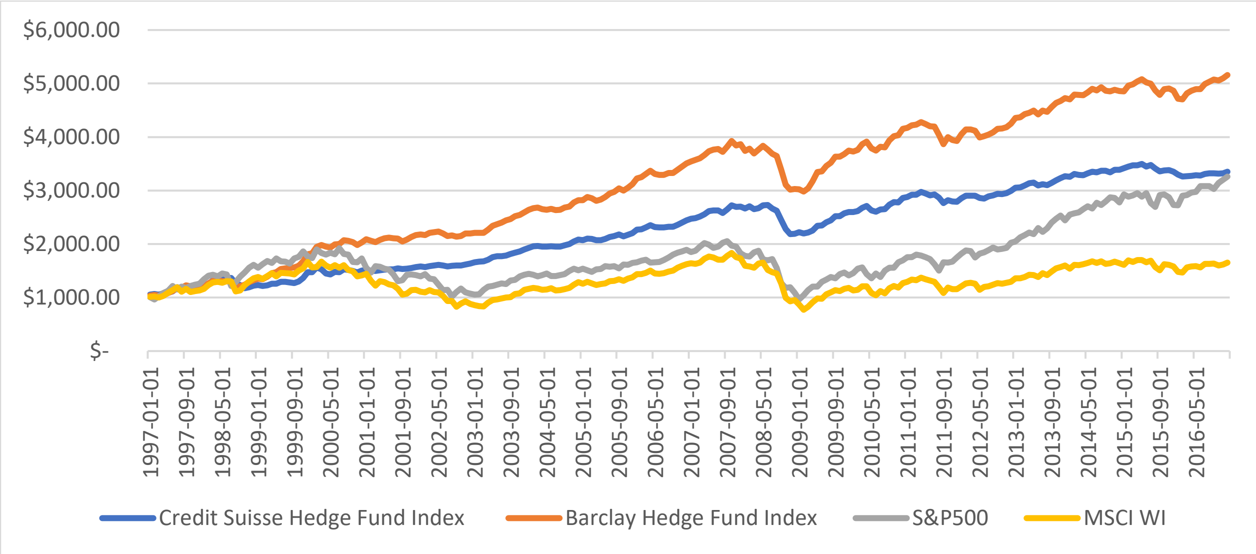
Table 3 : Hedge funds' Distribution: Skewness, Kurtosis and JB Test

Barclay				Credit Suisse			
Indice	***Skewness***	***Kurtosis***	***Jarque-Bera test***	***Indice***	***Skewness***	***Kurtosis***	***Jarque Bera test***
BCAI	-2.7412	23.0242	4310.2450	***CHF***	-0.3038	4.5358	27.2777
BDSI	-1.3376	3.8054	78.0547	***CCA***	-2.9366	20.2840	3332.2992
BEMI	-0.7048	3.5210	22.5837	***CDSB***	0.7794	1.5760	44.5770
BELBI	-0.6135	1.7525	30.6165	***CEM***	-1.3713	8.7554	406.4696
BELSI	0.8291	4.5236	50.7122	***CEMN***	-12.0230	169.8535	284182.9350
BEMNI	0.0152	1.5969	19.6963	***CED***	-2.1380	9.8419	650.9597
BEEI	1.6644	8.4097	403.4625	***CEDD***	-2.3895	13.2333	1275.5926
BEDI	-0.9920	4.0645	50.6987	***CEDMS***	-1.6909	6.7654	256.1410
BFIAI	-4.8361	41.2887	15595.7396	***CEDRA***	-1.0134	4.8457	75.1436
BFOFI	-0.7242	4.5349	44.5385	***CFIA***	-5.1687	42.4993	16670.5298
BGMI	0.7689	1.4815	46.7043	***CGM***	-0.1027	6.5044	123.2294
BHBI	2.3962	18.5253	2640.0240	***CLSE***	-0.0299	4.1647	13.6017
BMSI	-2.2004	12.5252	1100.9745	***CMF***	0.0865	-0.4415	118.7417
BTI	0.8212	4.4366	47.6113	***CMS***	-2.1686	10.4076	736.8365

As mentioned by Brooks and Kat (2002), hedge funds have high kurtosis and very low skewness. It is confirmed by the Jarcque-Bera test of normality (table 3) that their returns are not normally distributed.

Figure 15 shows the evolution of the value of $ 1000 USD invested in the two benchmarks as well as the hedge fund' index from 1997 to 2016:

Figure 15: Investments' value from 1997 until 2016



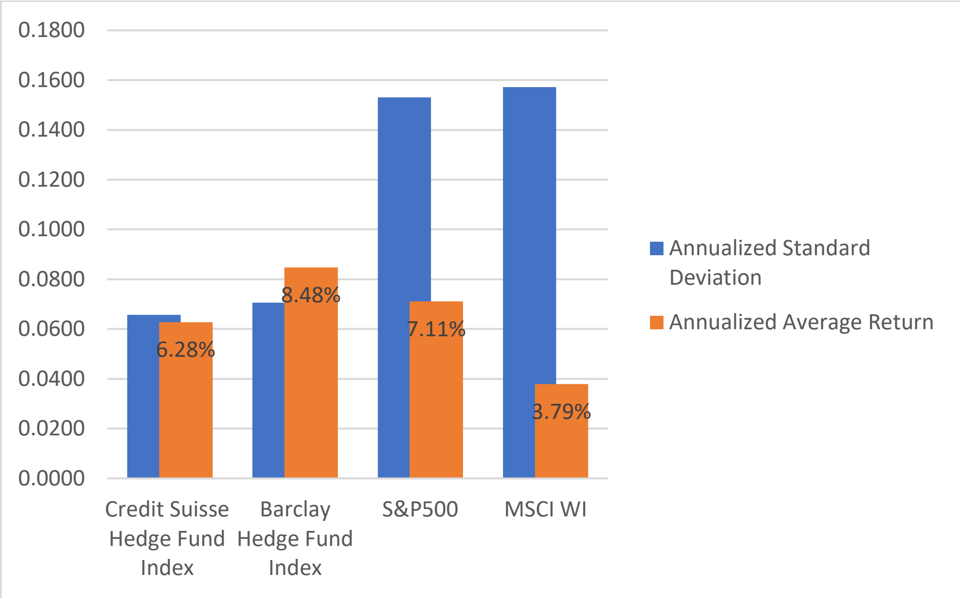
On a return basis, it would have been clearly preferable to invest in the Barclay hedge fund index as by having invested $ 1,000 in January 1997, we would end up with $ 5,158.93 in December 2016. Similarly, it outperformed the other from 2000 until today. One can observe that all these indices follow approximatively the same trend. During the crisis, we notice that though the S&P seems to be more impacted, it is the one that recovers the fastest to reach the Credit Suisse Hedge Fund index' yield.

The same analysis has been made on the aggregation of strategies that Barclay and Credit Suisse have in common (see appendix 11 to 14). We can notice, from this analysis, though most of Barclay's funds beat Credit Suisse's funds, the event driven fund of Credit Suisse seems to beat the one of Barclay.

As the figure 16 shows, the Barclay Hedge Fund Index doesn't only show off the best results in terms of returns but likewise on a risk basis with the lowest annual standard deviation that amounts to 0.062. On the contrary, the one that is considered as the worst investment between 1997 and 2017, the MSCI World Index, is the one that bears the greatest risk with 0.157 as standard deviation which confirms its position of bad investment.

Although this analysis is relatively poor, at this point, one can see the benefit to invest in hedge funds.

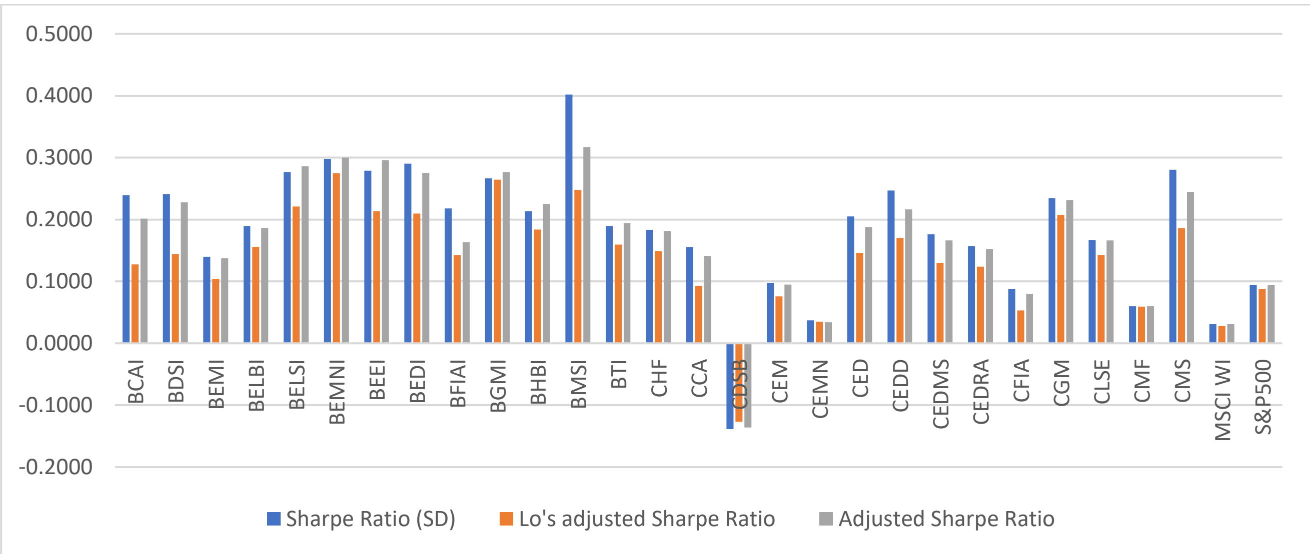
Figure 16: HFI and benchmarks' annualized SD and returns



5.2.1. Sharpe Ratios

As mentioned in section 4.6 Sharpe Ratio, it exists different variations of the reward-to-variability that have for purpose to improve its accuracy by filling its gaps. Figure 17 shows two of them, the Lo's adjusted Sharpe Ratio that considers the autocorrelation of the returns and the Adjusted Sharpe Ratio that takes into account the skewness and the kurtosis (the other variations being represented in figure 18).

Figure 17: Monthly Hedge funds' Sharpe ratios (1997-2016)



As expected, one can notice the Lo's Sharpe ratio is systematically lower than the other Sharpe ratios which show the autocorrelation bias when calculating this ratio. The adjusted Sharpe ratio, which takes into account the shape of the distribution is often close to the Sharpe ratio (i.e. the standard deviation Sharpe ratio). We can assume that the penalty factor for negative skewness and excess kurtosis must be very low except in the BMSI and the CMS case where the difference between the ratios seems to be significant.

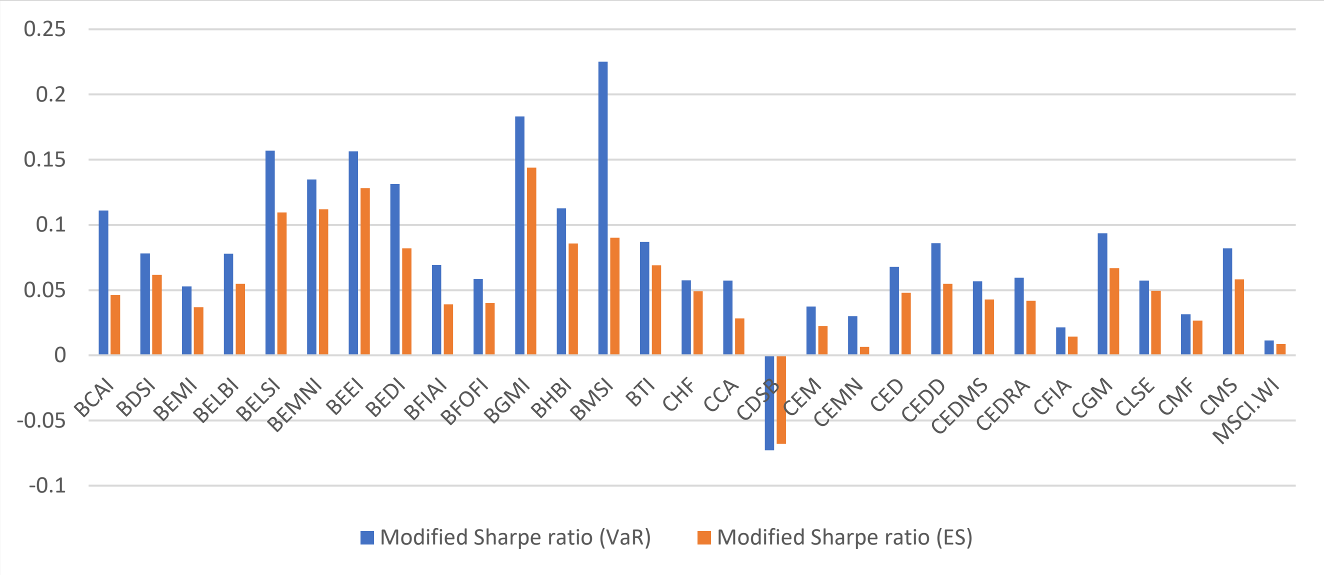
If we analyze the figure 17 in terms of ranking (some exceptions, e.g. BEEI VS BEDI), generally speaking, the trend is the same for all types of Sharpe Ratio. The outperforming strategies, starting with the best, are:

1. Barclay Multi Strategy Index (BMSI)
2. Barclay Equity Market Neutral Index (BEMNI)
3. Barclay European Equities Index (BEEI)
4. Barclay Event Driven Index (BEDI)
5. Credit Suisse Multi Strategy Index (CMS)

By taking a look at the figure 18 that shows the values for the modified Sharpe ratio, one can notice, on one hand, the difference between the latter and the other variations of the ratio (see figure 17) in terms of absolute value which is weaker than the other Sharpe ratio and on the other hand, the modification in the ranking made previously. Indeed, considering the modified Sharpe ratio, the most performing strategy is the fixed income arbitrage from BarclayHedge (BFIA) followed by the equity market neutral strategy (BEMNI). This trend's shift is probably due to the fact that taking account extreme value (as the VaR and ES give the maximum loss we can reach during one month with 99% of probability), the modified Sharpe ratio penalizes the funds that get extreme losses such as the multi-strategy index from Barclay.

