Universidad Rey Juan Carlos

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TESIS DOCTORAL

ANALYSIS OF HEDGE FUNDS, RISK MEASURES AND PORTFOLIO CONSTRUCTION

Doctorando

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RESUMEN

El propósito de los agentes financieros, en una economía de libre mercado, es captar el excedente de ahorro de los agentes con superávit y canalizarlo hacia actividades productivas deficitarias de recursos, maximizando la utilidad de la inversión.

El hecho de que cada individuo tenga una función de utilidad diferente repercute directamente en las decisiones de ahorro y de inversión cuando se enfrenta a la incertidumbre. Esta situación ha favorecido la evolución de los mercados financieros y la búsqueda de alternativas para la asignación de recursos, segregando riesgos. Las matemáticas nos han brindado formas cada vez más eficientes de entender estos riesgos. Hemos racionalizado la relación rentabilidad/riesgo, demandando mayores niveles de rentabilidad por la asunción de mayores riesgos. En este sentido la teoría de selección de carteras desarrollada por Markowitz (1952) supuso la piedra angular para poder describir con términos matemáticos este proceso.

El desarrollo de nuevos mercados continúa, hoy en día, persiguiendo el objetivo de optimizar la asignación de recursos. Términos como *shadow banking, private equity, crowdfunding, MAB, MARF, etc*. proporcionan y abren nuevas alternativas para la canalización de recursos.

En este contexto, no es sorprendente que la industria de las *inversiones alternativas* – activos diferentes a las acciones, bonos o liquidez – haya tenido un desarrollo vertiginoso en las últimas décadas. Un actor importante dentro de esta industria alternativa son los *hedge funds*, aunque, como explicaremos en esta tesis, no haya una definición precisa ni consenso de a qué nos referimos cuando hablamos de *hegde funds*. No obstante, características como; fondo no regulado, flexibilidad de inversión, posibilidad de utilizar todo tipo de instrumentos financieros y capacidad de apalancarse, son utilizadas comúnmente para describirles. La importancia de esta industria en el contexto de los mercados financieros internacionales es significativa y creciente.

Durante los primeros años de su creación los inversores se vieron hechizados por las elevadas rentabilidades generadas por estos fondos, altamente apalancados pero aparentemente con un bajísimo nivel de riesgo. La quiebra de Long Term Capital (1998) y el posterior rescate multimillonario coordinado por la FED para salvar a los mayores bancos de inversión, supuso el despertar a la realidad sobre esta incipiente industria.

La medición de la relación rentabilidad / riesgo en esta industria debía de ser analizada con modelos y tecnología diferentes a los usados para los activos financieros tradicionales.

Numerosos investigadores propusieron nuevas aproximaciones y modelos de medición de riesgos.

En paralelo, la industria aceleró su crecimiento con tasas anuales superiores al 25%. Los bancos de inversión vieron como los *hedge funds* proporcionaban una contribución cada vez mayor a sus cuentas de resultados y, protegieron, alentaron e incentivaron el desarrollo de la industria de los *hedge funds*.

Uno de los grandes argumentos esgrimidos a favor de esta industria, y de su crecimiento, es que el bajo nivel de correlación de sus rendimientos con respecto a los generados por activos tradicionales permite optimizar las carteras de inversión, por lo tanto, contribuir a una más eficiente asignación de recursos.

Legislaciones proclives hacia la banca de inversión favorecieron el entorno regulatorio para la creación de estos fondos. Mientras que otras legislaciones limitaron su creación y distribución en sus territorios.

Los estudios que abalan y apoyan esta industria se basan en que contribuye a dotar de mayor liquidez a los mercados financieros, y por tanto reducen su volatilidad. Los opositores defienden justamente lo contrario, argumentando que algunos mercados están saturados por *hedge funds*. Por lo tanto, sus decisiones de inversión, y particularmente desinversión, generan efecto contagio incrementando la volatilidad. Adicionalmente, el escaso nivel de regulación al que están sujetos estos fondos favorece situaciones de fraude, siendo quizás el caso de Madoff uno de los más famosos y recientes dentro de una larga lista.

Esta tesis pretende abogar por un estudio en profundidad de esta industria. Cualquier valoración tiene que estar íntimamente ligada a entender e identificar correctamente los riesgos asumidos.

Por ello, analizamos las diferencias a considerar entre analizar una inversión en *hedge funds* con respecto a la tipología de activos tradicionales. El estudio de los riesgos asumidos y cómo modelizarlos será una de las partes centrales de nuestro análisis. Esencial para incorporar correctamente este activo en los modelos de gestión de carteras. De esta forma, podremos demandar una rentabilidad acorde con el riesgo asumido y mejorar la eficiencia en la asignación de recursos.

Así mismo, propondremos una forma alternativa de replicar e identificar los riesgos asumidos mediante simples estrategias de derivados financieros. Los resultados obtenidos muestran como estos fondos asumen exposiciones a factores de riesgos diferentes a los tradicionales, pero como su correlación aumenta en situaciones de incremento de volatilidad, proporcionando escaso nivel de diversificación en los momentos que más se necesita.

Las distribuciones de los rendimientos que obtenemos mediante las estrategias propuestas – más eficientes y con similares niveles de rentabilidad absoluta - nos indican que estos fondos no obtienen rentabilidades superiores al mercado por el nivel de riesgo asumido, y por consiguiente nos lleva a cuestionar la justificación del elevado nivel de comisiones actualmente pagadas en la industria.

Posiblemente, un mejor entendimiento por parte de los inversores de los riesgos asumidos lleve a demandar una rentabilidad más adecuada en la inversión, reducir los niveles de comisiones y buscar un modelo de retribución más eficientes y menos asimétrico, desalentando así a los gestores de la toma de decisiones poco eficientes que contribuyen a aumentar el riesgo de su inversión, como el apalancamiento excesivo. Lo que a nuestro entender, repercutiría en una asignación más eficiente de recursos, contribuyendo a dotar de mayor liquidez a los mercados financieros, a completarlos, pero reduciendo de forma significativa su contribución a posibles incrementos de volatilidad en situaciones de stress.

ANTECEDENTES

Los antecedentes de la primera parte de esta tesis se basan en la Teoría de Selección de Carteras (TSC) de Markowitz (1952), posteriormente desarrollada por Edwin, Martin, Stephen y William (2003). Esta teoría nos permite ilustrar la búsqueda de activos no correlacionados como forma de optimizar las estrategias de inversión. Así mismo, introducen el concepto "*riesgo*", medido como la desviación estándar de los rendimientos, y su relación con el rendimiento esperado.

La Ley de los Grandes Números (LGN) y el Teorema Central del Límite (TCL) desarrollado por Laplace y DeMoivre justifican matemáticamente la robustez de TSC. No obstante, siguiendo planteamientos como los desarrollados por Berg y Van Rensburg (2007), Cvitani, Agarwal y Naik, Amenc (2003) o Amin y Kat (2003), demostramos la no idoneidad de estas teorías aplicadas a los *hedge funds* como alternativa de inversión. Este análisis lo completamos con un nuestro propio desarrollo que aboga por considerar la correlación como una variable estocástica dependiente del riesgo de la inversión y del mercado. Consecuentemente el análisis del riesgo se convierte en una de las piedras angulares a estudiar.

Dedicamos un capítulo de la tesis al análisis del riesgo. Comenzamos desarrollando los modelos de Sharpe y Sortino como introducción metodológica. Posteriormente pasamos a estudiar modelos más avanzados y apropiados, como la ratio Omega desarrollado por Keating y Shadwick (2002), aplicables a las inversiones en *hedge funds* al no tener que hacer asumpciones sobre las distribuciones de los rendimientos. De forma similar desarrollamos la explicación del concepto VAR como medida de riesgo y desarrollamos el modelo cuadrático (modelo delta-gamma) que a través de la expansión de Cornish Fisher permite estimar percentiles de una distribución usando los cuatro momentos básicos de una distribución, lo que permite tener en consideración la Skew negativa y el exceso de Kurtosis que presentan las distribuciones de rendimientos de *hedge funds*.

Modelos como los desarrollados por Kat y Miffre (2006), Agarwal y Naik (2000) o Mitchell y Pulvino (2001) establecen alternativas para replicar la no normalidad de los rendimientos de los *hedge funds* mediante modelos multifactoriales y opciones financieras compuestas. Nosotros desarrollamos nuestro propio modelo, Camarero y Pascual (2013), que nos permite mediante la calibración de estrategias en opciones financieras de primera generación replicar rendimientos absolutos y conseguir distribuciones de rendimientos más eficientes a las obtenidas por los *hedge funds*. Un posterior desarrollo de nuestros modelos nos permite identificar los diferentes factores de riesgos asumidos en cada estrategia de inversión, introduciendo así una nueva metodología para medir y cuantificar el riesgo de estas inversiones.

Consecuencia natural de los avances en el análisis y cuantificación de los riesgos en las inversiones en *hedge funds*, y en vista de los resultados obtenidos en nuestros modelos, corroboramos las conclusiones de los estudios realizados por Fung, Hsieh, Naik y Ramadorai (2006) o Kat y Miffre (2006) donde cuestionan la capacidad de los *hedge funds* de obtener rendimientos superiores para el nivel de riesgo asumido. Teorías que supusieron una ruptura con estudios anteriores realizados en este campo.

No obstante, la sencillez y robustez de nuestra aproximación nos lleva a cuestionar la justificación del actual sistema de retribución de la industria que, como señalan Garbaravicious y Dierick (2005) en sus estudios para el BCE, muestra una importante asimetría entre la recompensa y la pérdida, lo que concluimos incentiva a decisiones de asignación de recursos no eficientes.

OBJETIVOS

El objetivo de esta tesis es contribuir al mejor entendimiento de la industria de las inversiones alternativas y principalmente de los *hedge funds*. Este desarrollo lo realizamos con una introducción y contextualización tanto teórica como matemática. Comenzamos con un análisis estadístico y econométrico de las distribuciones de los rendimientos de las diferentes estrategias de *hedge funds*. Así mismo, estudiamos y evaluamos diferentes aproximaciones a la hora de medir el riesgo de una inversión en *hedge funds*. Posteriormente, realizamos un profundo análisis de la teoría de construcción de carteras, su base matemática y sus limitaciones a la hora de aplicarla a inversiones en *hedge funds*.

Estos desarrollos nos permiten introducir una forma alternativa, Camarero y Pascual (2013), de entender y cuantificar los riesgos asumidos en una inversión en *hedge funds*. Así mismo, conseguimos desarrollar modelos y estrategias de inversión que nos permiten replicar los rendimientos obtenidos en las diferentes estrategias de *hedge funds*. Lo que nos lleva a cuestionar la presunta superior capacidad de generar rendimientos absolutos por unidad de riesgo en estos fondos -justificación del actual sistema de remuneración de la industria-.