Though it exists several methodologies (see section 4.3.3 Value-at-Risk), the method that has been chosen here to get the VaR and the expected shortfall is the Historical method because, as it is not based on the normal distribution of returns and there is no assumption regarding the linearity between the portfolio and the underlying assets, it best fits to my evaluation.

Figure 18: Monthly Modified Sharpe Ratio (CL=99%,1997-2016)



In order to be the most accurate possible, I would only consider the ranking made on the modified Sharpe ratio as it seems to be more reliable given its properties. The ranking is the following:

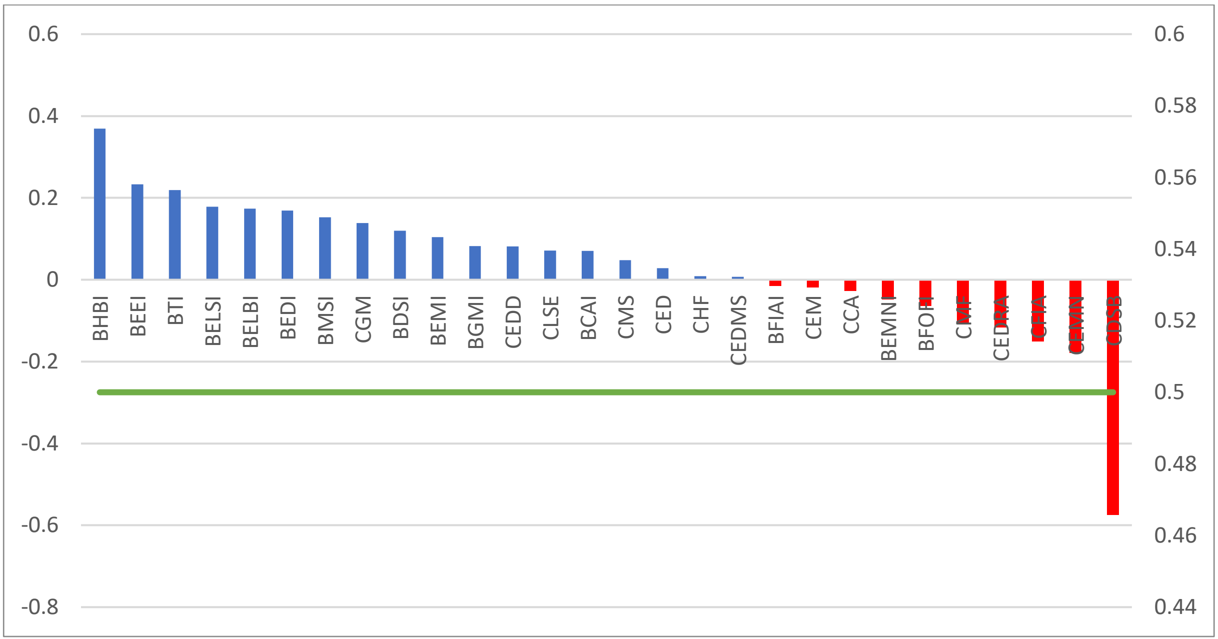
(1) Barclay Global Macro Index (BGMI)
(2) Barclay European Equity Index (BEEI)
(3) Barclay Equity Long/Short Index (BELSI)
(4) Barclay Equity Market Neutral Index (BEMNI)
(5) Barclay Multi Strategy Index (BMSI)

5.2.2. Information Ratio

The information ratio, as the Sharpe ratio, is a measurement of excess return not on the risk-free rate but on a specific benchmark, here the S&P 500. It is a way to evaluate the manager's skills by focusing on his ability to outperform the benchmark. In the same fashion, the information ratio indicates if the manager is able to produce excess returns for a certain period of time.

Figure 19 gives the values of the information ratio calculated from 1997 to 2016 for each hedge funds' strategy. We notice that almost 50% of the hedge funds get a negative information ratio. In literature review, several thresholds are defined as indicating a good "information ratio" and hence a good manager. We can read that 0.5 (Bacon, 2008) or 0.4 (Investopedia) is considered to be a good information ratio. Only one index reaches this threshold, the Barclay Healthcare & Biotechnology Index (BHBI). Then, we observe that the Barclay European Equities Index (BEEI) and the Barclay Technology index (BTI) don't perform too bad regarding the benchmark but we can assume that they can't sustain their performance on a long run.

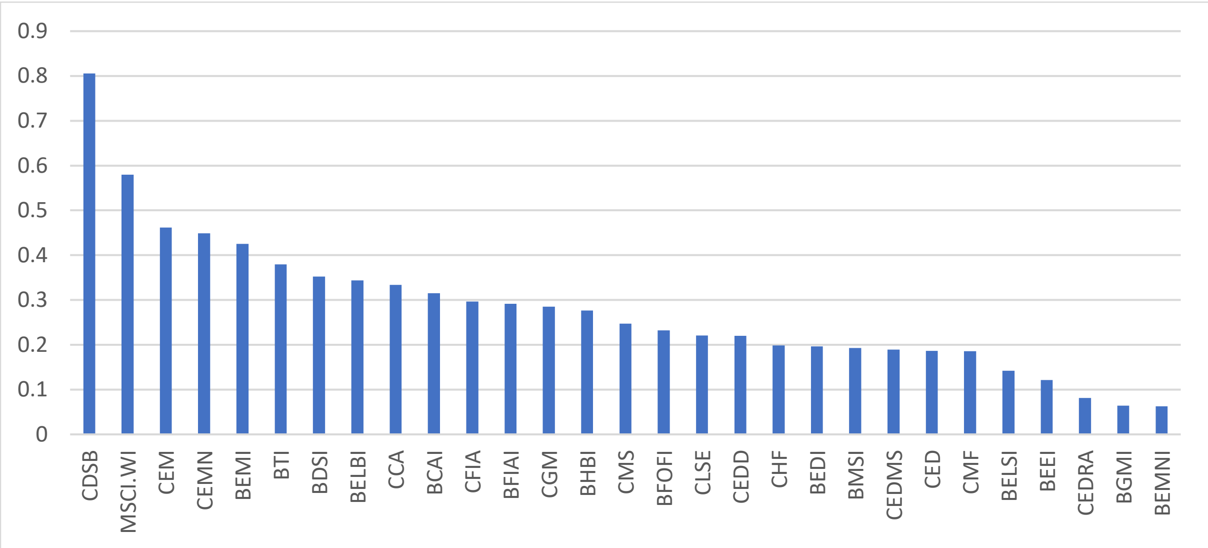
Figure 19 : Information ratio (1997-2016)



5.2.3. Calmar Ratio and Maximum Drawdown

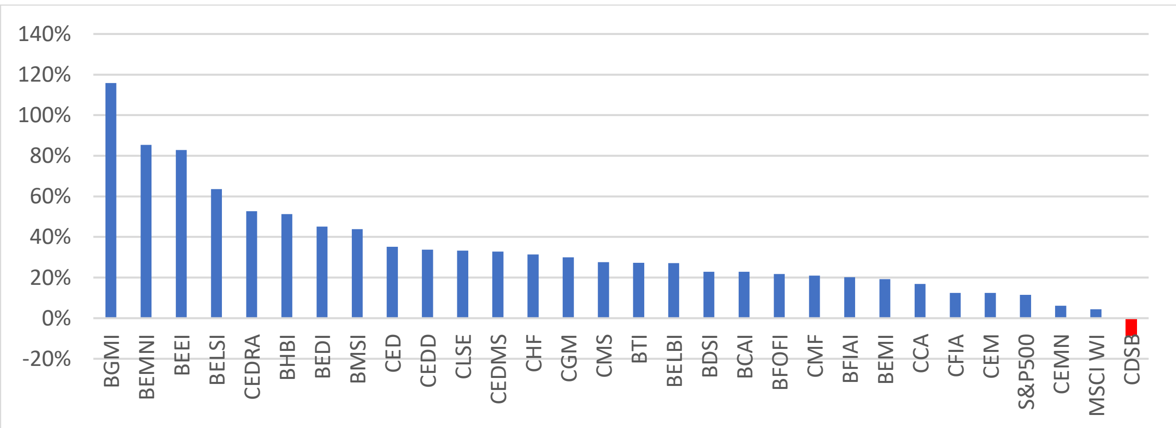
The Calmar Ratio is a kind of reward-to-variability ratio with the variability being the maximum drawdown (instead of tracking error for the information and standard deviation for the Sharpe ratio). As developed in section 4.3.2 Drawdown Analysis, the maximum drawdown represents the biggest peak-to-trough decline.

Figure 20: Maximum Drawdown (1997 – 2016)



Consequently, the highest the maximum drawdown the lowest the Calmar Ratio the worse off the investor. This ratio is particularly relevant as it only includes a certain period of time (generally the last 3 years). Indeed, if two funds are set up at different dates, one could have been hit by several adverse events while the other one would have been through relatively good cycles which could have an impact on a ratio that would take into account figures since the inception of the fund.

Figure 21: Calmar Ratio (1997-2016)



From figure 21, a ranking can be made:

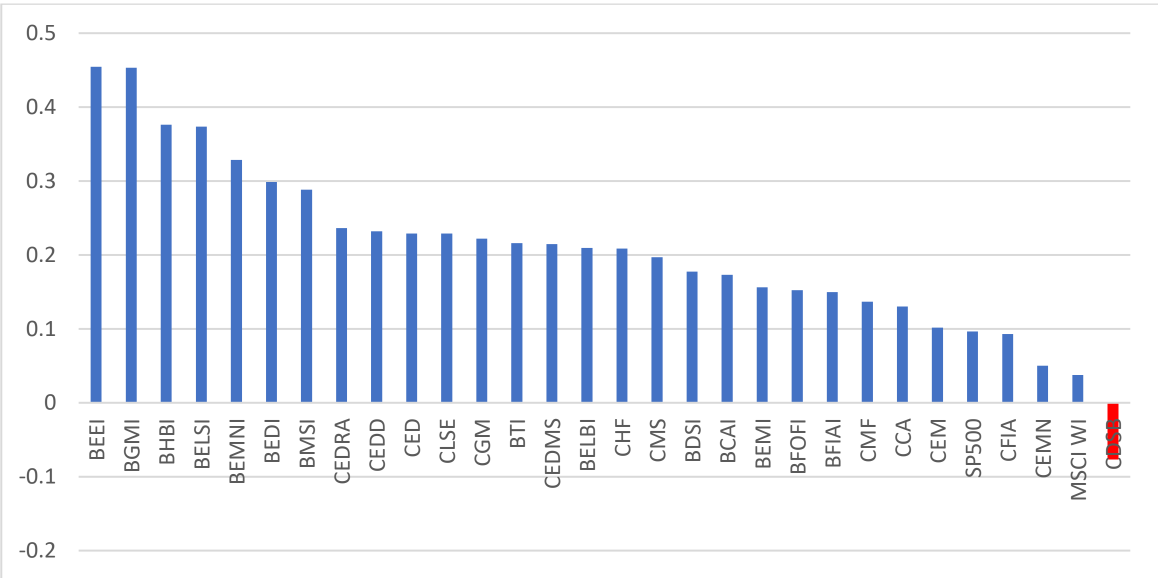
1. Barclay Global Macro Index (BGMI)
2. Barclay Equity Market Neutral Index (BEMNI)
3. Barclay European Equities Index (BEEI)
4. Barclay Equity Long/Short Index (BELSI)
5. Credit Suisse Event Driven Risk Arbitrage Index (CEDRA)

Once again, we observe that Barclay's managers outperform Credit Suisse's managers

5.2.4. Sterling Ratio

The Sterling ratio, by assuming that the future could be worse than what happened in the past, is a conservative version of the Calmar ratio (see section 4.9. Sterling ratio).