Como objetivo final deseamos contribuir a que tanto detractores como defensores de esta industria tengan una visión de la evolución vivida por la industria, y como los sucesivos avances que están contribuyendo a una mejor compresión de su riesgo, están incidiendo en una mayor eficiencia de esta importante industria que contribuye a completar y dotar de liquidez muchos mercados. No obstante, creemos que una mayor madurez de la industria pasará por una redefinición del actual sistema de remuneración que llevará a una mejor alineación de los intereses de los inversores y gestores, lo que repercutirá en una mejor asignación de recursos y menor generación de volatilidad o disrupciones en los mercados por parte de los *hedge funds*.

METODOLOGIA

La tesis presentada cubre diferentes campos de análisis. Primeramente se realiza un análisis estadístico y econométrico de las distribuciones generadas por las rentabilidades de las diferentes estrategias de *hedge funds* definidas.

Este análisis sirve de base para estudiar su aplicabilidad en los modelos de riesgos más comúnmente utilizados. Adicionalmente desarrollamos un profundo estudio de medidas de riesgos alternativas que permiten acomodar las peculiaridades de las distribuciones analizadas, como la ratio Omega o una aproximación al VAR cuadrático.

Los resultados previos sirven de base para el estudio de los modelos tradicionales de construcción de carteras basados en la esperanza y la varianza de las distribuciones. Analizamos las consecuencias y efectos de usar esta tecnología para asignar recursos a los *hedge funds*.

Posteriormente se proponemos un modelo alternativo para replicar la distribuciones de rentabilidades de las diferentes estrategias, para ello utilizamos derivados financieros. La construcción de las estrategias y los resultados son analizados usando los desarrollo tradicionales de la teoría de opciones propuesta por Black and Scholes. Un análisis econométrico completo es realizado de los resultados obtenidos en nuestros modelos justificando que son estadísticamente significativos y la calidad de los errores reportados.

CONCLUSIONES

El uso de los rendimientos generados por las diferentes estrategias de *hedge funds* como inputs para los modelos clásicos de construcción de carteras, basados en la teoría de Markowitz, llevan a concluir que la relación rentabilidad riesgo de estos fondos constituye una atractiva alternativa de inversión. No obstante, el modelo desarrollado por Markowitz obvia tres aspectos relevantes intrínsecos en las distribuciones de los rendimientos de los *hedge funds*: la existencia de momentos de orden superior (asimetría y exceso de curtosis), autocorrelación y el sesgo. Estas características pueden distorsionar los análisis tradicionales estadísticos sobreestimando la capacidad de generación de rendimientos y subestimando su volatilidad o riesgo implícito, lo que proporciona una imagen distorsionada sobre el verdadero atractivo de esta alternativa de inversión.

Los estudios estadísticos que hemos realizado de las series temporales generadas por los rendimientos de estos fondos, nos permiten concluir que gran parte del atractivo tradicionalmente otorgado a la inversión en *hedge funds* desparece cuando se ajusta el análisis por factores como autocorrelación, *survivorship bias* y se recoge la información implícita en las colas de las distribuciones.

No obstante, es importante entender las limitaciones de la tecnología usada. Exceso de rentabilidades obtenidas en un periodo específico pueden estar fuertemente condicionadas a la parte del ciclo económico en las que se generan. Partiendo de esta evidencia demostramos que una forma de mejorar los análisis de construcción de carteras es tratar la correlación como una variable estocástica.

Mediante la calibración de estrategias basadas en opciones financieras, poco intensivas en trading, hemos conseguido obtener rentabilidades similares y distribuciones más eficientes a las generadas por las diferentes estrategias de *hedge funds.* Estos resultados no llevan a cuestionar la capacidad de generar *alpha* – exceso de rentabilidad - de estos fondos. Nuestro análisis concluye que estas estrategias proporcionan exposición a factores de riesgo diferentes a la clase de activos tradicionales (acciones, bonos o liquidez).

La riqueza y variedad de factores de riesgo a explotar hace que la industria de los *hedge funds* contribuya de forma significativa a integrar y completar los mercados financieros, aunque muchas veces las decisiones de inversión son altamente consensuadas en el mercado. Estas afirmaciones deben ser contextualizadas por el riesgo asumido por estos fondos, generalmente con alto apalancamiento, en situaciones de reducción de liquidez en los mercados. En nuestros estudios demostramos que la correlación en los mercados depende de factores como la volatilidad. La consecuencia es que en periodos de incremento de volatilidad, las decisiones de inversión asumidas por los *hedge* *funds* - a excepción de las *contrarias* – tendrán un comportamiento similar al resto del mercado, no proporcionando diversificación y siendo penalizadas por la dificultad de deshacer las operaciones en periodos de baja liquidez.

Las estrategias que hemos desarrollado con nuestros modelos consiguen generar rentabilidades superiores a las proporcionadas por los *hedge funds,* en una situación de menores comisiones. Lo que nos lleva a cuestionar la justificación de las políticas de remuneración actualmente vigente en la industria, que adicionalmente presentan una importante asimetría que favorece la toma de riesgos excesivos. Lo que a su vez contribuye a una no eficiente asignación de recursos, disminuyendo anormalmente la volatilidad del mercado en ciertos momentos y amplificándolos en situaciones de crisis.

Todo lo anteriormente expuesto nos lleva a concluir que es necesario continuar mejorando el sistema retributivo de esta industria para incentivar una mejor y más eficientes asignación de recursos.

ACKNOWLEDGEMENTS

After completing my undergraduate degree in Business, Administration and Economics, I was satisfied. I did what was expected of me. Soon I started to work at the investment branch of a national bank. I had none idea what my job would be like, but I was on the verge of working in the “special situation team”, a cool name for a back office job. Nonetheless, it was the first step for me to wake up to reality, a university degree could not be more than a small step, the need to study a post graduate degree ignited.

I moved companies and in the meantime, I prepared for licenses and exams to try to move to London. Two years later, I was working as a trader for a hedge fund in the City. The willingness to learn was becoming stronger by the day.

My first idea was to study a MBA, but a new world of financial derivatives and models were starting to open in front of my eyes. I looked with envy at people with an engineering or mathematical background. They knew how to program computers, they knew a language that I could not understand.

The goal was clear. I needed to learn mathematics. During two and half years I completed a Msc. in Mathematics in the Cass Business School (City University). Learning passed from be a healthy curiosity to an obsession and a

passion. I could not wait to download a new paper, to study a new book or new research, to use the new language that I was learning.

After completing my Msc., during the following years, I moved jobs. I occupied several positions in a couple of investment banks. The objective was to always look for where I could learn more, regardless of titles or remuneration. I could never thank my parents and Maite enough for the support that they provided me during those years.

Several years later I came back to Spain. I decided to slow down and promised myself to work for a company longer than I had done before. I refused several offers from important Spanish banks. However, I needed more, I needed to share what I had learned and what I was learning.

Joaquín López Pascual provided me the opportunity to work at CUNEF, and he gave me the immense responsibility to contribute, not only in the teaching process, but to the education of CUNEF students.

Joaquín López Pascual encouraged me to continue with my training. He became a reference and a guide for me. I have to thank him for the trust and the continuous support that he has provided me during the last few years. He assumed the role of my professor and thesis director. We started with a new Msc., Master en Asesoramiento y Planificación Financiera as a requisite for the Ph.D. objective, we published papers and we continued our research with this thesis.

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Today, I am satisfied, I know that this is just one step more.

> *Todo lo importante que he aprendido en mi vida lo puedo resumir en tres frases; cuanto más compartes más tienes, ser humilde es el único camino que nos permite aprender y cuanto más amas más grande haces tu vida.*
>
> (Santiago Camarero 2014)

INTRODUCTION

This thesis attempts to contribute to a better understanding of the alternative investment industry and particularly to the hedge fund world. The term hedge fund is very lose and there is not a universally accepted definition. However, we will look for sharing characteristics as non-regulated funds, investment flexibility and leverage capacity in order to identify these funds.

The hedge fund industry has been loved and hated at the same time, using the same set of arguments with opposite conclusions. Supporters of the hedge fund industry argue that they help to complete the market providing a significant amount of liquidity that helps to reduce market volatility. Detractors say that their crowed behavior and the excessive risk assumed by these investors lead to unreasonable valuations and maximize positive or negative market moves, therefore increasing market volatility and don’t contribute to the efficient allocation of resources.

Our studies try to reconcile both views providing alternative and new approaches for studying the inherent risks of these investments. We published a summary of these studies at *Funds People magazine, June 2013*. This was the groundwork in a set of studies that we performed, aimed to design financial models able to replicate indexes hedge fund returns distributions. Studies that concluded with the publication in the *Revista Española de Financiación y*

Contabilidad (REFC) of our paper "Analysing hedge fund strategies through the use of an option based approach" (2013).

The sequence of the studies pursued, at first, to identify risk factors and to understand the risk assumed by the different hedge fund strategies. These results enable us to calibrate the correct exposure and to replicate index return distribution through simple financial derivatives strategies. The final results showed that for most of the strategies we are able to achieve superior returns when not adjusted by fees and provide more efficient return distributions. Diminishing problems, as the serial correlation of the returns which, as we argue in the following sections, raised serious questions regarding the possible smoothing returns policy applied by some managers in order to reduce the volatility of the returns.

Under our view, our research opens a new angle of study to a new inception question; **are hedge fund fees justified by the superior risk adjusted returns?**

We think that a negative answer to this question could change the hedge fund landscape in the future. Our studies convey that the fees charged in this industry are not justified by the generation of superior risk adjusted return. This conclusion is not trivial because under our view, an asymmetric and "excessive" fee by the risk assumed leads to the assumption of disproportionate risks, as for example too much leverage, therefore contributing to a non-efficient allocation of resources and increasing market volatility.

We conclude that a new fee structure model is needed in the hedge fund industry in order to support their role as efficient resource allocators, providers of liquidity and contributors to the market completeness trough the exploitation of different investment opportunities not targeted by other market players.

This study does not cover how to set this new fee structure model but we look forward to continuing with our investigation and research.

This thesis is organized as follows: First, after this introduction we start with the first chapter that provides a general overview of the hedge fund concept and the hedge fund industry. The second chapter is devoted to understanding the key characteristics of the hedge funds. This allows us to introduce the hedge fund industry evolution and to contextualize the growth and the progress seen during the last decade.

Chapter three provides a further in depth revision of the hedge funds classifying them according to their investment strategies. In this direction, the work and analysis performed by data vendors in order to build hedge funds indexes is key for our later analysis. Therefore we study how these data vendors built these indexes and provided an analysis of the challenges and limitations found. Characteristics as the *survivorship bias* condition any analysis based on indexes data.