Figure 22: Sterling ratio (1997-2016)



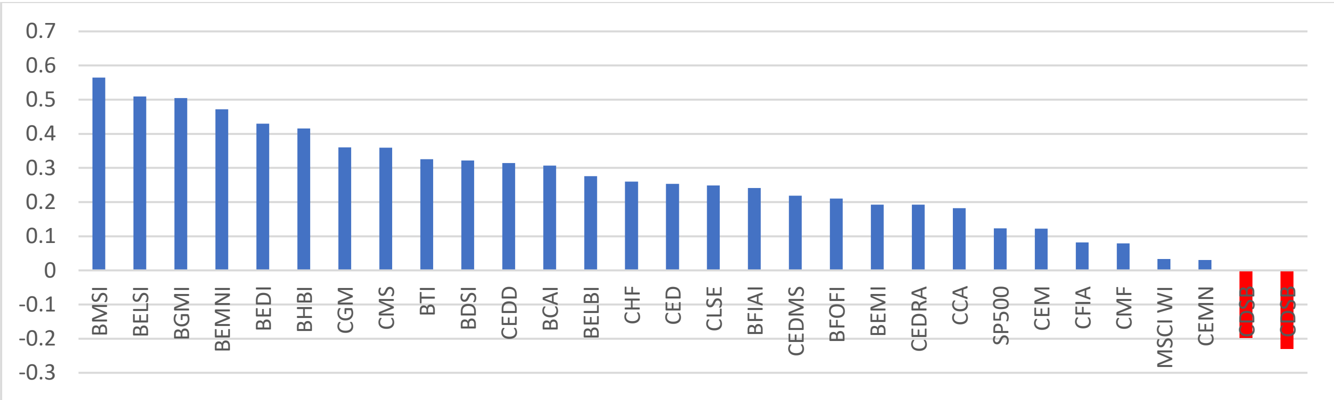
Such as the Sharpe ratio, it is a measure of the reward we get compared to the risk we take. The higher the Sterling ratio the better. Per se, one can conclude that the Barclay European Equities Index (BEEI) and the Barclay Global Macro Index (BGMI) outperform the other indices regarding this ratio.

We conclude that the top five is the same (the top ranked being the BEEI with 0.4546), except that the Credit Suisse is not anymore in the top of the ranking and is replaced by the Barclay Healthcare & Biotechnology Index (BHBI).

5.2.5. Sortino Ratio

The Sortino ratio is especially relevant as its interpretation is interesting. Indeed, it only considers the returns' volatility for the returns being under a predefined threshold named the Minimum Acceptable Return (MAR). It is interesting because, as an investor, I'm not really concerned about the volatility of the highly positive returns. However, as my returns reach a threshold, I want to be able to estimate their volatilities.

Figure 23: Sortino ratio (MAR=0.2%)



The MAR chose for the Sortino ratio here amounts to 0.2% which represents the mean monthly risk-free rate.

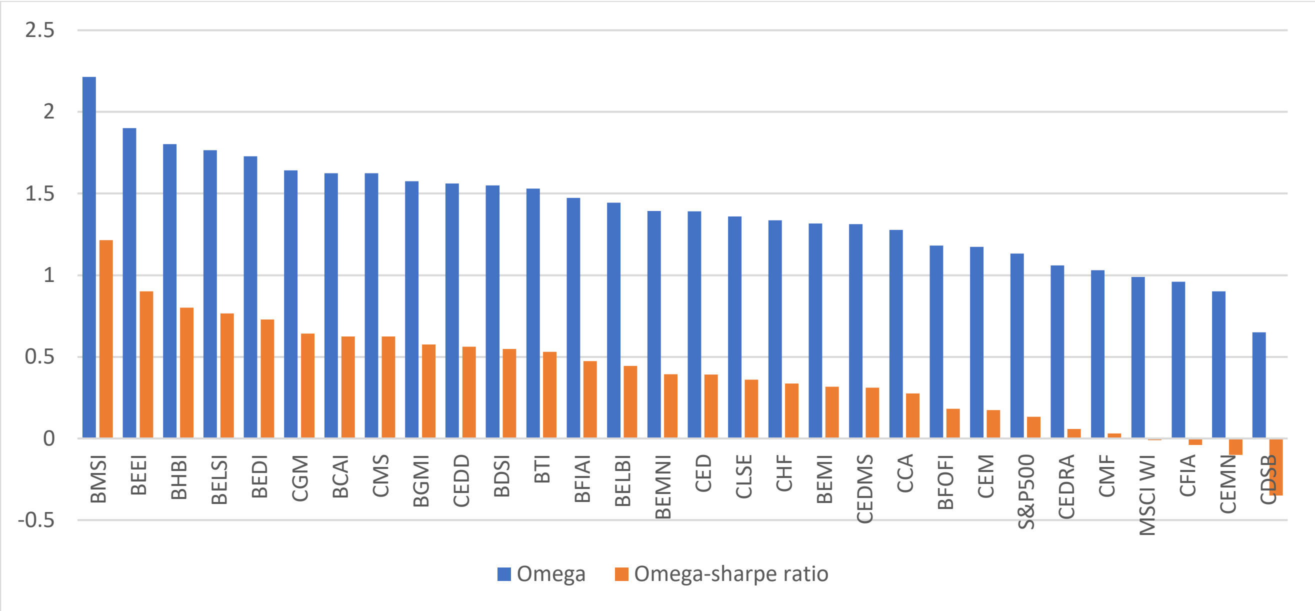
Once again, we observe that the top five remains almost unchanged (see figure 23):

1. Barclay Multi Strategy Index (BMSI)
2. Barclay Equity Long/Short Index (BELSI)
3. Barclay Global Macro Index (BGMI)
4. Barclay Equity Market Neutral Index (BEMNI)
5. Barclay Event Driven Index (BEDI)

5.2.6. Omega

Being defined as the probability to reach the MAR, investors expect to get the highest possible Omega.

Figure 24: Omega (MAR=0.2%) and Omega Sharpe ratio



With a MAR being the monthly risk-free rate, the highest omega is held by the Barclay Multi Strategy Index (nearly 3) followed by the Barclay European Equities Index and the Credit Suisse Multi-Strategy Index.

5.2.7. Value-at-risk and Expected Shortfall

It is interesting to know approximately what could be our biggest losses within a day or a month. The VaR and the expected shortfall are the solutions to answer this question.

With a certain confidence level, I will be able to approximate my future largest losses within a certain timeframe.

Although it is computed with parameters that the investor fixes, we are able to find the different VaR depending on our needs with the help of this formula:

$$VaR_{CL\%}^{N-days} = VaR_{CL\%}^{1-day} * \sqrt{N}$$

Which would be equal to

$$VaR_{99\%}^{1-day} = \frac{VaR_{99\%}^{21-days}}{\sqrt{21}}$$

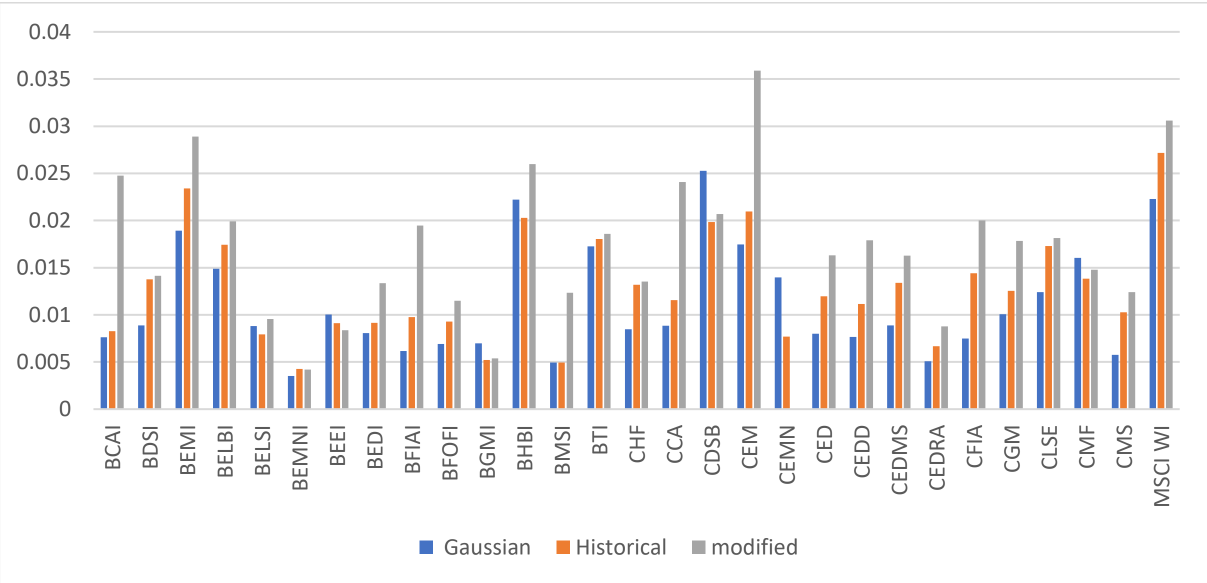
if we assume that one month contains on average 21 trading days.

Or more generally:

$$VaR_{CL'\%}^{N-days} = VaR_{CL\%}^{1-day} * \sqrt{N} * \frac{N^{-1}(CL'\%)}{N^{-1}(CL\%)}$$

One only need to calculate a VaR with a certain confidence level and timeframe. From the latter you will be able to compute all the variations you need to make relevant conclusions.

Figure 25: VaR 99% - 1 day

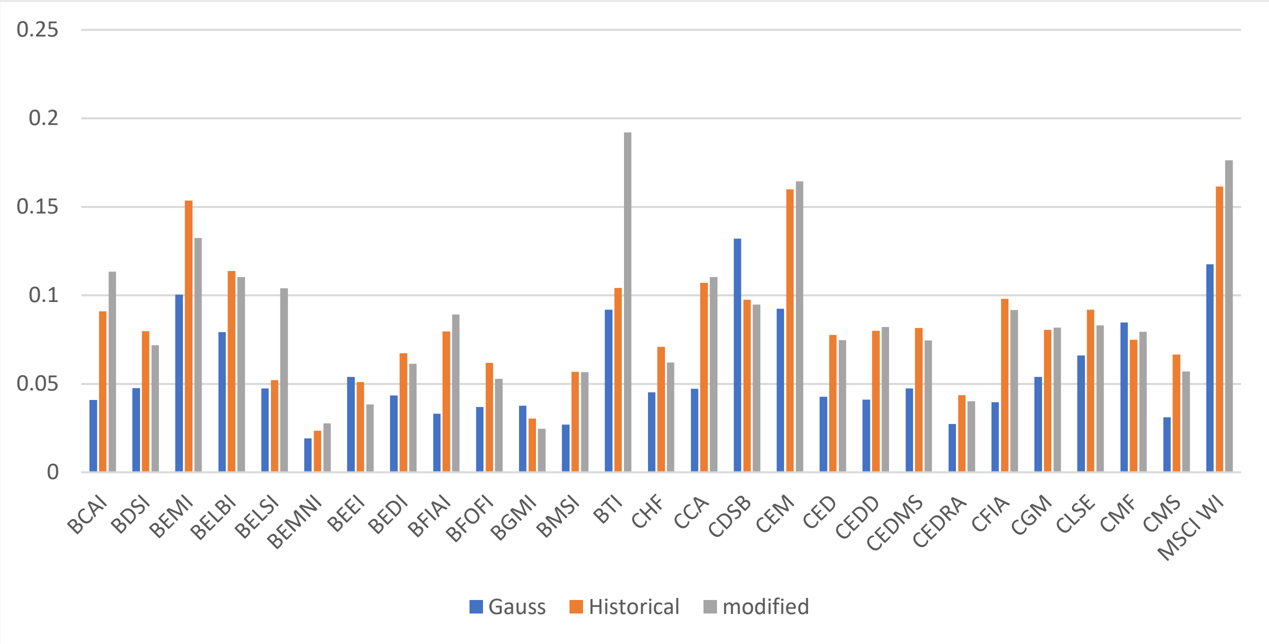


As explained hereinbefore, I chose the historical methodology because of its properties that fit particularly well to hedge funds' returns. Since the bigger the VaR, the worse off the investor, I want to select the fund that bears the lowest VaR hence the Barclay Equity Market Neutral Index (BEMNI). Indeed, selecting this fund, I expect to lose, as the largest loss, 1.95% of the value of my fund within one day with 99% confidence level. On the opposite, the Barclay Emerging Market Index (BEMNI) seems very risky as it displays a VaR of 2.34% which is the highest one what could explain its sharp fall in terms of asset under management after the 2007 crisis (see figure 3 in section 3.1.2 Hedge funds).

But what happens to my portfolio beyond this 99%? To answer this question, the ES must be computed (figure 26).

The BEMNI being still the less risky, I can conclude that beyond my 99%, I can expect to lose on average 2.35% of my fund's value within 1 month against 15.36% for the BEMI.

Figure 26: CVaR 99% - 1 month



5.3. Conclusion on Hedge Funds performance analysis

Though it exists other performance measurements (see appendix 7 and 8), based on the results obtained until here, I can already select the top 4 index I could include in my diversified portfolio: BEMNI, BMSI, BELSI and BEEI. Indeed, one can notice that most of the time, these indices are the one that performs the best.

As I want to select the best one relative to my portfolio and not on an "absolute" basis, my final decision will depend on the correlation of these funds with the diversified portfolio derived from El-Erian (see section 5.4 for further information about the portfolio).

Table 4: Selected indices and diversified portfolio - Correlation

	Diversified Portfolio	*BELSI*	*BEMNI*	*BEEI*	*BMSI*
Diversified Portfolio	1				
BELSI	0.1007	1			
BEMNI	-0.0111	0.4884	1		
BEEI	0.1540	0.9045	0.4893	1	
BMSI	0.2441	0.8141	0.4303	0.7617	1

We can conclude that the BEMNI should be the best strategy to include in the chosen portfolio as it gets the weakest correlation (i.e. -0.0111) which will reduce the risk my portfolio bears by enhancing the diversification effect.

5.4. Hedge fund's impact on a diversified portfolio

5.4.1. Methodology

This section has for purpose to show the effect in terms of risk-return of including a hedge fund in a diversified portfolio.

The first step is to build the portfolio mentioned above. To do so, I will construct a multi-asset portfolios derived from El-Erian (2008) and inspired by Laly and Petitjean (2016). Table 4 describes the "benchmark" portfolio, which is the portfolio without any hedge fund, and the share each asset has in the portfolio. The has been collected on Bloomberg from 2002 to 2016.

Table 5: Diversified portfolio's asset allocation

Description	Ticker	Weight
S&P500 Index	SP500 Index	25%
iShares MSCI EAFE Index	EFA	15%
Vanguard Emerging Markets Stock Index Fund	VEIEX	15%
Vanguard Long-Term Treasury Fund	VUSTX	10%
Vanguard Inflation-Protected Securities Fund	VIPSX	10%
PIMCO Global Bond Fund	PIGLX	10%
Real Estate Investment Trust	REIT Index	15%

The second step consists in the construction of four portfolios based on the benchmark portfolio. The first one will contain 5% of the Barclay Equity Market Neutral Index; in the second one, I will include 10 % of the Barclay Equity Market Neutral Index; the third one will consist in a portfolio with 5% of the Barclay Hedge Fund Index and the last one 10% of the Barclay hedge fund Index (table 6).

Table 6: Extended diversified portfolios 'asset allocations

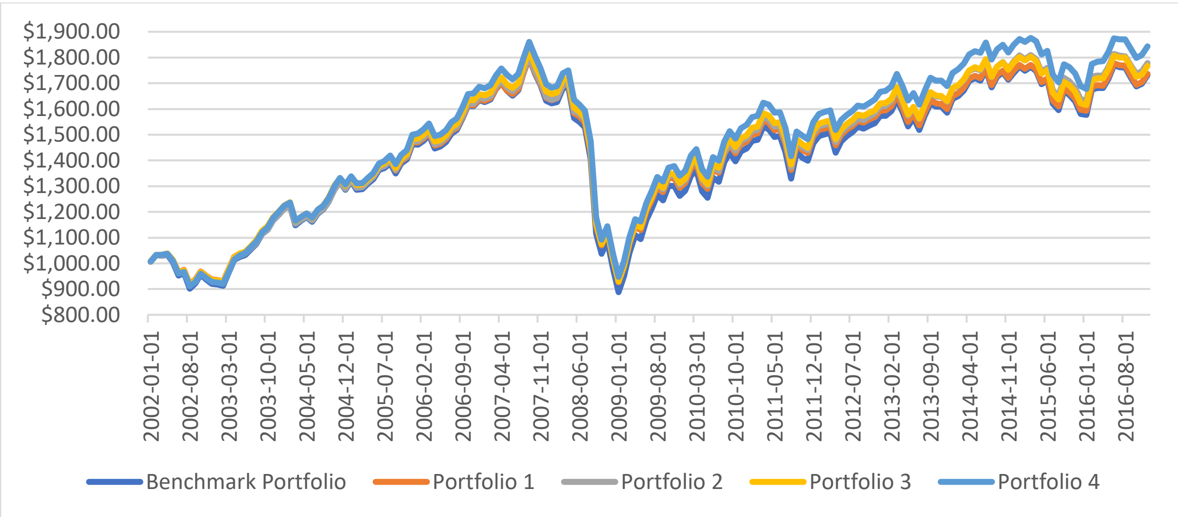
Asset	P1 Weight	P2 Weight	P3 Weight	P4 Weight
SP500 Index	20%	20%	20%	20%
EFA	15%	15%	15%	15%
VEIEX	15%	15%	15%	15%
VUSTX	10%	10%	10%	10%
VIPSX	10%	10%	10%	10%
PIGLX	10%	5%	10%	5%
REIT Index	15%	15%	15%	15%
BEMNI	5%	10%	0%	0%
BHFI	0%	0%	5%	10%

The third step is similar to section 5.2. Hedge funds' performance except that I will focus on the performance of my five portfolios. Using the tools developed in section 4. Theoretical Framework, one will be able to see what impact hedge funds have in a portfolio.

5.4.2. Performance Analysis

Figure 27 shows us what value our investment would have today if we had invested in 2002 in the five portfolios built in section 5.4.1. Methodology.

Figure 27: Diversified portfolios investments' value from 2002 to 2016



It is obvious that by adding hedge funds to our diversified portfolio, its performance in terms of returns has increased. The best performer is the portfolio 4 that is composed among other by 10% of the Barclay Hedge Funds Indices. The benchmark portfolio which doesn't include any hedge fund get the lowest value at the end of the year 2016 with $ 1,731.37. One can notice that by adding hedge funds to my portfolio, I succeed to increase my return by more than $ 100 for an investment of $ 1000 on 14 years which is substantial when we know professional investors invest billions of dollars on the market.

Table 6 summarizes descriptive statistics for the monthly returns of the five portfolios. We observe that when we add hedge fund in the portfolio, there is an increase of the leptokurtosis. The hedge fund's insertion has also an impact on the skewness of the distribution as it becomes more and more negatively skewed. Plus, the test on normality (see appendix 20) confirms that the distributions of these portfolios are not normal.

Table 7: Diversified portfolios' – Descriptive statistic

	Benchmark portfolio	*Portfolio 1*	*Portfolio 2*	*Portfolio 3*	*Portfolio 4*
Annualized return (Geo. mean)	3.73%	3.74%	3.91%	3.87%	4.16%
Annualized SD	0.1218	0.1154	0.1138	0.1160	0.1151
Global return	66.45%	65.51%	67.67%	67.44%	71.54%
Kurtosis	6.8745	7.3177	7.5084	7.4976	7.8671
Skewness	-1.4714	-1.5302	-1.5661	-1.5611	-1.6289
Plage	0.3014	0.2887	0.2865	0.2921	0.2932
Minimum	-0.2058	-0.1979	-0.1966	-0.2000	-0.2007
Maximum	0.0956	0.0908	0.0899	0.0921	0.0925

The annualized returns are higher in portfolio 4 which confirms the fact that on a return basis, the portfolio with the highest weight of hedge fund outperforms the others. As regard to the risk, the portfolio including the highest weight of the Barclay Equity Market Neutral Index (portfolio 2) is the less risky with a standard deviation of 0.1138. The riskiest portfolio is the one without hedge fund with 0.1218 of standard deviation. One can observe the same trend with the systematic risk that is the lowest in the portfolio 2 with 0.69. As we include more hedge funds in the portfolio, it seems to decrease the exposure of the portfolio to the market.

5.4.2.1. CAPM

It is interesting to look at how the CAPM can inform us on the portfolios' returns. Table 8 summarizes some relevant figures relative to the CAPM:

Table 8: Diversified portfolios – CAPM analysis

	P Bench.	P 1	P 2	P 3	P 4
Alpha	-0.0007	-0.0005	-0.0004	-0.0004	-0.0002
t*/ H0: α=0	-0.6070	-0.4594	-0.3589	-0.3766	-0.1889
2-tailed p-value	0.5447	0.6465	0.7201	0.7069	0.8504
Annual. α	-0.0086	-0.0065	-0.0048	-0.0054	-0.0026
Beta	0.7537	0.7035	0.6999	0.7066	0.7060
t*/ H0: β=0	26.8285	25.0447	26.0316	24.9394	25.7257
2-tailed p-value	0.0000	0.0000	0.0000	0.0000	0.0000
R^2	0.8017	0.7789	0.7920	0.7775	0.7880
Correlation	0.8954	0.8826	0.8899	0.8818	0.8877

First, one can observe that all the alphas are negative. However, none of them are significantly different from zero. Consequently, it seems to have no abnormal return in any portfolio.

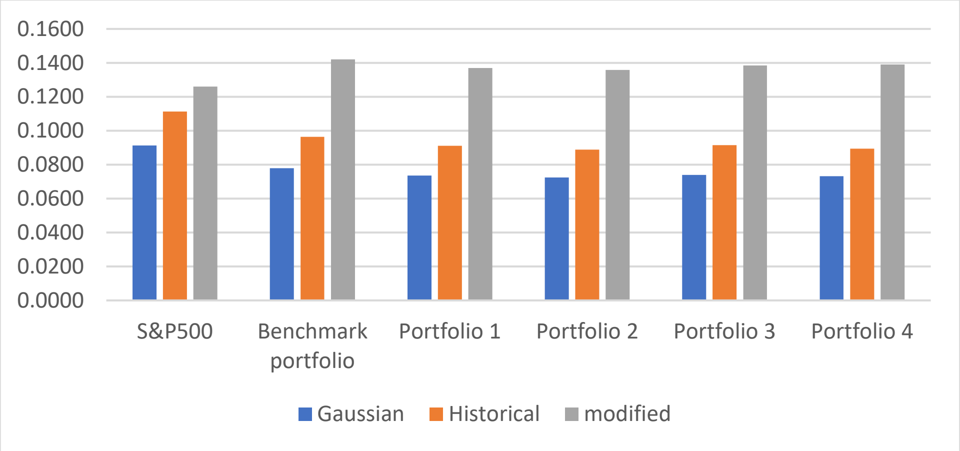
Then it is interesting to look at the betas as they are all significant. They seem relatively high but decrease as the hedge fund's weight increase in the portfolio. The lowest beta belongs to the portfolio 2 with 0.6999 followed by the portfolio 1 with 0.7035. This is due to the fact that the BEMNI has a very low correlation with the market (2.62%).

The CAPM doesn't seem too bad at explaining the returns of the portfolios as the model explains between 77.75% and 80.17% of the returns. However, we can't really determine the impact of the hedge fund's inclusion on the R^2 as when its weight (i.e. the hedge fund's weight) increases within the portfolio, the R^2 increases as well (from 77.89 to 79.20 for the portfolios with the BEMNI and from 77.75% to 78.80% for the portfolio including the BHFI) but remains below the R^2 of the benchmark portfolio .

5.4.2.2. *VaR, CVaR and Maximum Drawdown*

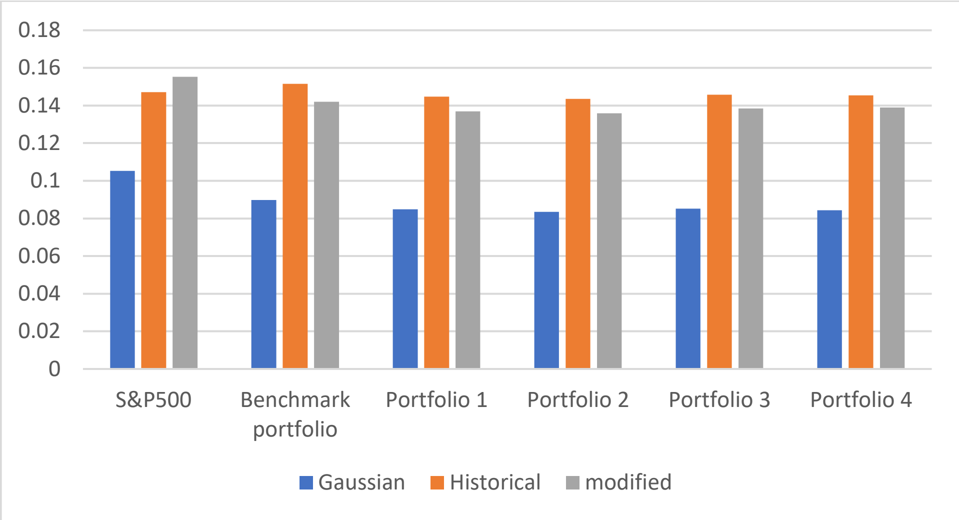
Considering the VaR, one can observe that the diversified portfolio, especially the portfolio 2 and 4 that includes the highest weight of the hedge funds' index, is less risky than the benchmark (S&P 500). Furthermore, we notice the VaR slightly decreases as the weight of the hedge fund in the portfolio increases. For example, analyzing the historical, we can conclude that within a month, the benchmark portfolio can lose a maximum of 9.64% of its value while the portfolio 4 will lose 8.95% of its value with a confidence level of 99%. The S&P 500, all other things being equal, will lose a maximum of 11.14% of its value.

Figure 28: Diversified portfolio VaR (CL=99% - 1 month)



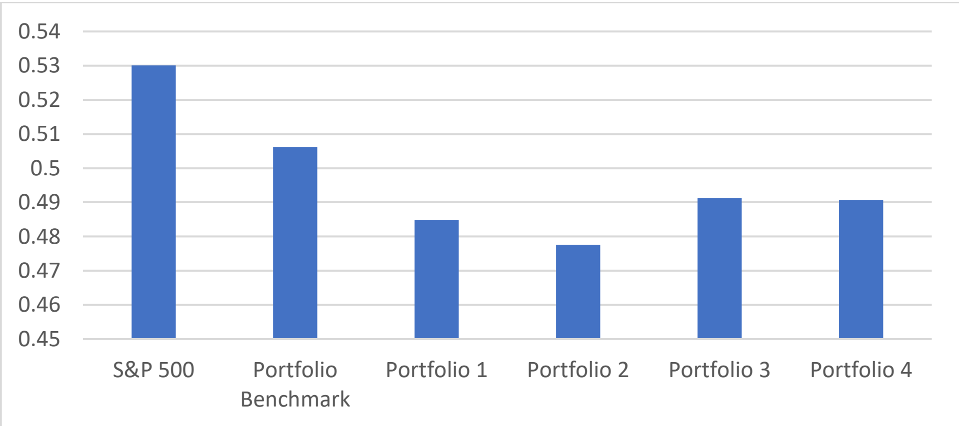
If the investor wants to be more accurate in his risks management, he can look further by analyzing what happened if we go beyond this 99%. If things do get really bad, I can expect to lose 14.55% of my portfolio 4 on average while my benchmark and my portfolio benchmark will lose 14,71% and 15,15% respectively during one month. The lowest CVaR, no matter the method used, is the portfolio 2' CVaR. This could be due to the fact that the hedge fund's strategy selected (Equity Market Neutral) has the weakest expected shortfall among all the strategies (2.35% historical CVaR).