In chapter four we study the statistical properties of the different hedge fund strategy return distributions. We also analyse the different risk measures traditionally used and the evolution seen in this field during the last years, as the development of the concept of the *Omega function*. We study the limitations and the implications of applying each different risk measures to hedge funds, showing how traditional models tend to underestimate the true risk assumed, due to the non normality and serial correlation of the return distributions.

In chapter five, we discuss the implication that the previous analysis has on the portfolio construction using traditional models, as the Capital Asset Pricing Model (CAPM) based on a mean variance approach. We also discuss in detail the Central Limit Theorem (CLT) as a mathematical background for any mean variance model. We show how the non-stationary of the mean and standard deviation, and the non independency of the processes generating the returns unable the use of the CLT for hedge fund returns, where a significant amount of information is embedded in the tails of the distributions. The results obtained prove that hedge funds lose a large part of their attractiveness when considering the combined effects of fat tails, autocorrelation and survivorship bias. Furthermore, their status of being considered return enhancers during bear markets as standalone assets and, as risk diversifiers in a portfolio context due to their alleged low correlation with stocks and bonds is being questioned.

In chapter six, we propose an option based approach for replicating hedge fund return distribution. We show how we are able to replicate more efficient return distributions with a low intensive trading approach. This technology allows us to identify the different risk factors exposed in each different hedge fund strategy and to manage and control the risks with financial option technology. Nonetheless, the superior robustness of the return distributions achieved with our option model, challenge the ideas that hedge funds achieve superior risk adjusted returns and therefore the justification of their current fee structure.

CHAPTER I

1. GENERAL OVERVIEW

1.1. Approximation to the hedge fund concept

There is no universally accepted definition of *hedge fund*. However, the common characteristics of the term hedge fund are; private investment fund that invest in a wide range of assets and employs a great variety of investment strategies. Due to their nature hedge funds have almost no restrictions in the use of derivatives, leverage or short-selling. This combination, of capacity, instruments and flexibility in their investment decisions, creates a significant difference with respect to the more regulated, mutual funds. Also, the combination of these resources has allowed hedge fund to exploit new market opportunities creating a new set of investment strategies.

Typically, the fees of fund managers are related to the performance of the fund in question and managers often commit their own money. Although they typically target high net worth individuals and institutional investors, their products have recently become increasingly available to retail investors due to the development of funds investing in hedge funds and structured financial instruments with hedge fund-linked performance. Hedge funds are primarily domiciled in offshore centres because of the ensuing light regulatory treatment and favourable tax regimes. A multitude of parties are involved in the operation of such funds: managers, administrators, custodian banks, prime brokers, investors, etc.

Since the late 1980s, the number of hedge funds has risen by more than 25% per year. The value of assets under management has grown as well. In 1990, $39 billion was invested in hedge funds. In 2003, the estimated figure was $700 billion. As of June 2013, the estimated size of the global hedge fund industry was US$2.4 trillion, managed by 5,000 single-manager hedge funds (*source Tremont Company*). Nonetheless, their active role in financial markets means that they are much more important than suggested by their size alone.

1.2. *Investment strategies*

There is also no consensus regarding the number of investment strategies used by hedge funds. Although the investment strategy, by definition, varies widely, hedge funds can be broadly classified as directional (positive or negative Beta), market neutral (zero Beta) or event driven funds (oportunistic Beta).

As finance technology evolves the set of investment assets is constantly increasing, therefore new investment strategies are continually developing to exploit market opportunities. Even hedge funds that invest in the same asset class might deploy their strategies taking exposure to different risk factors. For example a hedge fund investing in convertible bonds could be aiming to get equity, credit, volatility, liquidity, interest rate exposure, or a combination of several of them. The exposure to each of these factors could be exploited through different investment strategies. Therefore, it is important to note that different investment strategies provide a different degree of return and risk.

1.3. The Capital Asset Pricing Model

The CAPM (Capital Asset Pricing Model) assumes that the risk-return profile of a portfolio can be optimized, in other words, an optimal portfolio displays the lowest possible level of risk for its level of return. The risk of a portfolio comprises systematic risk, also known as undiversifiable risk, and unsystematic risk which is also known as idiosyncratic risk or diversifiable risk.

Unsystematic risk can be diversified away to smaller levels by including a greater number of assets in the portfolio. However the investor´s goal is not only to reduce risk, it is also to maximize returns. Therefore the inclusion of new assets will be assessed as a function of its contribution to the portfolio risk-return. The optimal combination of assets weight will lead to the efficient frontier.

As we will show in this work, the search for uncorrelated returns, in order to reduce the unsystematic portfolio risk under CAPM assumption, have lead the growth of the *alternative investment industry*. The common characteristics of the players in this industry is that invest in assets or take exposure to risk factors outside of the three “traditional asset types” (stocks, bonds and cash). This departure from the traditional assets class is not trivial, we will show that each specific asset class have characteristics that might require departures from the traditional CAPM model in order to asses correctly the optimal risk return portfolio.

The traditional CAPM approach is not prepared to cope with negative skewness, excess kurtosis or serial correlation on the assets return. Not to account for these statistical properties leads systematically to over/under invest on the wrong asset class due to a mislead assessment of the assumed risk. In other words, to demand lower return for the true embedded risk.

1.4. Historical return analysis

The historical return analysis provides an important source of information for evaluating and understanding hedge funds investment styles.

Through explicit or implicit analysis we can try to explain the funds performances and to classify investment styles.

- *Explicit analysis*. The aim is to identify and measure the sensitivity of real factors that explain the historical returns. An example could be to model the returns as a linear function of various macro-economic factors or indexes.

- *Implicit analysis*. The idea is to identify certain statistical factors that explain the historical returns. One of the most used methods is the principal component analysis (PCA). The PCA ranks explanatory factors with the highest possible variance with the constraint that each one has to be orthogonal to the previous components.

In addition, comparing the time series returns of a hedge fund against the returns of its peer group will allow us to assess the investment skills of the manager.

CHAPTER II

2. HEDGE FUND HISTORY AND KEY CHARACTERISTICS

2.1. *Hedge fund definition*

There is no a universally accepted definition of *hedge fund*. However, the common characteristics of the term hedge fund are; private investment fund that invest in a wide range of assets and employs a great variety of investment strategies. Due to their nature hedge funds have almost no restrictions in the use of derivatives, leverage or short-selling. This combination, of capacity, instruments and flexibility in their investment decisions, creates a significant difference with respect to the more regulated, mutual funds.

Also, the combination of these resources has allowed hedge fund to exploit new market opportunities creating a new set of investment strategies.

This definition is in line with statements stated by other researchers.

The US President's Working Group on Financial Markets (1999) characterized such entities as "*any pooled investment vehicle that is privately organized, administered by professional investment managers, and not widely available to the public"*.

Garbaravicius and Dierick, (2005) stated "*There is no common definition of what constitutes a Hedge Fund; it can be described as an unregulated or loosely regulated fund which can freely use various active investment strategies to achieve positive absolute returns*". As they stated hedge funds have a role as providers of diversification and liquidity, and they contribute to the integration and completeness of financial markets. As active market participants they often take contrarian positions, thus contributing to market liquidity, dampening market volatility and acting as a counterbalance to market herding. In addition, they offer diversification possibilities and allow new risk-return combinations to be achieved, leading to more complete financial markets. It can also be argued that by eliminating market inefficiencies hedge funds have probably contributed to the integration of financial markets.

This assessment is challenged from some regulators as the ECB and FED that state that under normal conditions, hedge funds contribute to the liquidity and efficient functioning of financial markets, however, in certain cases, especially in small or medium sized markets, their actions can be destabilizing. They argued that since 2001, hedge fund returns have become less widely dispersed, which could be a broad indication that hedge fund positioning is becoming increasingly similar, Rising correlations could be a sign that hedge fund managers are employing models that are too similar and are no longer creating true alpha – or excess returns – that are uncorrelated with other managers within the same strategy, even though they may still outperform other types of investments.

These findings are in line with the conclusions reached in the chapter 6 of this dissertation, where we challenge the idea that the hedge fund industry is able to generate alpha. Our findings establish that hedge funds are proving exposure to risk factors different to the traditional assets classes - equity, bonds and cash – however, we differ in the conclusion. To reach different assets classes reaches the investment spectrum and contribute very decisively to the integration and completeness of financial market

2.2. Common characteristics of hedge funds

Due to the broad and loose definition given to the term hedge fund, it is not always easy to identified investment vehicles that can be branded under this term. Nonetheless, we can try to provide some characteristics shared for most of these funds.

- *Hedging the risk*. The first point to take in consideration is that nowadays *hedge fund* control the risks factors that they want to be exposed to, applying various sophisticated investment techniques, which exceed the classic concept of “hedging out” the risk. The use of complex derivatives is common between a large numbers of hedge funds. As we will show in next sections, the hedging performed by hedge funds usually leads to take exposure to a set of different risk factors. Therefore the term "hedge" creates a miss conception of the real risk assumed by the hedge fund.

- *Return adjusted to risk objective*: Hedge funds main objective is to produce positive absolute returns, however in nowadays it is more frequent to link the absolute return objective to a maximum level of risk, usually expressed as VAR figure o maximum withdraw.

- *Investment strategies:* It is not possible to enclose hedge funds under a set of predefined strategies technique. New products and instruments open the door to a continuous innovation in this front. A group of hedge fund investing in the same underlying could be deploying a huge number of different strategies. For instance, a convertible bond investor could be trying to benefit from equity appreciation, increase of volatility, gamma scalping, credit spread compression, pure carry trade, capital structure arbitrage, relative value, etc.

- *Incentive structure and life expectancy:* Hedge funds typically usually charge 1-2% management fee and up to 20% performance fee, and the average lifespan of a hedge fund is around 3.5 years (Koh, Lee and Phoon, 2001). Performance fees are typically asymmetric, as they reward positive absolute returns without a corresponding penalty for negative returns. However, in instances where managers commit their own money, the preservation of capital is very important and the motivation to take excessive risks is to some extent curtailed.

Nonetheless, the pressure experienced, in each day a more competitive industry, is driven a fee reduction, particularly for new comers. Additionally, it is common the use of high *water marks* [1]and *hurdle rates*[2] as part of the incentive program.

We will show empirically in this paper that under our view, this general industry fee structure is not justified with the level of achieved returns. We will show that most of the managers are trackers of specific risk factors outside of the traditional asset classes, not showing superior capacity for generating alpha. Through a low intensive trading approach, and low fee, we show how to replicate these investments, achieving more efficient time series returns and with lower fee (Camarero y López, 2013).