Figure 29: Diversified portfolios' CVaR (CL=99% - 1 month)



The portfolio that experienced the largest peak to trough is the benchmark portfolio with 0.51. However, the latter has a lower maximum drawdown than the S&P 500 that obtained 0.53. The weakest peak to trough has been made by the portfolio 2 which is consistent with the CVaR analysis.

Figure 30: Diversified portfolios' Maximum Drawdown

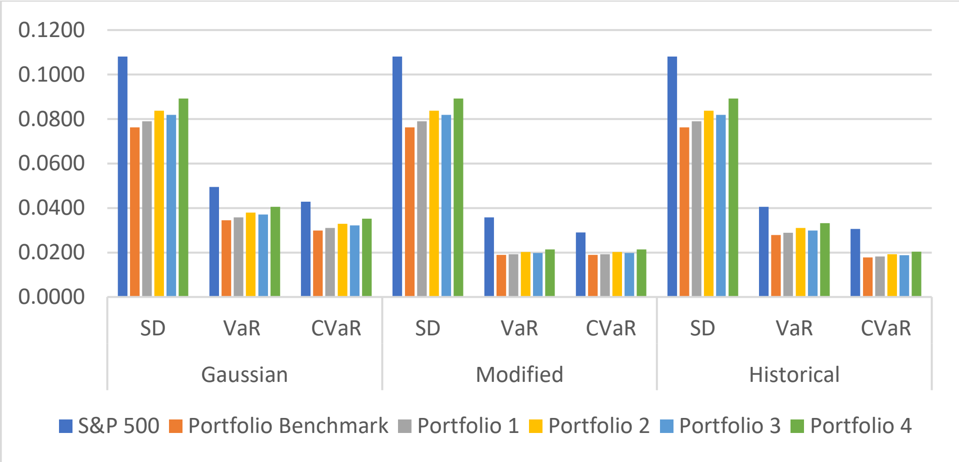


5.4.2.3. Sharpe and Treynor ratios

Though the S&P 500 gets the highest Sharpe ratio, one can notice that the inclusion of hedge fund tends to increase the Sharpe ratio.

Figure 31 shows the modified Sharpe ratios (i.e. the one with the VaR and the CVaR on the denominator) versus the standard deviation's Sharpe ratio. We see that the difference between the S&P 500's ratio and the portfolios' ratios tends to get smaller as we look at the modified versions of the Sharpe ratio against the classic one. This is probably due to the fact that S&P 500 has less skewness and kurtosis than the portfolio which has an impact on the ratio since the SD Sharpe ratio doesn't consider these two factors.

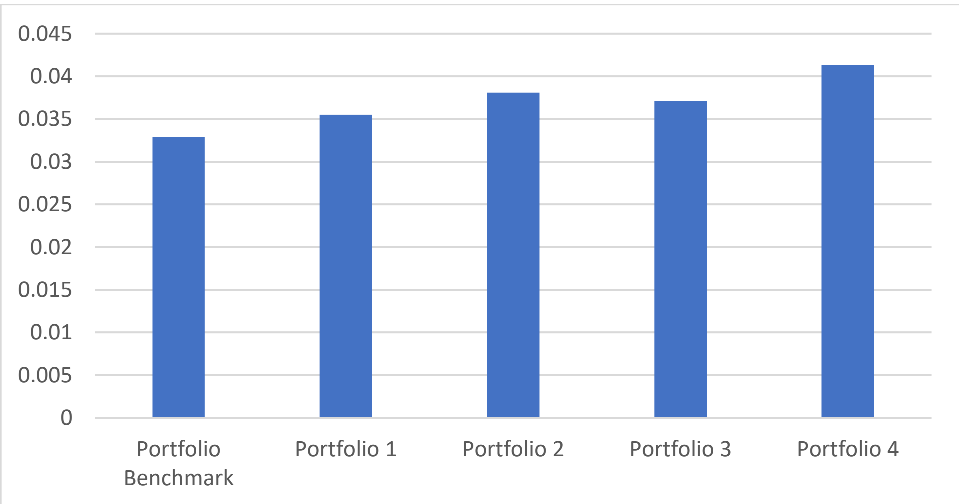
Figure 31: Diversified portfolios' Sharpe ratios (CL=99% for the Modified Sharpe Ratio)



Since we already analyze the impact of the hedge fund's inclusion on the systematic risk of a portfolio (beta), we can anticipate the trend concerning the Treynor Ratio. Indeed, as developed earlier, the Treynor ratio doesn't the whole volatility as risk measure (as the Sharpe ratio) but only the systematic part. Therefore, it gives us an idea about the excess return we get compared to the systematic risk our portfolio bears. The highest Treynor ratio amounts to 0.0413 (portfolio 4) against 0.0329 for the worst one (benchmark portfolio).

In the context of our evaluation, it is a relevant ratio as the portfolios are diversified. By only considering the systemic risk, the Treynor ratio assumes that the portfolio is diversified. Consequently, in the case of this thesis, it is a relevant ratio as our portfolios are effectively diversified.

Figure 32: Treynor Ratio

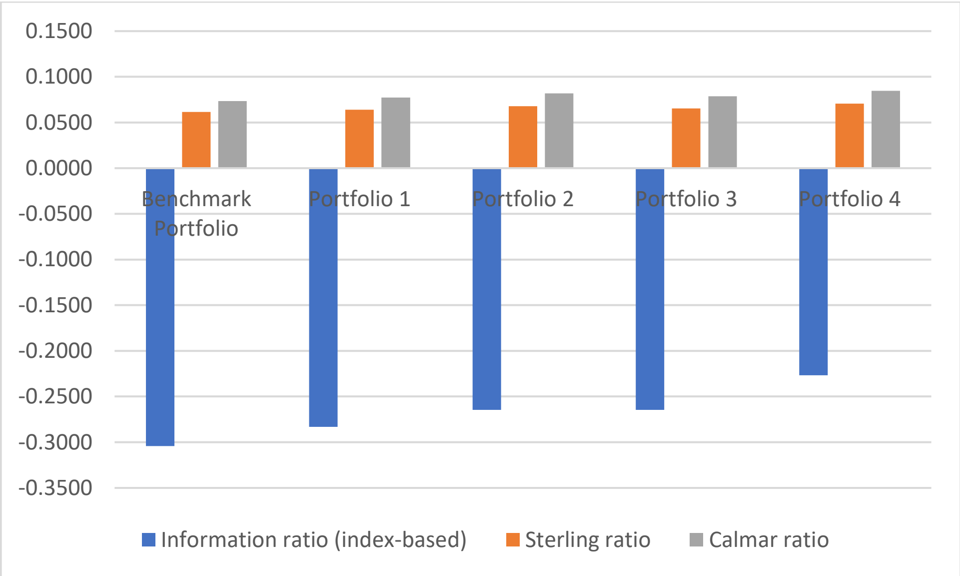


5.4.2.4. *Information, Calmar and Sterling ratios*

The information ratios remain very low compared to what we obtained in the section 5.2 hedge funds' performance. It could be interpreted as the fact that the five portfolios are not able to beat the benchmark which is the S&P 500. This interpretation is consistent with the Sharpe ratio results obtained in section hereinbefore.

However, after the inclusion of the hedge funds, we observe an increase of the information from -0.3042 for the benchmark portfolio to -0.2265 for the portfolio 4.

Figure 33: Diversified portfolios' Information, Sterling and Calmar ratios



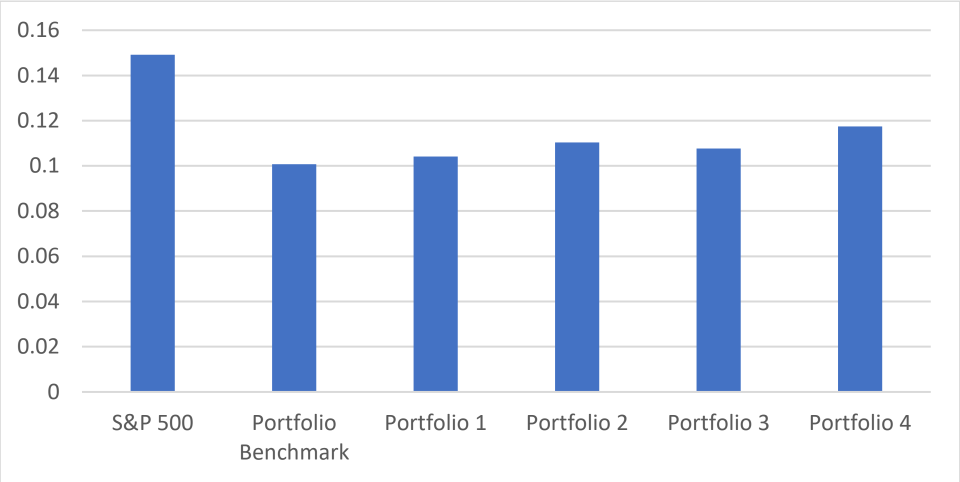
The Calmar and Sterling ratios display relatively low values that range from 0.073 to 0.084 and 0.061 to 0.070 respectively. These low ratios are the consequence either of a low excess return or of a high maximum drawdown.

The same trend as before is observed; the inclusion of the hedge fund has a positive impact on the portfolio. More accurately, in this case, it is better to add the hedge fund index rather than only the funds that use the Equity Market Neutral strategy.

5.4.2.5. *Sortino and Omega ratios*

As an investor, I want to know how my bad returns behave. Indeed, as long as my portfolio generates returns above the goal I have fixed, I'm not worried. The downside risk is a statistical tool used to capture this behave. By fixing a threshold (section 4.3.3. MAR and Calmar Ratio), I can compute the volatility of the returns under this MAR. This figure will be useful as a risk measure for the Sortino ratio. The lower my downside deviation, the higher my Sortino, the better off I am as an investor.

Figure 34: Diversified portfolios' Sortino ratio (MAR=0.1%)



By fixing the MAR at the monthly risk-free rate (which is averaged at 0.1% monthly here), we notice that the benchmark (S&P 500) outperforms the others. However, the insertion of our hedge funds' indices is a good idea as it improves the Sortino ratio when we increase the funds' weight within the portfolio. This is mainly due to the fact that as the hedge fund's share increases inside the diversified portfolio, the annualized downside deviation decreases from 0.1049 for the benchmark portfolio to 0.0878 for the portfolio 4. Thus, when you add the new asset, the "bad" returns volatility decreases which is positive for our portfolio.

The Omega ratio is calculated as the upside potential divided by the downside potential. Therefore, we can interpret it as the Sharpe ratio with the reward being the upside potential[12] and the variability being the downside potential[13]. The higher the upside potential or the lower

[12] Sum of maximum between the return in a period i minus the MAR and zero the whole thing divided by the number of periods studied

[13] Maximum between zero and the MAR minus the return in a period i the whole thing divided by the number of periods studied

the downside potential, the better for the portfolio's performance as it means that we outperformed relative to the MAR or that our "bad" returns are close to the MAR that we set.

Figure 35: Diversified portfolios' Omega

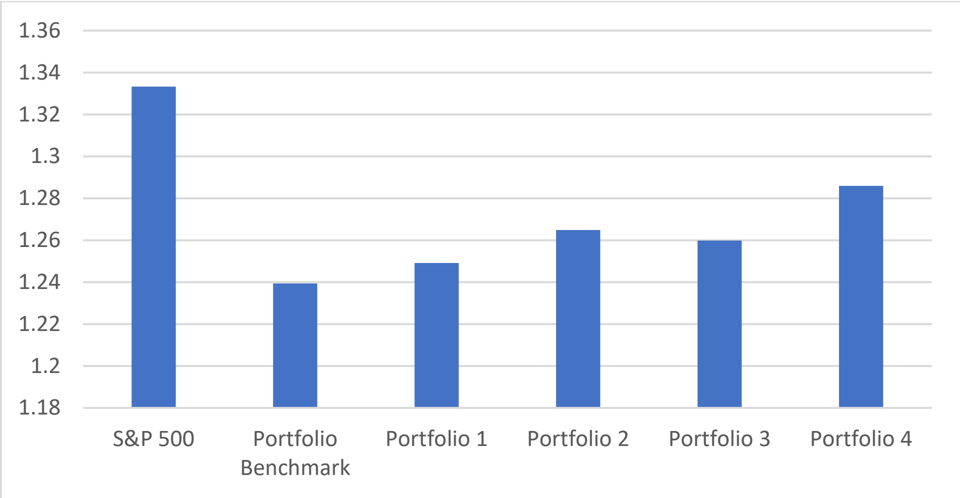


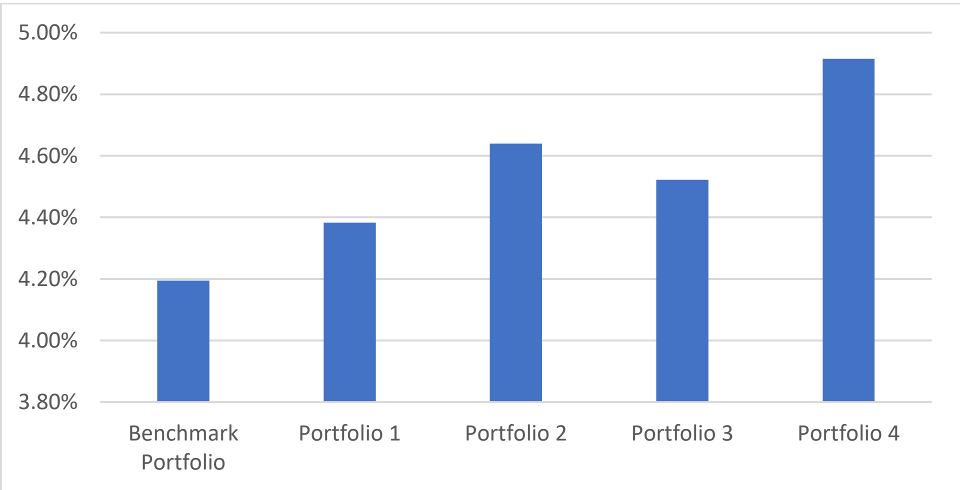
Figure 35 explicitly shows that we are in the same trend as before. Even though we don't beat the market, the omega is improved thanks to the hedge fund. It seems to have a significant difference between the benchmark portfolio and the portfolio 4 (0.05 point of difference).