- *Subscription:* Many successful hedge funds have subscription restrictions and the hedge fund managers can discriminate who will invest in their funds. It is also common to have different investors categories where the latest investors support higher fees and/or a significant worsen of the withdrawal conditions.

1 A *watermark* is a fund valuation below which performance fees are not paid. With a high watermark, performance (incentive) fees are paid only if cumulative performance recovers any past shortfalls. Therefore, a hedge fund manager who loses in the first year and then merely regains that loss in the second year will not receive an incentive payment for the second year's gain.
2 The *hurdle rate* is the minimum return that must be generated before fund managers may receive any performance allocation.

- *Withdrawal:* Many hedge funds play with maturity mismatch between assets and liabilities therefore is common the use of lock up periods and maximum amount withdraw in each redemption window. As we will saw later on part of the extra returns provided from many hedge funds come because they are liquidity providers in illiquid markets.

- *Regulation:* Hedge funds are loosely or not regulated depending on their onshore or offshore residence. It is very difficult to regulate hedge funds directly given the ease with which they can change their domicile and avoid regulation. Therefore regulators are increasingly focusing on indirect regulation which targets the counterparties of hedge funds, in particular banks. Such indirect regulation aims at enhancing risk management practices in banks and improving disclosure by hedge funds.

- *Disclosure:* Hedge funds do not have any formal obligation of public disclosure, they adhere to voluntary disclosure to investors or same data vendors.

- *Domicile:* Hedge funds can be domiciled in onshore or offshore locations. Around half of the number of hedge funds was registered offshore at the end of 2007 according to IFSL Research 2008. The most popular offshore location has been the Cayman Islands (57% of offshore funds), followed by British Virgin Islands (16%) and Bermuda (11%). The

US was the most popular onshore location, accounting for nearly two-thirds of the number of onshore funds, with European countries accounting for most of the remainder. The funds domiciled in the EU and/or with managers residing in the EU, are mainly established in Luxembourg and Ireland and their managers are generally based in London.

2.3. Key differences between hedge funds and mutual funds

It is also important to highlight some of the most important differences between hedge funds and mutual funds. We consider the following as the most obvious ones:

- *The degree of regulation*. Whereas mutual funds are required to adhere to strict financial regulations, including the types and levels of risks, the hedge funds are free to pursue practically any investment strategy with any level of risk.

- *The fund portfolio composition and leverage*. The majority of mutual funds are composed of equities and bonds with little or no leverage at all, whereas hedge fund portfolio usually uses leverage and compositions are far more varied, with possibly a significant weighting in non-equity and non-bond assets such as derivatives. Hedge funds obtain leverage in a number of ways, but they typically prefer derivatives and other arrangements where positions are established by posting margins rather than the full face value of a position. Repurchase agreements and short sales are also quite popular techniques. Direct credit in the form of loans is rather uncommon, but credit lines for liquidity purposes are widely used.

- *The historical return characteristics and distribution* of hedge funds tend to differ significantly from these of traditional asset classes. It will be shown in the section 4 that unlike mutual funds, hedge funds returns are not normally distributed; they tend to exhibit not only fat tails but also serial correlation and are subject to various biases.

2.4. The first hedge fund

It is generally reported that A. W. Jones set up the first hedge fund in 1949, although some researchers argue that other managers set up earlier structures that should have received this denomination.

Nonetheless, Jones structured his fund as a limited partnership with fewer than 99 investors to avoid the regulatory requirements of the US Investment Company Act of 1940. He stipulated that the general partner or fund manager would take 20% of the profits as compensation. His investment approach involved using leverage to increase the fund exposure and to magnify returns while at the same time using short selling of stocks to reduce market risk. His aim was to hedge out market risk by taking as many short as long positions so that his fund was market neutral. In other words, returns would depend not on whether the stock market went up or down in a specific period, but rather on whether he picked the right stocks.

In its early years, the hedge fund industry remained relatively small and attracted little publicity. But the number of hedge funds, and the total assets under management, began to increase significantly during the 1990s. The rate of growth has accelerated considerably in the last few years.

We find several reasons that can help us to explain this growth:

- The attractiveness of the hedge fund remuneration structure has been a big incentive for setting up this type of funds.

- Favorable regulation

- Positive publicity. The industry moves billions of dollars and constitute an important source of income for the big investment banks who have a big incentive to support this industry. Nonetheless, as we explain in section six our findings question if it is justified the current fee structure for this industry due to the absence of capacity to generate extra returns in a consistent basis.

2.5. *Hedge fund industry evolution*

The hedge fund industry has experienced significant growth over the last 2 decades for a number of reasons. Firstly, these type of funds have received a positive publicity in the mass media, despite few notorious cases of failure or fraud, as it was the case of Long-Term Capital management (LTCM), George Soros' Quantum Fund, Julian Robertson's Tiger Management fund and more recently Bernard L. Madoff Investment Securities LLC's fraud case, the hedge funds in general have been able to convince the investment community that they can live up to the expectations to deliver absolute returns. This alleged ability to generate superior returns, and thus *alpha*, due to their unique dynamic trading strategies, the low correlation with returns on bonds and equities, and the perceived beneficial diversification effect to traditional portfolios has led to significant cash inflows in the last years from institutional investors into hedge funds.

With no doubt, the most popular failure was the default of LTCM in September 1998, that force to the Federal Reserve Bank of New York organized a bailout of $3.6 billion by the major creditors to avoid a wider collapse in the financial markets.. Its fall-out on world financial markets brought hedge funds to the attention of the global financial community.

LTCM was founded in early 1994 as a Delaware limited liability partnership, and its main fund, Long-Term Capital Portfolio, was domiciled in the Cayman

Islands. Many prominent names from Wall Street and academia were present among its principals and investors, including Nobel Prize laureate Myron Scholes. At the beginning of 1998, LTCM managed approximately $4.8 billion. Their market positions were supported by extremely high leverage, with balance sheet assets being more than 25 times higher than equity of assets. Roger Lowesten described the situation is his book "*When Genius Failed: The Rise and Fall of Long-Term Capital Managemen*t".

Secondly, the investment banks have been the big sponsors and supporters of these funds. They found in their trades a very profitable source of income. Therefore it is not surprising to find bias reports from investments banks explaining the superior capacity for gerenerating returns of this industry. According with information reported by the Bank for International Settlements (BIS), some of the largest prime brokers, primarily the US ones, have become very dependent on the income stream from prime brokerage services to hedge funds. In some cases, such income is reported as making up more than a quarter of their trading and commission income or an eighth of total revenue.

Thirdly, although primarily aimed at institutional investors and high net worth individuals, hedge funds have already become more widely accessible through the emergence of *funds of funds* (FOF), which are mutual funds that hold portfolios of hedge fund investments that are sold to a wider investor community. These funds popularity has grown significantly in recent times as they provide a broad exposure to the hedge fund sector and diversify away the risks associated with an investment in individual funds.

As last argument, after the burst of the Internet bubble in the beginning of the 21st century, many institutional investors tried to make up for the losses incurred by them due to the poor performance of the global equity markets by increasing their allocations to hedge funds. This has led to an increased interest of institutional investors such as pension funds, endowments and foundations who were looking for a greater diversification of their portfolios with alternative investments in vehicles that feature absolute return strategies and positive returns in both declining and rising securities markets, while attempting to protect the investment principal.

As a result of all these factors, the assets under management (AUM) by the hedge fund industry have grown exponentially, as well as the number of hedge funds, which have increased significantly their number: from as few as 300 funds in 1990 to more than 5,000 at present. These funds allegedly manage assets of more than 2.3 trillion USD as June 2013 managed by 5,000 single-manager hedge funds (Tremont Company). Although the average hedge fund size is typically less than US $100 million, with nearly half under US $25 million (Garbaravicius and Dierick, 2005) and despite representing a small fraction of the total asset management industry, hedge funds are believed to exercise a disproportionately substantial influence on the financial and economic sector in relation to their size due to dynamic and leveraged trading strategies, which is in contrast to traditional asset classes that typically engage in buy-and-hold strategies (Fung and Hsieh, 1999).

A more cuestionable argument could be the “institutionalization” of the hedge fund industry. The increased level of trust in the way hedge funds operate prompted by some regulatory changes, which contributed to among others increased transparency, better compliance, and higher operational standards.

2.6. *The life cycle of Hedge funds*

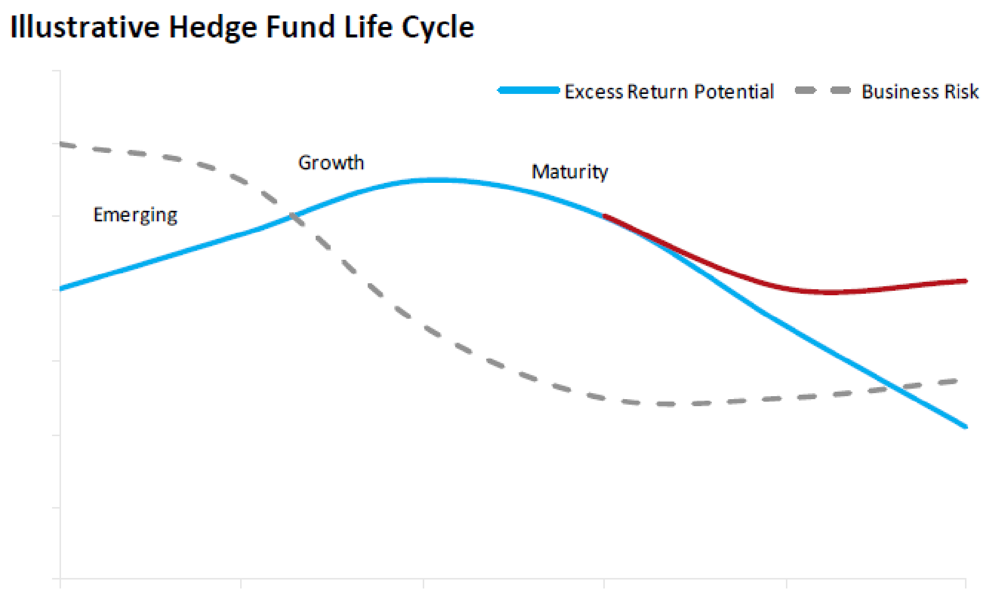
The life cycle of a business refers to the various stages of development of a company, from beginning as a start-up, to hiring its first employees, to expanding into new markets. Each stage has its own unique characteristics, and the focus of a company’s managers will reflect the current stage of its life cycle.

Hedge funds experience a similar life cycle. Incentives, opportunities, and risks evolve as a hedge fund progresses through its natural evolution as a business. Understanding where a hedge fund manager is in their life cycle has important implications for investors, including knowing when to hire or terminate a manager relationship, and how to establish proper expectations for return, volatility, and correlation. Incorporating a life cycle analysis into the manager selection process, rather than using a selection process based solely on historical performance, investors can substantially improve the likelihood of superior performance.

While each manager is unique and will have a distinct life cycle, hedge funds generally exhibit similar patterns of progression. Following the example of *Fund Evaluation Group* they broadly classify the life cycle of a hedge fund into four stages: Emerging, Growth, Maturity, and Decline (leading to Closure or Revitalization). Each underlying stage exhibits similar characteristics, including size, age, infrastructure, process, uniqueness, and investor base.

According to a study by analytics firm *PerTrac*, smaller funds outperformed much larger funds in 13 of the last 16 years. Other academic studies also reached similar conclusions. Getmansky, M (2004) noted a “positive and concave relationship between fund size and performance, which suggests funds have an optimal size and that exceeding that size has a negative impact on performance.”

Figure 1. Hedge Fund life Cycle



Source: *Fund Evaluation Group*

Despite these researches, however, super-sized funds have garnered a disproportionate share of industry assets and institutional investor attention. As of September 30, 2012, the largest 5% of all hedge funds accounted for over 62% of industry assets. The trend does not appear to be changing, as the largest funds (>$5 billion) attracted the vast majority of hedge fund capital flows in 2012. One could easily hypothesize many reasons for this trend, from the entrance of larger pension investors, the perceived safety of larger, less volatile funds, lower monitoring and due diligence costs, to herding, and career risk. While size is often the most widely cited characteristic impacting success, others researchers has identified a number of other qualities that significantly impact performance. The most notable qualities are:

- the size of the investment team

- the number of key decision makers
- the number of funds.
- fund age and age of key decision makers
- compensation structure
- investor base stability
- ownsership structure

2.7. *Hedge fund liquidation*

Since the late 1980s, the number of hedge funds has risen by more than 25% per year. The value of assets under management has grown as well. In 1990, $39 billion was invested in hedge funds. In 2003, was the estimated figure $700 billion. As of June 2013, the estimated size of the global hedge fund industry was US$2.4 trillion it managed by 5,000 single-manager hedge funds (Tremont Company).

However, alongside the tremendous growth, there has also been a significant attrition in the industry. The annual liquidation rate in the hedge fund industry is 7.10% compared to 1.00% in the mutual fund industry (Getmansky, M 2004). Despite the increased interest in hedge funds as an asset class, we have only a limited understanding of what drives hedge fund continuation and liquidation.

However the liquidation rate does not show an uniform distribution, very much link to the economic cycle. Hedge fund liquidations rose to a three-year high in

2012 as the European debt crisis and concerns about global economic growth hurt performance for the $2.4 trillion industry, according to Hedge Fund Research Inc. According with their data, the number of firms shut jumped to 873, the most since 2009. Smaller hedge funds were hardest hit by the global financial turmoil as the crisis made it more difficult to raise money from investors.

Liquidation can appear in two forms: *failure* of the fund or *closure* of the fund.

- *Failure* can happen due to fraud, forced liquidation due to levered positions that falls below a threshold, or concentrated bets that go against the manager's strategy.

- *Closure* can happen if a hedge fund exhausts all opportunities within a category, cannot obtain more capital, or has a bad performance.

In the first case, as in bankruptcy, hedge fund managers and investors incur significant costs due to the loss of the capital. The incentive structure, in particular the presence of high watermarks, is equally responsible for the high rates of attrition. Indeed, it is not economic for managers to continue operating a fund that has suffered large losses, making the prospect of receiving performance fees in the future very remote.

Different fund characteristics such as fund returns, flows, asset size and age affect the liquidation of hedge funds. Returns are affected by abilities of fund managers, costs, and exogenous shocks to hedge fund investment portfolios. The performance-flow relationship is positive and concave. Getmansky, M (2004) showed that hedge funds that follow more directional strategies are more likely to have a higher effect of past returns on future flows than funds with more event-driven strategies.

2.8. Structure and parties involved

Hedge fund managers are typically reluctant to undertake administrative duties and prefer to concentrate on their proprietary investment strategies. Support services are therefore often outsourced to administrators, in particular by smaller funds. Administrators handle a variety of tasks, including the setting up of a hedge fund, the valuation and calculation of its net asset value, record-keeping and accounting, legal advice, reporting and the processing of investor transactions. Administrators are usually hired by offshore hedge funds; onshore hedge funds tend to rely on prime brokers for operational support, although this is changing as well.

Prime brokers are banks or securities firms offering brokerage and other professional services to hedge funds and other large institutional clients. Prime brokerage services involve financing, clearing and settlement of trades, custodial services, risk management and operational support facilities. Clients may also be offered access to research and consulting services. For new hedge funds, capital introduction services, whereby prime brokers introduce managers to potential investors, may be particularly vital. The major share of prime brokers' income comes from trading commissions, collateralised cash lending and stock or bond lending to facilitate short-selling.

The assets of a hedge fund are sometimes deposited with a custodian bank instead of a prime or clearing broker. Compared to the latter, a custodian bank is subject to fiduciary duties and has an obligation to protect the fund's assets and to act in its best interests. This arrangement provides an additional safeguard to hedge fund investors, as the prime broker holds fund assets largely as a principal and as a security against underlying fund positions, i.e. mainly to protect its own interests.

CHAPTER III

3. HEDGE FUND INDEXES AND INVESTMENT STRATEGIES

Hedge funds have no formal obligation to disclose their results, however most of the funds release, at least monthly, their returns to attract new investors. With this information some data vendors have built performance hedge fund indexes, as well as sub indexes according to the fund strategy.

3.1. *Hedge fund classification*

The historical return analysis provides an important source of information for evaluating and understanding hedge funds investment styles. Through explicit or implicit analysis we can try to explain the funds performances and to classify investment styles.

- *Explicit analysis*.

  The aim is to identify and measure the sensitivity of real factors that explain the historical returns. An example could be to model the returns as a linear function of various macro economic factors or indexes.

In the simplest form, we try to find where the hedge fund returns show sensitivity to the market return:

$$y_t = \alpha + \beta x_t$$

Where

$y_t = independent\ variable, hedge\ fund\ return$

$x_t = market\ return$

The basic idea is that a hedge fund shows uncorrelated returns to the market, therefore β should be always 0.

However according with the β, we can classify funds under three different groups:

$\beta > 1\ \Longrightarrow$ Directional hedge funds

$\beta \approx 0\ \Longrightarrow$ Relative value of arbitrage funds

$\beta < 1\ \Longrightarrow$ Short bias funds

- *Implicit analysis*.

The idea is to identify certain statistical factors that explain the historical returns. One of the most used methods is the principal component analysis (PCA). The PCA ranks explanatory factors with the highest possible variance with the constraint that each one has to be orthogonal to the previous components. The biggest problem is that to match the explanatory factors with real factors is not always possible.

Although these methods will allow us to classify funds in a homogenous group, the reality is that they ignore important information regarding the funds exposure and real sensitivity to the relevant risk factors.

Some researchers highlight the importance of the economic cycles when analyzing Hedge Funds performance, Chesney, M and Baumgart, C (2010) sated that Hedge funds' main objective is to deliver absolute returns to their investors in both bull and bear markets due to their alleged low correlation with bonds and stocks.

Consistently profitable returns are expected from all hedge funds, but the performance analysis of the different hedge fund strategies has shown that hedge funds did not perform well during the financial crisis and the analysis of historical returns did not prevent for this event.

Since hedge funds provide liquidity to global markets, develop complex risk management tools, serve as an anticipator of economic imbalances and attempt to correct these by arbitraging away noticeable inefficiencies, nonetheless hedge funds are a positive market participant and contribute to financial stability.

3.2. Hedge fund indexes and data description

There are three major providers of hedge fund databases commonly used by public bodies: the Trading Advisors Selection System (TASS), the Centre for International Securities and Derivatives Markets (CISDM) (former MAR/Hedge) and Hedge Fund Research (HFR). The different databases cover only part of the global hedge fund industry and to some extent overlap, as some hedge funds report to more than one data provider. Certain databases may have strong regional biases. For example, Eurekahedge focuses primarily on Asian hedgefunds.

Other providers are:

- Zurich Capital Markets
- CSFB Tremont
- Hennesse
- Tuna
- Barclays

Each database represents only a sample of the whole hedge fund universe. Hedge funds join public databases largely for marketing purposes in order to attract additional funds for investment.

The process of building a hedge fund index is complex due to the nature of the information treated. A hedge fund could be taken an opportunistic exposure or drifting its published investment style without notice. Therefore, it is important to filter from a quantitative and qualitative point of view any new data.

- Qualitative, through manager's due diligence.
- Quantitative, through statistic, cluster or correlation analysis, besides Monte Carlo simulations.

The objective is to identify and to group hedge funds that really compete using similar investment strategies.

Nevertheless, there are other important problems as the *survivorship bias*. Many hedge funds that were included at some point in the indexes might now not comply with the index requirements or might be defunct. For example, HFR minimizes this problem by trying to receive a fund's performance until the point of the final liquidation of the fund.

HFR has developed a series of benchmark indexes designed to reflect hedge fund industry performance by constructing equally weighted composites of constituent funds. The indexes are produced from their database feed for more than 17,000 funds.

HFR database and index classification are between the most used by researchers and professionals in the field. Wharton Research Data Services (WRD) http://whartonwrds.com/archive-pages/our-datasets/hfr/hfr-faq/ defines HFR as "HFR Database, the most comprehensive resource available for hedge fund investors, includes fund-level detail on historical performance and assets, as well as firm characteristics on both the broadest and most influential hedge fund managers. HFR has developed the industry's most detailed fund classification system, enabling granular and specific queries for relative performance measurement"

HFR has created the following index classification.

Table 1. Hedge Fund Strategy Classification

Hedge Fund Strategy Classifications			
Equity Hedge	Event Driven	Macro	Relative Value
Equity Market Neutral	Activist	Active Trading	Fixed Income - Asset Backed
Fundamental Growth	Credit Arbitrage	Commodity: Agriculture	Fixed Income - Convertible Arbitrage
Fundamental Value	Distressed / Restructuring	Commodity: Energy	Fixed Income - Corporate
Quantitative Directional	Merger Arbitrage	Commodity: Metals	Fixed Income - Sovereign
Sector: Energy/Basic Materials	Private Issue/ Regulation D	Commodity: Multi	Volatility
Sector: Technology/Healthcare	Special Situations	Currency: Discretionary	Yield Alternatives: Energy Infrastructure
Short Bias	Multi-Strategy	Currency: Systematic	Yield Alternatives: Real Estate
Multi-Strategy		Discretionary Thematic	Multi-Strategy
		Systematic Diversified Multi-Strategy	

Source: www.hedgefundresearch.com

It is important to highlight the work done in the indexes analysis field by some researchers. Amin and Kat (2003) found that concentrating on surviving funds only will overestimate the mean return on individual hedge funds by approximately 2 per cent and will introduce significant biases in estimates of the standard deviation, skewness and kurtosis.