5.4.2.6. M-Squared

How much am I rewarded if I take a certain amount of risk? That's the question the M^2 tries to answer. Figure 36 shows the MM of my five portfolios

On a risk-adjusted basis, the portfolio 4 has the highest excess return which is 4.92% against 4.19% for the benchmark portfolio.

Figure 36: Diversified portfolios' M^2



5.4.3. Conclusion

The inclusion of hedge funds' index to a portfolio seems to be a good idea as we obtained solely positive results with regard to the performance measurement used.

We observed that by adding the hedge fund index of Barclay (BHFI), we are able to increase the risk-return. Furthermore, the more weight we place in the portfolio, the greater is the performance. No matter the measurement, we noticed an improvement as we put more hedge fund's index weight.

Relative to the Barclay Equity Market Neutral Index (BEMNI), the results appear to be less conclusive but we can still observe an improvement of the portfolio on a risk adjusted basis. This improvement seems to be mainly due to the fact that the strategy has a low correlation with the market. Indeed, one can see that on a risk basis, the portfolios including the BEMNI have a lower risk than the other. Plus, this risk continues to decrease as we increase the allocation of the strategy in the portfolio.

Nevertheless, at the sight of the results, we are tempted to conclude that it could be better to include the hedge fund index as a whole (which is the average of all the funds the database contains) than solely one strategy. However, this conclusion requires more researches.

6. Conclusion

Throughout this thesis, I provided a performance analysis, firstly of the hedge funds indices from the Credit Suisse and the Barclay databases then of the inclusion of hedge funds indices within a diversified portfolio built based on the El-Erian's neutral asset mix portfolio.

Through my first analysis, I find that, using the data from Credit Suisse and Barclay from 1997 to 2016, the Barclay indices outperform the Credit Suisse most of the time. Overall, the best performance on a risk-adjusted basis has been obtained by the Barclay's indices. If we compare the performances by strategy (Credit Suisse VS Barclay), one can conclude that Barclay's managers showed more skills than Credit Suisse manager during this period. One can take as example the comparison relative to the convertible arbitrage strategy (see appendix 10). The BCAI obtained an adjusted Sharpe ratio of 0.4420 where the CCA obtained 0.3192. The BCAI's information ratio amounts to 0.07 against -0.028 for the CCA. The same trend is observed if we analyze the M^2 which is equal to 14.85% for the BCAI and 10.09% for the CCA.

Then, the first analysis demonstrates that from 1997 to 2016, the hedge funds' indices used are able to beat the market. This conclusion is consistent with the one made by the research department of the Center for International Securities and Derivatives Markets (CISDM) in 2006 (see section 2.3.5 performance of hedge VS the market and within a portfolio). Indeed, if we compare the HF indices to benchmarks selected (S&P500 and MSCI WI), one can notice that for all the performance measurements available, most of the indices beats the two benchmarks. For example, the modified Sharpe ratios (with a historical VaR 99% - 1 month as denominator) for the S&P 500 and the MSCI WI amount respectively to 0.037 and 0.0113 against 0.1109 or 0.22 for the BCAI and the BMSI.

Finally, taking the top five of the performance measurements computed, I conclude that the four of best strategies to include in a diversified portfolio where the following: BEMNI, BMSI, BELSI and BEEI. These four indices were ranked, most of the time, in the top 5 of all ratios (or at least in the top 10). They clearly outperformed the other indices. I decide to include the Barclay Market Neutral Index (BEMNI) subsequent to the correlation analysis. Indeed, my goal was to determinate the index with the lowest correlation relative to the multi-asset portfolio. With a correlation -0.01, the BEMNI obtained the lowest correlation and thus has been selected to be included within the diversified portfolio.

The second analysis focuses on the risk-return contribution of hedge funds in a diversified portfolio. Before starting the analysis, the multi-asset portfolio must have been built. To do so, I was inspired by Laly and Petitjean (2016) by creating a portfolio derived from the multi-asset portfolio from El-Erian (2008). My version of the portfolio is composed of seven assets: SPX, EFA, VEIEX, VUSTX, VIPSX, PIGLX, REIT. To these seven assets, I added 2 others, the Barclay Hedge Fund Index which is an average of all the funds being available in the Barclay's database and the Barclay Equity Market Neutral Index that has been one of the best performers among all the strategies analyzed. This inclusion has been made in two step in order to see what is its impact. The first step was to construct two derived versions of the multi-asset portfolio by adding 5% of the BEMNI in one portfolio (portfolio 1) and 5% in the other one (portfolio 3) reducing the share of the worst performer in terms of return, PIGLX, by 5 percent. The second step consisted in the construction of two additional portfolios, but this time including 10% of the BEMNI (portfolio 2) and 10% of the BHFI (portfolio 3) reducing the weight of the second worst performer in terms of return, the VUSTX. The results we obtained were similar from those of Fung and Hsieh (1997), Amin and Kat (2002) and the CISDM (2006). First of all, one observed that, as we include the HF indices, the more weight of indices we added to the portfolio, the better was the risk-adjusted performance of the portfolio. Then, I noticed that the BHFI was a better performance enhancer than the BEMNI. If we take a look at the figures, overall, one can point out that the portfolios including the BHFI outperforms the one including the BEMNI (with the same weight of index; 5% VS 5% or 10% VS 10%).

The second observation was that even if a part of this improvement is due to the returns, another one is attributable to the risk decrease. One can observe at the section 5.4.2.2 VaR, CVaR and Maximum Drawdown that the risk decrease when we include the HF indices. Plus, in this case, the insertion of the BEMNI made the risk the portfolios lower (portfolio 1 and 2 VS the benchmark portfolio) than in portfolio 3 and 4 (that included the BHFI). This is probably the consequence of the fact that, as mentioned by Schneeweis, Kazemi and Martin (2002), the equity market neutral strategy is a "risk reducers and diversifiers" for traditional portfolio (stock and bond) because it is, by definition, sensitive to other market factors.

Nevertheless, to conclude to significant improvement in the risk-adjusted performance, further investigation must be made.

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Appendices

Appendix 1 : Jensen's Alphas and p-value - Barclay's strategies

Indice	Jensen's alpha	Two-tailed p-value
BCAI	0.0040	0.05%
BDSI	0.0048	0.04%
BEMI	0.0055	3.79%
BELBI	0.0060	0.49%
BELSI	0.0056	0.00%
BEMNI	0.0026	0.00%
BEEI	0.0065	0.00%
BEDI	0.0054	0.00%
BFIAI	0.0029	0.16%
BFOFI	0.0024	1.48%
BGMI	0.0044	0.00%
BHBI	0.0101	0.17%
BMSI	0.0050	0.00%
BTI	0.0070	0.48%

Appendix 2 : Jensen's Alphas and p-value - Credit Suisse's strategies

Indice	Jensen's alpha	Two-tailed p-value
CHF	0.0035	0.51%
CCA	0.0028	2.82%
CDSB	-0.0066	3.51%
CEM	0.0036	13.88%
CEMN	0.0012	52.10%
CED	0.0037	0.17%
CEDD	0.0043	0.02%
CEDMS	0.0035	0.62%
CEDRA	0.0017	2.30%
CFIA	0.0013	23.41%
CGM	0.0055	0.02%
CLSE	0.0044	1.32%
CMF	0.0022	30.31%
CMS	0.0037	0.00%

Appendix 3 : Betas and p-value – Barclay strategies

Indice	***Beta***	***Two-tailed p-value***
BCAI	0.0589	2.12%
BDSI	0.0398	18.31%
BEMI	0.0415	48.43%
BELBI	0.0482	31.44%
BELSI	0.0165	57.83%
BEMNI	0.0051	68.63%
BEEI	0.0172	61.01%
BEDI	0.0228	41.11%
BFIAI	0.0405	5.23%
BFOFI	0.0162	46.72%
BGMI	-0.0060	79.94%
BHBI	0.0930	19.44%
BMSI	0.0315	8.23%
BTI	0.0558	31.24%

Appendix 4 : Betas and p-value – Credit Suisse strategies

Indice	***Beta***	***Two-tailed p-value***
CHF	0.0014	96.04%
CCA	0.0624	2.83%
CDSB	-0.0153	82.63%
CEM	0.0075	88.97%
CEMN	-0.0314	45.18%
CED	-0.0001	99.60%
CEDD	0.0167	52.10%
CEDMS	-0.0131	64.94%
CEDRA	0.0285	8.99%
CFIA	0.0366	12.48%
CGM	-0.0421	20.69%
CLSE	0.0345	38.41%
CMF	-0.0556	25.31%
CMS	0.0384	5.70%

Appendix 5 : Returns' distribution – Barclay strategies

Indice	Skewness	Kurtosis	Bera-Jarque test
BCAI	-2.7412	23.0242	4310.2450
BDSI	-1.3376	3.8054	78.0547
BEMI	-0.7048	3.5210	22.5837
BELBI	-0.6135	1.7525	30.6165
BELSI	0.8291	4.5236	50.7122
BEMNI	0.0152	1.5969	19.6963
BEEI	1.6644	8.4097	403.4625
BEDI	-0.9920	4.0645	50.6987
BFIAI	-4.8361	41.2887	15595.7396
BFOFI	-0.7242	4.5349	44.5385
BGMI	0.7689	1.4815	46.7043
BHBI	2.3962	18.5253	2640.0240
BMSI	-2.2004	12.5252	1100.9745
BTI	0.8212	4.4366	47.6113

Appendix 6 : Returns' distribution – Credit Suisse strategies

Indice	Skewness	Kurtosis	Bera-Jarque test
CHF	-0.3038	4.5358	27.2777
CCA	-2.9366	20.2840	3332.2992
CDSB	0.7794	1.5760	44.5770
CEM	-1.3713	8.7554	406.4696
CEMN	-12.0230	169.8535	284182.9350
CED	-2.1380	9.8419	650.9597
CEDD	-2.3895	13.2333	1275.5926
CEDMS	-1.6909	6.7654	256.1410
CEDRA	-1.0134	4.8457	75.1436
CFIA	-5.1687	42.4993	16670.5298
CGM	-0.1027	6.5044	123.2294
CLSE	-0.0299	4.1647	13.6017
CMF	0.0865	-0.4415	118.7417
CMS	-2.1686	10.4076	736.8365

Appendix 7: Table of measurements – Barclay strategies

	BCAI	BDSI	BEMI	BELBI	BELSI	BEMNI	BEEI	BEDI	BFIAI	BFOFI	BGMI	BHBI	BMSI	BTI
Information ratio (index-based)	0.0703	0.1195	0.1037	0.1739	0.1781	-0.0477	0.2330	0.1690	-0.0148	-0.0642	0.0824	0.3694	0.1527	0.2192
Treynor_ratio	0.8423	1.4589	1.4344	1.4602	4.1125	6.2545	4.5193	2.9009	0.9046	1.7833	-8.6571	1.2712	1.9702	1.4487
Active Treynor ratio	0.8236	1.4730	1.6364	1.5498	4.2155	6.2917	4.6580	2.9481	0.8854	1.8200	-8.9790	1.3758	1.9486	1.5555
Modified treynor ratio	5.4922	9.5124	9.3526	9.5209	26.8144	40.7807	29.4668	18.9143	5.8981	11.6275	-56.4466	8.2883	12.8461	9.4457
M squared	0.1485	0.1492	0.0874	0.1178	0.1697	0.1824	0.1711	0.1774	0.1370	0.1052	0.1642	0.1296	0.2410	0.1172
Excess M squared (simple)	0.0876	0.0883	0.0265	0.0570	0.1089	0.1215	0.1102	0.1166	0.0762	0.0443	0.1034	0.0687	0.1802	0.0563
Excess M squared (compounded)	0.0826	0.0833	0.0250	0.0537	0.1026	0.1145	0.1039	0.1099	0.0718	0.0418	0.0974	0.0648	0.1698	0.0531
Monthly downside risk	0.0129	0.0145	0.0281	0.0217	0.0107	0.0051	0.0111	0.0123	0.0119	0.0107	0.0082	0.0246	0.0086	0.0214
Downside volatility	0.0447	0.0502	0.0973	0.0751	0.0371	0.0175	0.0383	0.0426	0.0411	0.0370	0.0284	0.0853	0.0298	0.0740
Sortino ratio	0.3070	0.3222	0.1928	0.2755	0.5089	0.4721	0.5679	0.4292	0.2411	0.2101	0.5044	0.4155	0.5651	0.3252
Downside potential	0.0038	0.0056	0.0124	0.0099	0.0049	0.0022	0.0050	0.0049	0.0029	0.0044	0.0043	0.0106	0.0025	0.0100
Upside potential	0.0077	0.0103	0.0178	0.0159	0.0103	0.0045	0.0113	0.0102	0.0057	0.0067	0.0084	0.0208	0.0074	0.0170
Omega	2.0496	1.8297	1.4376	1.6012	2.1213	2.1083	2.2597	2.0741	1.9954	1.5048	1.9676	1.9670	2.9156	1.6930
Omega Sharpe ratio	1.0496	0.8297	0.4376	0.6012	1.1213	1.1083	1.2597	1.0741	0.9954	0.5048	0.9676	0.9670	1.9156	0.6930
Upside down ratio	0.5996	0.7106	0.6333	0.7338	0.9628	0.8980	1.0186	0.8287	0.4834	0.6263	1.0257	0.8451	0.8602	0.7944
Kappa 3	0.1565	0.2063	0.1255	0.1845	0.3409	0.3157	0.3880	0.2651	0.1209	0.1332	0.3772	0.2790	0.3040	0.2252