These findings add one extra layer of complication to the hedge fund world analysis and to the quality of the data used for researchers and investors in their analysis. Any conclusions reached through the study of indexes data should be very seriously challenged.

3.3. *Investment strategies*

As we pointed previously, there is no consensus in the number of investment strategies used by hedge funds. In addition, the number of strategies is continually increasing in parallel to the development of new products. We will provide the most relevant characteristics of the main groups. We will use for the analysis the monthly performance of the HFRI Indexes from June 2007 to March 2011.

3.3.1. Arbitrage strategies.

The aim is to exploit relative mispricing in certain securities, looking for negative correlation in the returns of the selected securities.

Arbitrage hedge fund achieved consistent small positive returns, with low volatility; however in times of stress it would suffer large losses, larger than predicted by their historical volatility of the returns.

We will analyse some of these strategies in further detail.

a) *Volatility strategy.*

These funds trade volatility as an asset class through both listed and unlisted instruments. The instruments used are mainly derivatives or other types of assets with embedded derivatives. The price of these instruments depends on the volatility level; therefore hedging other risk factors, it is possible to isolate the exposure to the volatility.

Figure 2. The distribution of Volatility index returns.

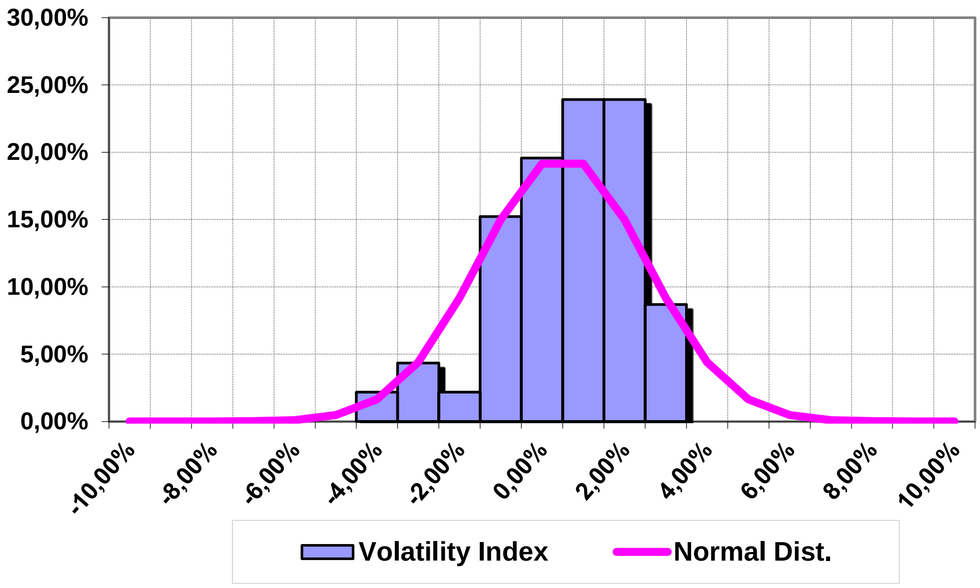


Table 2.The statistics of the Volatility index return distribution

Volatility	
Mean	0,040%
Median	0,652%
Desv. Stand	1,704%
Skew	- 0,8604
Kurtosis	0,494
Min.	- 4,53%
Max.	2,76%
N. of positive	56,52%
N. of negative	43,48%

b) *Relative value strategy.*

This type of funds looks for discrepancies in the market price of certain securities. The opportunities could be identified through the use of fundamental, macro models or quantitative analysis. There are no restrictions in terms of the securities used.

The strategy returns distribution shows the highest median between the analysed strategies, low variance and a fat tail to large negative returns from the equity market.

Figure 3. The distribution of Relative Value Arbitrage returns.

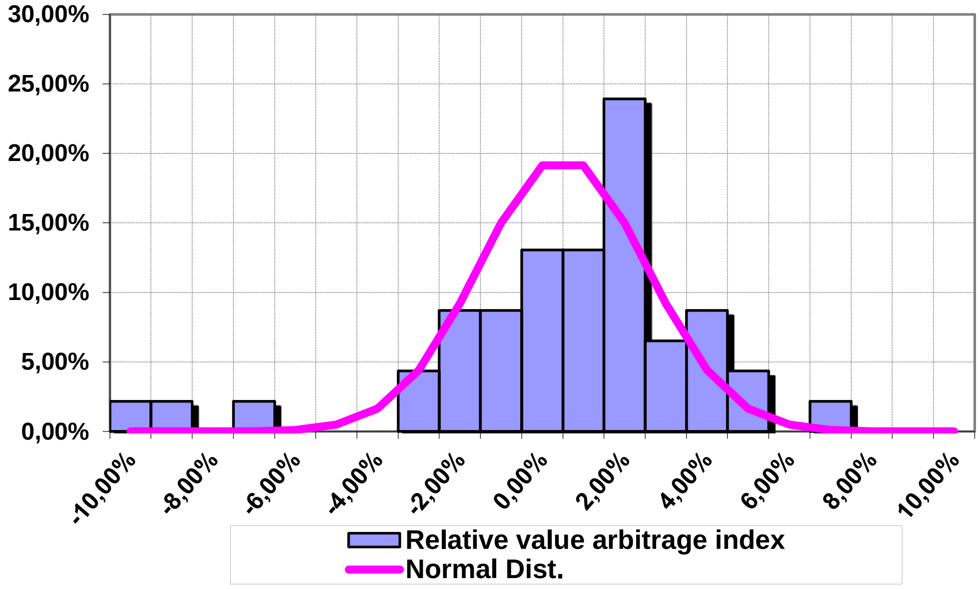


Table 3. The statistics of the relative value arbitrage returns

Relative value arbitrage	
Mean	-0,043%
Median	0,650%
Desv. Stand	3,592%
Skew	-1,7597
Kurtosis	5,135
Min.	-14,11%
Max.	6,81%
N. of positve	58,70%
N. of negative	41,30%

3.3.2. Equity hedge strategies.

This group concentrates the largest number of hedge funds. Their strategy is to take long and short positions in the equity market. The analysis could be performed through quantitative or fundamental analysis. Some of these funds, in addition to equities, use other market securities as; derivatives, Exchange-Traded Funds or Contracts for Differences.

a) *Equity market neutral strategy.*

The aim of these strategies is to be market neutral in dollar or beta terms through the purchase and sale of securities, usually their net equity market exposure is not greater than 10% long or short. According to HFRI information, they include Factor-based and Statistical/Trading strategies. Factor-based techniques consist of finding factors that have a common effect between securities. Statistical strategies usually apply some type of mean reversion approach between sectors or securities.

The return distribution shows very concentrated mass around the centre, large number of small positive returns, low variance and no fat tails at either side. This strategy shows the lowest median and variance between the analysed strategies.

Figure 4: The distribution of Equity market neutral returns.

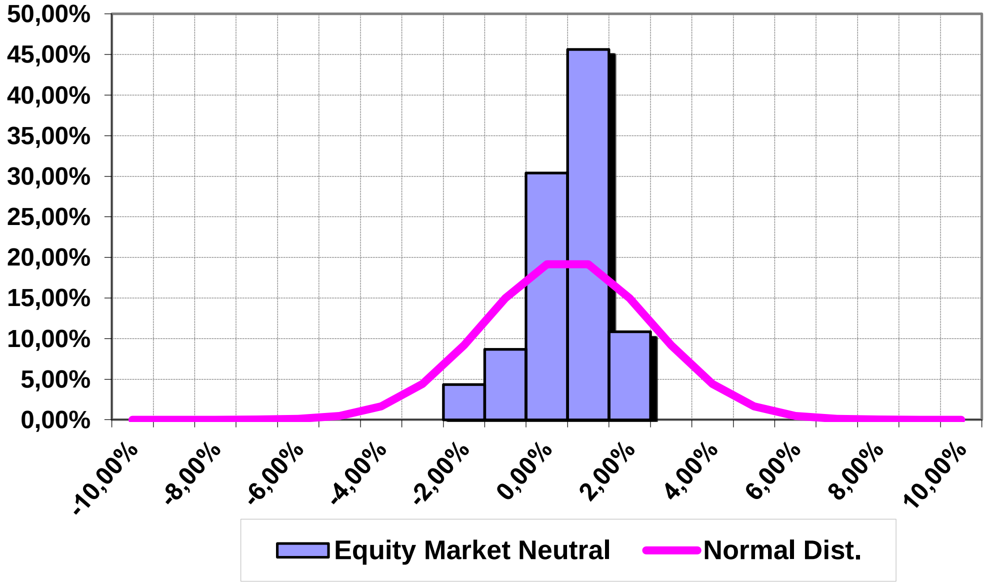


Table 4. The statistics of the Equity market neutral returns

Equity Market Neutral	
Mean	0,024%
Median	0,160%
Desv. Stand	0,923%
Skew	-1,1060
Kurtosis	1,731
Min.	-2,87%
Max.	1,45%
N. of positive	56,52%
N. of negative	43,48%

b) Short bias strategy.

These funds have the common characteristic of being net short equity exposure through the selling of overvalued securities. The level of short exposure varies between funds. The aim of the managers is to outperform in a declining equity market and not to suffer in a bullish equity market.

The returns do not seem concentrated around any point of the distribution. It shows a high variance and fat tails on both sides.

Figure 5. The distribution of Short Bias returns

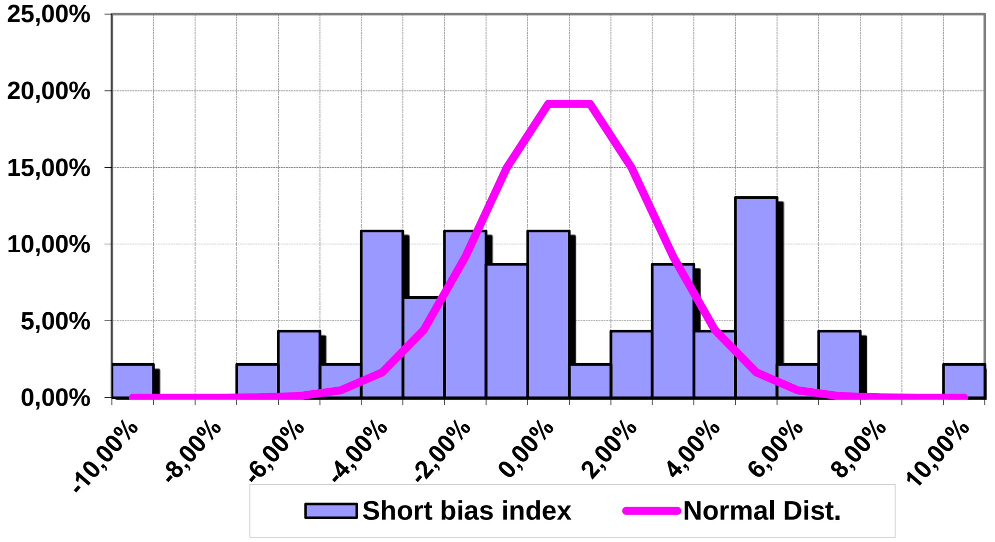


Table 5 The statistics of the Short bias returns

Short bias	
Mean	-0,241%
Median	-0,659%
Desv. Stand	4,282%
Skew	0,0240
Kurtosis	- 0,521
Min.	-10,09%
Max.	9,58%
N. of positive	41,30%
N. of negative	58,70%

3.3.3. Fund of funds.

A fund of hedge funds is an investment vehicle whose portfolio consists of shares in a number of hedge funds. They follow this strategy by constructing a portfolio of other hedge funds. How the underlying hedge funds are chosen can vary. A fund of hedge funds may invest only in hedge funds using a particular management strategy. Or, a fund of hedge funds may invest in hedge funds using many different strategies in an attempt to gain exposure to all of them.

The benefit of owning any fund of funds is experienced management and diversification. A portfolio manager uses his or her experience and skill to select the best underlying funds based on past performance and other factors. If the portfolio manager is talented, this can increase return potential and decrease risk potential.

Figure 6. The distribution of Fund of Funds returns

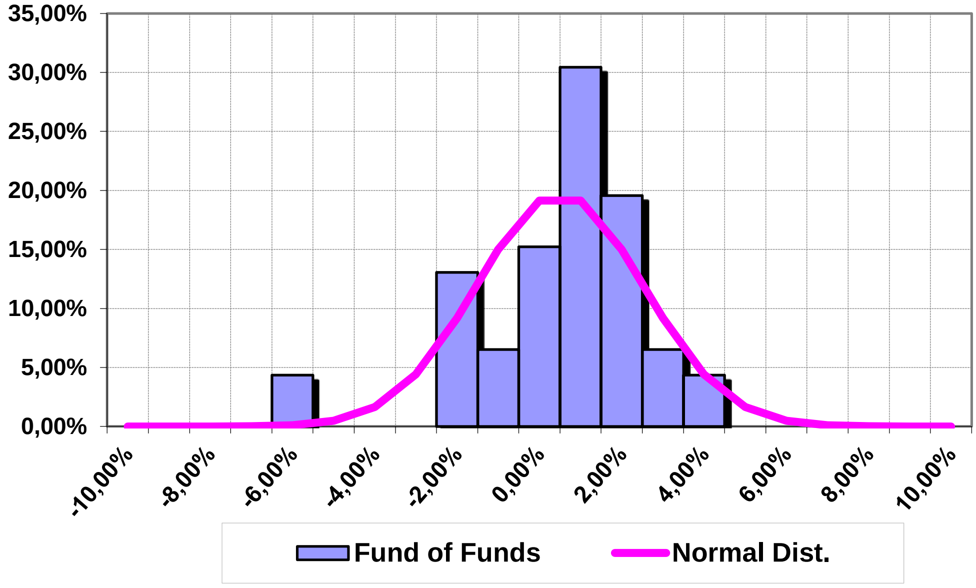


Table 6. The statistics of the Fund of Funds returns

Fund of Funds	
Mean	-0,063%
Median	0,357%
Desv. Stand	2,054%
Skew	- 1,2695
Kurtosis	2,258
Min.	-6,54%
Max.	3,32%
N. of positve	60,87%
N. of negative	39,13%

CHAPTER IV

4. ANALYSYS OF HEDGE FUND RETURN DISTRIBUTION AND RISK MEASURES

4.1. Hedge fund return distribution

Most of the strategies, except *Short Bias*, show common characteristics as negative skewness, positive excess kurtosis and serial correlation.

<< See table 2 around here >>

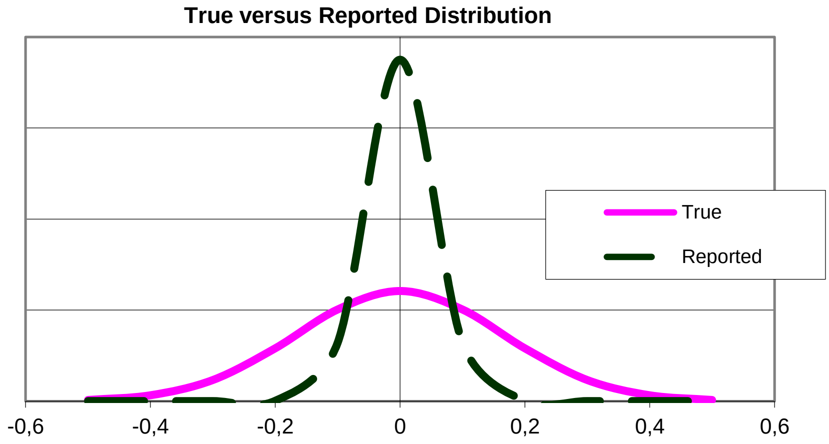
The main consequence of these characteristics is that left tail of the return distribution is longer than the right side; therefore large losses are bigger than those suggested by the standard deviation. Furthermore, the serial correlation of the returns does not show that the model underestimates the true variance and reduces the effective number of degrees of freedom in a time series. In the case of hedge funds analysis, it means that we will be underestimating the true risk of our investment and, over allocating to hedge funds when we undertake a mean variance portfolio analysis.

Table 2. Summary Statistics of Hedge Funds Returns.

	S&P 500	Volatility	Event Driven	Fund of Funds	Distressed / Restructuring	Equity Market Neutral	Emerging Market	Relative Value Arbitrage	Merger Arbitrage	Short Bias	Quantitative Directional
Mean	-0,144%	0,040%	0,264%	-0,063%	0,223%	0,024%	0,318%	-0,043%	0,266%	-0,241%	0,048%
Median	0,925%	0,652%	0,614%	0,357%	0,407%	0,160%	1,162%	0,650%	0,423%	-0,659%	0,580%
Stand. Desv.	5,775%	1,704%	2,454%	2,054%	2,561%	0,923%	4,373%	3,592%	1,068%	4,282%	3,096%
Skew	- 0,627	- 0,860	- 1,174	- 1,269	- 0,988	- 1,106	- 0,940	- 1,760	- 1,094	0,024	- 0,840
Kurtosis	0,287	0,494	2,411	2,258	1,827	1,731	2,247	5,135	1,210	- 0,521	0,771
Min.	-16,942%	-4,535%	-8,191%	-6,536%	-7,934%	-2,872%	-14,446%	-14,111%	-2,896%	-10,087%	-9,145%
Max.	9,39%	2,76%	4,74%	3,32%	5,55%	1,45%	9,62%	6,81%	2,07%	9,58%	4,89%
N. of positive	54,348%	56,522%	63,043%	60,870%	58,696%	56,522%	54,348%	58,696%	71,739%	41,304%	56,522%
N. of negative	45,65%	43,48%	36,96%	39,13%	41,30%	43,48%	45,65%	41,30%	28,26%	58,70%	43,48%

Source: Monthly returns Bloomberg.

Figure 7. Effect of the serial correlation in a distribution



Brooks and Kat (2002) argued that the serial correlation of the hedge funds returns seems inconsistent with the notion of efficient markets. According to them, one possible explanation could be the fact that many hedge funds invest in illiquid or complex assets.

To find up-to-date valuations of these assets is not always an easy task; therefore sometimes they use the last reported transaction price or model valuations. López and Cuellar (2007), explained the hedge fund returns serial correlation with similar arguments, affirming that real state valuations show the same problem due to the illiquid securities to appraise. These explanations are also consistent with Agarwal, V., Daniel, N.D and Naik, N.Y findings. They found that hedge funds, up to a certain extent, manage the reported returns in order to "smooth" their return distributions.

These findings are linked to a completely new set of research in this filed.

Several studies have analysed hedge fund performance and many of them stated that hedge funds generate superior returns (Fung and Hsieh (1997); Brown, Goetzmann and Ibbotson (1999)). However new studies have started to raise doubts about this supposedly superior managers skills. Fung, Hsieh, Naik, Ramadorai (2006) noted that the inflow of new capital has led to erosion of superior performance over time, even for high ability funds.

Kat and Miffre (2006) argue that most of the previous analysis on hedge fund performance ignored the non normality of the returns, thereby suggesting superior performance where there actually may be none. Malkiel and Saha (2005) study arrives to similar conclusions, arguing that hedge funds are riskier and provide lower returns than is commonly supposed.

4.2. Ratios as valid risk measures

Our previous findings have important implications in other broadly used techniques for the valuation and analysis of hedge funds.

The analysis of hedge funds performances through ratios is an easy and intuitive way to measure the efficiency of an investment. López de Prado (2008) appoints that the *Sharpe* ratio has become the 'gold standard' of performance evaluation. Although many researchers, Sharpe himself, study the deficiencies and limitations of the ratio, rating agencies and institutional investors include this ratio in their performance and risk measurements as put forward by López and Cuellar (2007).

The two most commonly used ratios are; *Sharpe* and *Sortino*, both measure the excess returns of an investment per unit of risk.

In the case of the *Sharpe* ratio, the unit of risk is calculated as the standard deviation of the investment returns.

$$Sharpe\ ratio\ = \frac{E[R - R_F]}{\sigma}$$

Where

R is the asset return

R_F is the risk free rate

σ is the standard deviation of the excess of the asset return

For the *Sortino* ratio, the unit of risk is measured as the standard deviation of the negative returns. In other words, it is a measure of excess return against downward price volatility.

$$Sortino\ ratio\ = \frac{R - R_F}{\sigma_d}$$

Where

R is the asset return

R_F is the risk free rate

σ_d is the standard deviation of the negative asset return

The statistical characteristics of the hedge funds returns, that we have described in the previous section, result in overestimated Sharpe or Sortino ratios, as the standard deviation does not include all the inherent asset risk. Therefore these ratios tend to overvalue the efficiency of hedge funds and, once more, lead to over allocate in this asset class.