Appendix 8 : Table of measurements – Credit Suisse strategies

	CHF	CCA	CDSB	CEM	CEMN	CED	CEDD	CEDMS	CEDRA	CFIA	CGM	CLSE	CMF	CMS
Information ratio (index-based)	0.0088	-0.0277	-0.5747	-0.0188	-0.1788	0.0281	0.0815	0.0074	-0.1168	-0.1514	0.1386	0.0714	-0.1099	0.0481
Treynor_ratio	29.2931	0.5536	5.8093	4.6936	-0.1987	-330.8696	3.1063	-3.0559	0.7448	0.4196	-1.4981	1.4825	-0.3136	1.2021
Active Treynor ratio	30.8574	0.5410	4.9561	5.8084	-0.4572	-346.7363	3.1753	-3.2953	0.7222	0.4153	-1.6296	1.5631	-0.4856	1.1814
Modified treynor ratio	190.9983	3.6097	37.8777	30.6036	-1.2955	-2157.3489	20.2538	-19.9251	4.8562	2.7356	-9.7679	9.6666	-2.0447	7.8380
M squared	0.1169	0.1009	-0.0626	0.0644	0.0309	0.1293	0.1528	0.1126	0.1037	0.0643	0.1451	0.1060	0.0449	0.1720
Excess M squared (simple)	0.0561	0.0400	-0.1235	0.0035	-0.0300	0.0684	0.0919	0.0517	0.0429	0.0035	0.0843	0.0451	-0.0160	0.1112
Excess M squared (compounded)	0.0528	0.0377	-0.1164	0.0033	-0.0282	0.0645	0.0866	0.0487	0.0404	0.0033	0.0794	0.0425	-0.0151	0.1048
Monthly downside risk	0.0124	0.0153	0.0348	0.0274	0.0274	0.0137	0.0131	0.0148	0.0082	0.0142	0.0142	0.0173	0.0221	0.0101
Downside volatility	0.0430	0.0530	0.1205	0.0949	0.0947	0.0475	0.0455	0.0512	0.0283	0.0492	0.0493	0.0598	0.0765	0.0349
Sortino ratio	0.2604	0.1823	-0.1973	0.1219	0.0297	0.2532	0.3148	0.2187	0.1921	0.0821	0.3600	0.2483	0.0791	0.3596
Downside potential	0.0051	0.0048	0.0226	0.0110	0.0047	0.0050	0.0045	0.0056	0.0035	0.0037	0.0054	0.0076	0.0128	0.0032
Upside potential	0.0083	0.0075	0.0158	0.0143	0.0055	0.0084	0.0087	0.0089	0.0050	0.0049	0.0106	0.0119	0.0145	0.0068
Omega	1.6345	1.5859	0.6966	1.3031	1.1727	1.6967	1.9151	1.5759	1.4538	1.3130	1.9450	1.5609	1.1366	2.1212
Omega Sharpe ratio	0.6345	0.5859	-0.3034	0.3031	0.1727	0.6967	0.9151	0.5759	0.4538	0.3130	0.9450	0.5609	0.1366	1.1212
Upside down ratio	0.6707	0.4934	0.4530	0.5239	0.2018	0.6166	0.6588	0.5983	0.6154	0.3442	0.7409	0.6909	0.6577	0.6804
Kappa 3	0.1653	0.0976	-0.1609	0.0735	0.0124	0.1503	0.1770	0.1347	0.1208	0.0419	0.2191	0.1611	0.0614	0.2056

Appendix 9 : Correlation – Indices & Benchmarks

	Rf	S&P500	BCAI	BDSI	BEMI	BELBI	BELSI	BEMNI	BEEI	BEDI	BFIAI	BFOFI	BGMI	BHBI	BMSI	BTI	CHF	CCA	CDSB	CEM	CEMN	CED	CEDD	CEDMS	CEDRA	CFIA	CGM	CLSE	CMF	CMS	MSCI WI
Rf	1.0000																														
S&P500	-0.0344	1.0000																													
BCAI	0.0694	0.1440	1.0000																												
BDSI	0.0455	0.0817	0.7001	1.0000																											
BEMI	0.0466	0.0440	0.5440	0.7111	1.0000																										
BELBI	0.0757	0.0642	0.5554	0.7509	0.8230	1.0000																									
BELSI	0.2115	0.0377	0.4734	0.6629	0.7554	0.9190	1.0000																								
BEMNI	0.2618	0.0208	0.1850	0.2696	0.2328	0.3720	0.5169	1.0000																							
BEEI	0.2161	0.0357	0.4286	0.5843	0.6332	0.7022	0.8413	0.4530	1.0000																						
BEDI	0.1170	0.0508	0.6312	0.8592	0.8066	0.8906	0.8311	0.3484	0.6955	1.0000																					
BFIAI	0.0407	0.1183	0.7398	0.6686	0.4618	0.4710	0.3975	0.1720	0.3936	0.5346	1.0000																				
BFOFI	0.2078	0.0462	0.6474	0.7904	0.7920	0.8476	0.8864	0.5307	0.8211	0.8555	0.6207	1.0000																			
BGMI	0.1884	-0.0168	0.3142	0.4338	0.6011	0.6521	0.7469	0.5087	0.6881	0.6089	0.2797	0.7615	1.0000																		
BHBI	0.0896	0.0849	0.3185	0.4568	0.4550	0.6637	0.7508	0.3216	0.6498	0.5599	0.2677	0.6274	0.4652	1.0000																	
BMSI	0.2362	0.1090	0.8564	0.7813	0.6695	0.7286	0.6991	0.4090	0.6380	0.8062	0.7170	0.8575	0.5644	0.4683	1.0000																
BTI	0.1360	0.0672	0.3392	0.5147	0.6217	0.8128	0.8619	0.3330	0.6544	0.6746	0.2661	0.7053	0.5672	0.7721	0.5271	1.0000															
CHF	0.0877	-0.0003	0.5810	0.7244	0.7421	0.7771	0.8171	0.5003	0.7862	0.7751	0.5780	0.9154	0.7687	0.5991	0.7350	0.6491	1.0000														
CCA	0.0600	0.1373	0.9266	0.7075	0.5244	0.5067	0.4399	0.2241	0.4180	0.6284	0.7735	0.6419	0.2944	0.2815	0.8512	0.2909	0.5754	1.0000													
CDSB	0.1161	-0.0123	-0.3532	-0.5774	-0.6535	-0.8242	-0.7012	-0.1619	-0.4778	-0.7071	-0.2919	-0.5773	-0.4528	-0.5741	-0.4614	-0.7158	-0.5433	-0.3085	1.0000												
CEM	-0.0132	0.0049	0.4931	0.6621	0.9406	0.7599	0.7304	0.2586	0.6531	0.7409	0.4559	0.7828	0.6222	0.4579	0.6076	0.5978	0.7932	0.4890	-0.5967	1.0000											
CEMN	0.1563	-0.0468	0.2927	0.3405	0.2453	0.3045	0.2413	0.1794	0.2004	0.2949	0.2586	0.3092	0.1716	0.1823	0.3194	0.1807	0.3132	0.2013	-0.1758	0.2004	1.0000										
CED	0.0797	-0.0045	0.6305	0.8847	0.7513	0.8069	0.7345	0.3646	0.6384	0.9152	0.5786	0.8383	0.5539	0.4841	0.7827	0.5637	0.7888	0.6407	-0.6227	0.7300	0.2994	1.0000									
CEDD	0.0561	0.0364	0.6099	0.8713	0.6998	0.7492	0.6524	0.2866	0.5378	0.8627	0.5834	0.7453	0.4599	0.4103	0.7113	0.4992	0.7038	0.6093	-0.5876	0.6757	0.3471	0.9402	1.0000								
CEDMS	0.0874	-0.0327	0.6065	0.8443	0.7494	0.7961	0.7528	0.4007	0.6807	0.8927	0.5466	0.8551	0.5861	0.5119	0.7780	0.5790	0.8124	0.6257	-0.6051	0.7363	0.2556	0.9753	0.8470	1.0000							
CEDRA	0.1266	0.1027	0.4806	0.5862	0.6104	0.6576	0.6167	0.3118	0.4814	0.7359	0.3410	0.6137	0.4620	0.4156	0.6219	0.5154	0.5554	0.4816	-0.4827	0.5761	0.1785	0.6857	0.6158	0.6760	1.0000						
CFIA	-0.0581	0.0902	0.7621	0.6097	0.4603	0.3999	0.3044	0.1051	0.3274	0.4634	0.8697	0.5593	0.2516	0.1978	0.6808	0.1600	0.5648	0.7850	-0.2252	0.4518	0.3044	0.5094	0.5139	0.4839	0.3070	1.0000					
CGM	0.1081	-0.0830	0.3252	0.3427	0.3925	0.3285	0.4166	0.3686	0.5158	0.3575	0.3900	0.5660	0.6249	0.2126	0.4095	0.2282	0.7608	0.3544	-0.1258	0.5137	0.0636	0.4065	0.3268	0.4543	0.2644	0.4274	1.0000				
CLSE	0.0905	0.0551	0.4764	0.6519	0.7252	0.8771	0.9259	0.5348	0.7923	0.7848	0.4334	0.8850	0.7421	0.7452	0.6734	0.8184	0.8788	0.4440	-0.6815	0.7372	0.2252	0.7378	0.6529	0.7552	0.5907	0.3668	0.4671	1.0000			
CMF	0.0245	-0.0773	-0.0780	-0.1141	-0.0471	-0.0469	0.0240	0.2390	0.0636	-0.0453	-0.1095	0.1290	0.5158	-0.0760	0.0584	-0.0631	0.1700	-0.1031	0.0657	-0.0110	-0.0159	-0.0408	-0.0843	-0.0151	-0.0519	-0.0607	0.3059	0.0821	1.0000		
CMS	0.0494	0.1158	0.7700	0.6913	0.5006	0.5737	0.5207	0.3330	0.5211	0.6317	0.7193	0.7312	0.4433	0.3477	0.8290	0.3381	0.6744	0.7705	-0.3297	0.4777	0.3773	0.6350	0.5863	0.6292	0.3977	0.6919	0.3977	0.5604	0.0779	1.0000	
MSCI WI	-0.0047	0.1025	0.5013	0.6502	0.7490	0.8802	0.7218	0.2032	0.5632	0.7638	0.4505	0.6846	0.5129	0.4820	0.6153	0.6405	0.6421	0.4424	-0.7636	0.6740	0.2907	0.6945	0.6495	0.6747	0.5751	0.3971	0.2358	0.7202	-0.0575	0.5291	1.0000

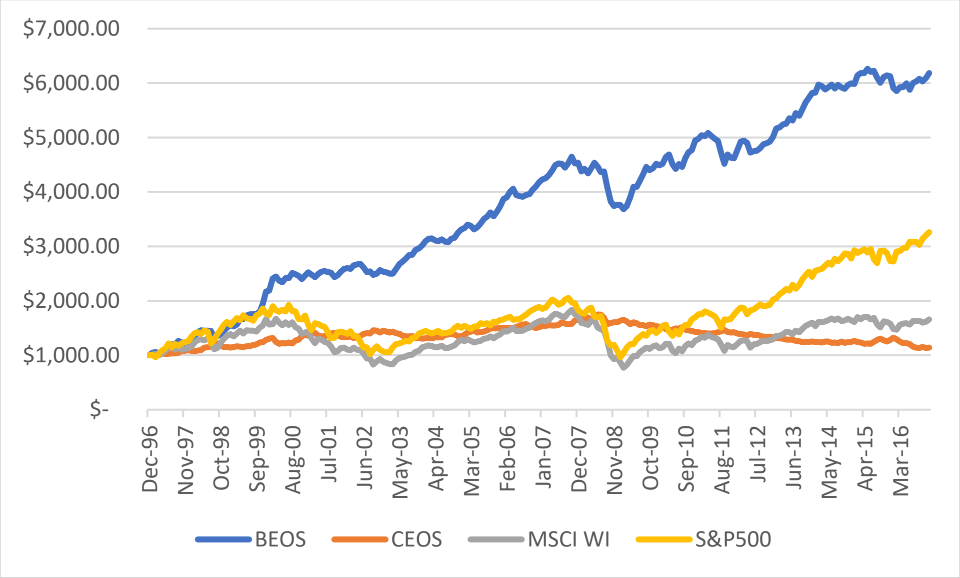
Appendix 10 : Sharpe ratios – Barclay and Credit Suisse strategies

*The Modified Sharpe ratios' parameters are : CL = 99% - 1 month. The Modified Sharpe ratio with the historical VaR is noted "VaRH SR", the modified Sharpe ratio with the Expected shortfall is noted "ESH SR", SR (SD) represents the classic VaR and ASR is the Adjusted Sharpe Ratio (see section 4.5)

Indice	SR (SD)	VaRH SR	Lo's SR	ASR	ESH SR
BCAI	0.2392	0.1109	0.1276	0.2016	0.0463
BDSI	0.2410	0.0780	0.1441	0.2276	0.0617
BEMI	0.1397	0.0528	0.1042	0.1373	0.0369
BELBI	0.1897	0.0779	0.1557	0.1863	0.0547
BELSI	0.2766	0.1570	0.2210	0.2858	0.1096
BEMNI	0.2981	0.1348	0.2749	0.2999	0.1121
BEEI	0.2791	0.1564	0.2133	0.2958	0.1282
BEDI	0.2901	0.1314	0.2094	0.2751	0.0821
BFIAI	0.2181	0.0694	0.1423	0.1632	0.0391
BGMI	0.2665	0.1832	0.2642	0.2768	0.0402
BHBI	0.2132	0.1127	0.1839	0.2251	0.1440
BMSI	0.4019	0.2250	0.2477	0.3169	0.0856
BTI	0.1896	0.0869	0.1596	0.1941	0.0900
CHF	0.1833	0.0576	0.1485	0.1812	0.0690
CCA	0.1552	0.0572	0.0922	0.1407	0.0491
CDSB	-0.1385	-0.0727	-0.1266	-0.1362	0.0283
CEM	0.0975	0.0373	0.0757	0.0951	-0.0679
CEMN	0.0368	0.0301	0.0350	0.0338	0.0224
CED	0.2052	0.0677	0.1459	0.1877	0.0064
CEDD	0.2467	0.0859	0.1701	0.2161	0.0479
CEDMS	0.1759	0.0567	0.1301	0.1664	0.0548
CEDRA	0.1569	0.0595	0.1239	0.1524	0.0427
CFIA	0.0876	0.0213	0.0528	0.0799	0.0417
CGM	0.2342	0.0935	0.2078	0.2314	0.0144
CLSE	0.1668	0.0572	0.1423	0.1664	0.0668
CMF	0.0599	0.0314	0.0594	0.0600	0.0493
CMS	0.2802	0.0821	0.1857	0.2450	0.0266
MSCI WI	0.0310	0.0113	0.0275	0.0309	0.0582
S&P500	0.0944	0.0371	0.0876	0.0938	0.0087

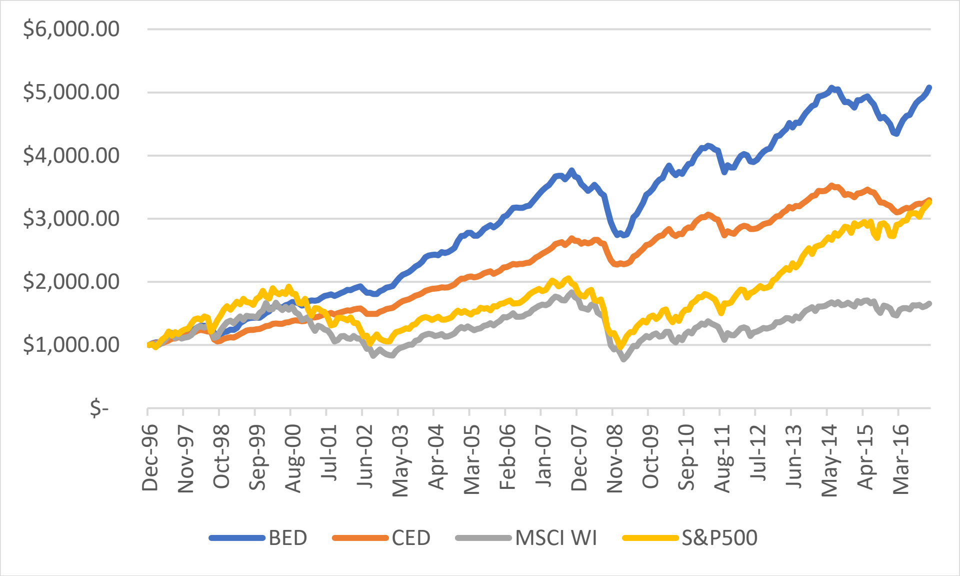
Appendix 11 : Comparison between Equity Oriented Strategies and Benchmarks

* This figure shows the value of different portfolio in 2016 for an investment of $ 1000 in 1997. BEOS represents the Barclay Equity Oriented Strategies which is an average of the EO' substrategies. CEOS represents the same concept for Credit Suisse.



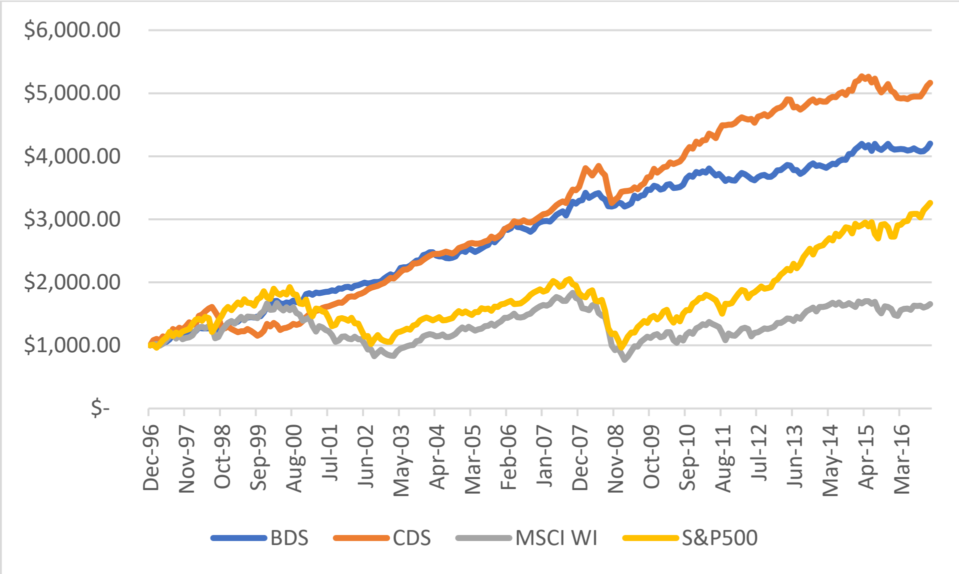
Appendix 12: Comparison between Event Driven Strategies and Benchmarks

* This figure shows the value of different portfolio in 2016 for an investmentf $ 1000 in 1997. BED represents the Barclay Event Driven Strategies which is an average of the ED' substrategies. CED represents the same concept for Credit Suisse.



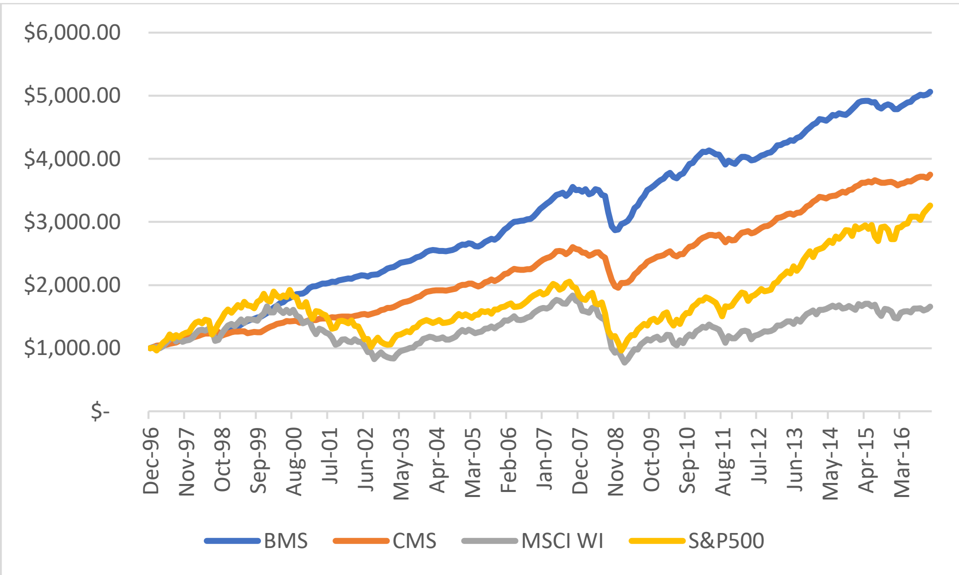
Appendix 13: Comparison between Directional Strategies and Benchmarks

* This figure shows the value of different portfolio in 2016 for an investment of $ 1000 in 1997. BDS represents the Barclay Directional Strategies which is an average of the DS' substrategies. CDS represents the same concept for Credit Suisse.



Appendix 14: Comparison between Multi Strategy Strategies and Benchmarks

* This figure shows the value of different portfolio in 2016 for an investment of $ 1000 in 1997. BMS represents the Barclay Multi Strategy Strategies which is an average of the MS' substrategies. CMS represents the same concept for Credit Suisse.



Appendix 15: VaR 99% - 1 month

*For the 4 portfolios including hedge funds' indices, the benchmark portfolio and the S&P500

	VaR 99% 1 month		
	Gaussian	*Historical*	*modified*
S&P500	0.0913	0.1114	0.1261
Benchmark Portfolio	0.0779	0.0964	0.1420
Portfolio 1	0.0736	0.0912	0.1369
Portfolio 2	0.0725	0.0888	0.1358
Portfolio 3	0.0739	0.0915	0.1385
Portfolio 4	0.0731	0.0895	0.1390

Appendix 16: CVaR 99% - 1 month

	ES 99% 1 month		
	Gaussian	*Historical*	*modified*
S&P500	0.1054	0.1471	0.1552
Benchmark Portfolio	0.0898	0.1516	0.1420
Portfolio 1	0.0849	0.1448	0.1369
Portfolio 2	0.0836	0.1435	0.1358
Portfolio 3	0.0853	0.1458	0.1385
Portfolio 4	0.0844	0.1455	0.1390

Appendix 17: CAPM

* Results associated to the CAPM for the 4 portfolios including hedge funds' index and the benchmark portfolio

	Alpha	*Beta*	*R-squared*	*Annualized Alpha*	*Correlation*	*Tracking Error*	*Information Ratio*	*Treynor Ratio*
S&P500 Benchmark Portfolio	-0.0007	0.7537	0.8017	-0.0086	0.8954	0.0650	-0.3042	0.0329
Portfolio 1	-0.0005	0.7035	0.7789	-0.0065	0.8826	0.0692	-0.2830	0.0355
Portfolio 2	-0.0004	0.6999	0.7920	-0.0048	0.8899	0.0678	-0.2644	0.0381
Portfolio 3	-0.0004	0.7066	0.7775	-0.0054	0.8818	0.0693	-0.2646	0.0371
Portfolio 4	-0.0002	0.7060	0.7880	-0.0026	0.8877	0.0680	-0.2265	0.0413

Appendix 18: Modified Sharpe ratio - 99% 1 month

	SD	*VaR*	*CVaR*
S&P500	0.1081	0.0358	0.0291
Benchmark Portfolio	0.0763	0.0189	0.0189
Portfolio 1	0.0790	0.0192	0.0192
Portfolio 2	0.0838	0.0203	0.0203
Portfolio 3	0.0818	0.0198	0.0198
Portfolio 4	0.0893	0.0214	0.0214

Appendix 19 : Performance Measurements

	Worst Drawdown	*Information Ratio*	*Omega*	*Sortino ratio*	*Upside potential ratio*	*Sterling ratio*	*Calmar ratio*
S&P500	0.5301	x	1.3332	0.1492	0.5897	0.0905	0.1076
Benchmark Portfolio	0.5062	-0.3042	1.2393	0.1007	0.5411	0.0615	0.0736
Portfolio 1	0.4848	-0.2830	1.2492	0.1042	0.5416	0.0640	0.0772
Portfolio 2	0.4776	-0.2644	1.2649	0.1104	0.5290	0.0677	0.0819
Portfolio 3	0.4913	-0.2646	1.2598	0.1077	0.5244	0.0654	0.0788
Portfolio 4	0.4907	-0.2265	1.2860	0.1174	0.5128	0.0705	0.0848

Appendix 20: Portfolios' returns distribution

	Benchmark portfolio	Portfolio 1	Portfolio 2	Portfolio 3	Portfolio 4
Skewness	-1.4714	-1.5302	-1.5661	-1.5611	-1.6289
Kurtosis	6.8745	7.3177	7.5084	7.4976	7.8671
Bera-Jarque test	177.5380	210.0628	226.0261	224.8248	257.2594

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