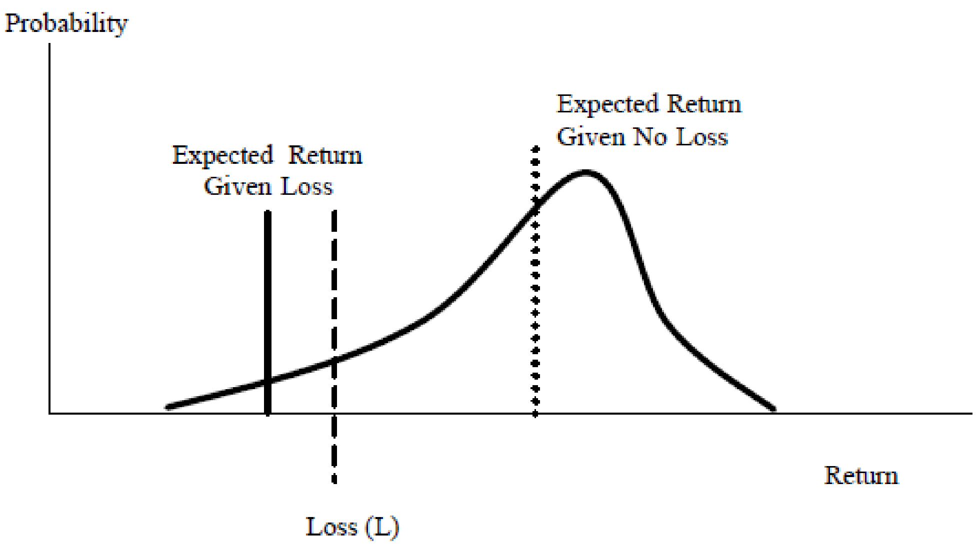
An approach, in order to overcome these limitations, was proposed by Shadwick and Keating who developed a new ratio called the *Omega function*.

As we illustrated in section 4.1; negative skewness, positive excess kurtosis and serial correlation of hedge fund returns underestimates the true variance and reduces the effective number of degrees of freedom in a time series. Therefore large losses in hedge fund investments are bigger than those suggested by the standard deviation, consequently *Sharpe* and *Sortino* ratios systematically underestimate the true risk of a hedge fund investment and lead to overweight to this asset class.

There is a very substantial body of work that seeks to extend the mean-variance framework of modern finance to encompass higher moments. The theoretical difficulties within that literature arise from the need to specify the form of a utility function and the substitution across moments. In addition, there are serious obstacles to incorporating the effects of higher moments in performance measurement, as data is often both sparse and noisy. This means that estimation of the moments is error prone and any attempt to attribute performance characteristics to them individually is therefore difficult if not impossible to do reliably.

New approaches try to overcome these limitations. The most successful one is the *Omega* ratio developed by Keating and Shadwick (2002). Although the approach is similar to the previous ratios, the *Omega* ratio considers all the moments of the distribution and differentiates between the excess upward and downward returns volatility (some researchers have named this ratio as the *sharper Sharpe*). It avoids the problem of estimating individual moments by measuring their total impact, which is of course precisely what is of interest to practitioners. The performance measure is a natural feature of the returns distribution, it is obtained through the cumulative distribution and hence there is no need to know any of the individual moments in order to observe their effect in total. In fact its construction from a returns distribution is entirely canonical, requiring no choices and admitting no ambiguity which is not already present in the data. As such it may be regarded as an extension of the notion of the cumulative distribution. It is a function that may be evaluated at any value in the range of possible returns, so that it allows performance comparisons with respect to any 'risk' threshold in this range. That is why the use of a function of returns rather than a single number to measure performance is essential

Following Keating and Shadwick (2002) approach we begin with an elementary heuristic. A direct analogy might be a simple bet. The investment situation differs from a standard gamble in that the "stake" is unknown at the outset. We wish to know what we stand to win if we win and what we stand to lose if we lose. In order to investigate this we need only specify the loss threshold L. This is the conditional expected return given loss. The return expectation is the conditional expected return given gain rather than the unconditional mean of the distribution.

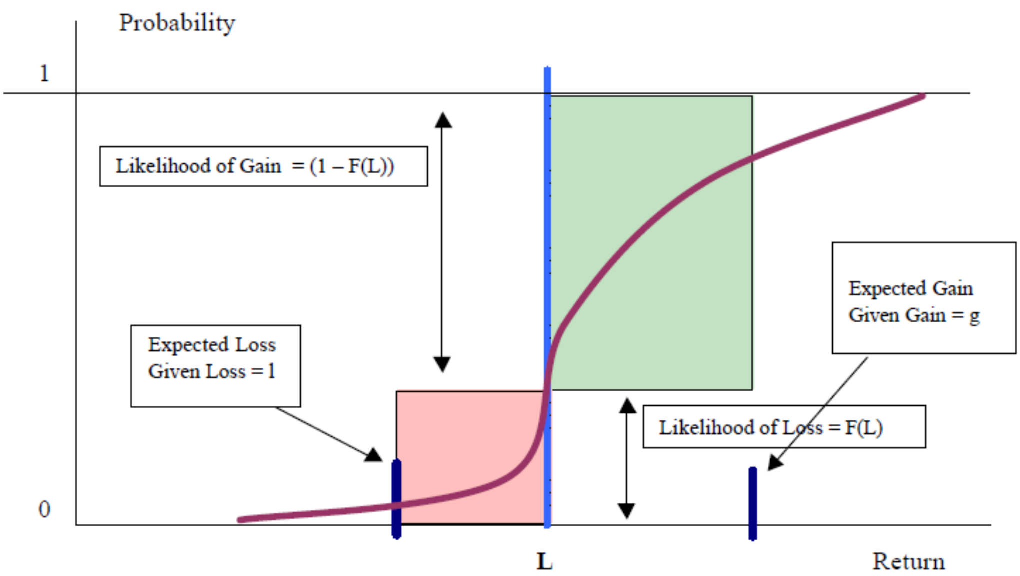


The diagram above shows the conditional expected returns given loss and no loss for an arbitrary distribution of returns. The partitioning of the distribution by the loss line (L) may be around a zero return as would be implicit in the gambling analogy or it may be any other exogenously specified level. This may, for example, be the return from a benchmark index or an absolute rate of return such as that used in actuarial assumptions. It should be immediately recognized that this partitioning changes both expected gain and expected loss as it is varied.

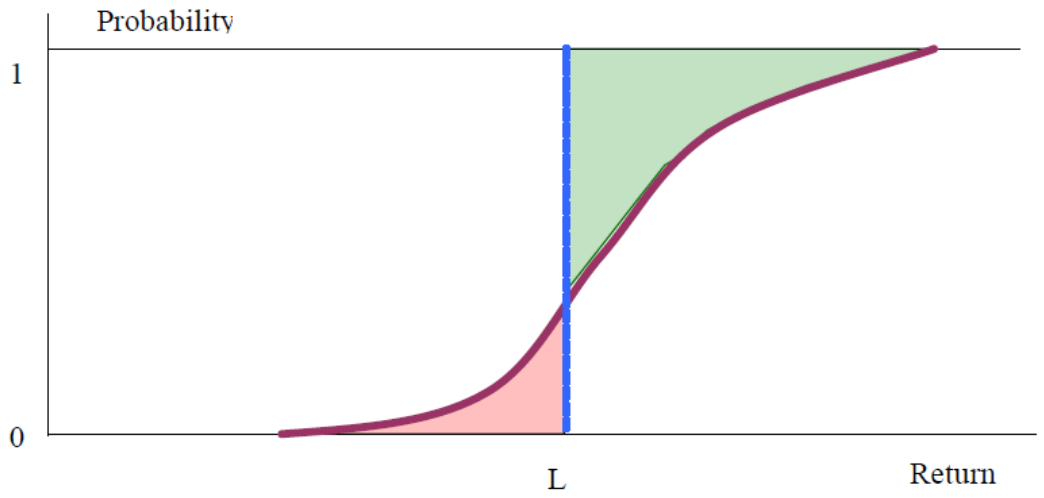
The ratio of these two returns is directly analogous to the odds in a standard bet. If we now add consideration of the likelihood of each expectation, through a likelihood ratio, we have a measure of the quality of the bet taken, or in investment terms the portfolio performance. The likelihood ratio is the ratio of the areas to the right and left of the partitioning (L) in the diagram above. This statistic, which we shall refer to as $\Omega(r)$, is given by

$$\Omega(r) = \frac{\mathrm{E}(\mathrm{r}|\mathrm{r} \geq \mathrm{L})(1 - F(L))}{\mathrm{E}(\mathrm{r}|\mathrm{r} \leq \mathrm{L})\, F(L)}$$

where F is the cumulative distribution of the returns series. Graphically this statistic may be illustrated in terms of F as follows. The $\Omega(r)$, statistic is the ratio of the crosshatched and striped areas.



If we consider the limit in which the unit of gain or loss is allowed to tend to zero and sum the gains and losses with their appropriate weights.



Therefore, in order to calculate the Omega ratio we define a minimum threshold return r, any lower return will be considered as a loss

$$\Omega(r) = \frac{\int_r^b [1 - F(x)]dx}{\int_a^r [F(x)]dx}$$

where:

x is the random one-period return on an investment
r is a threshold selected by the investor
a and b denote the upper and lower bounds of the return distribution, respectively.

This approach could be also understood as the ratio between a call and a put option with the strike the specified threshold.

4.3. VAR measures

We find similar problems when we consider another broadly use alternative approach for risk measure, the *Value at Risk* (VAR). Once again, the basic idea behind the simplest Value at Risk form is that risk can be measured by the standard deviation of unexpected outcomes, (σ) also called volatility.

Measurement of linear exposure to movements in underlying risk variables appear in different forms:

- In the fixed income market, exposure to movements in interest rates is called duration.
- In stock market, this exposure is called systemic risk, or beta (β).
- In derivatives markets, the exposure to movements in the value of the underlying asset is called delta (Δ).
- In the case of hedge funds, this exposure is more difficult to assess. At least in theory, we are in front of hedge or beta neutral investments. As we will show, it has been a lot research assessing if the term “beta neutral” is correct. However, more importantly a group of researchers has concentrated in to replicate the no linear behavior of hedge fund exposure. The most promising research trend has been to focus on the use of derivatives for taking in consideration both, the non normality and the non linearity of hedge funds returns.

The Value at Risk

The Value at Risk approach tries to provide us with an answer about what is the most that we can lose in an investment, with certain confidence level, on a specific time horizon. Thus, the one week Value at Risk on a specified investment, at 95% confidence level, will tell us that there is a 5% chance than the value of our investment losses more than the Value at Risk figure on any given week. In other words, as Jorion, P. (1997) stated *- the VAR summarizes the expected maximum loss over a target horizon within a given confidence interval-*

Therefore, the first point that we need to asses is the probability distribution of individual risks, the correlation across these risks and the effect of such risk on value.

There are three basic approaches that are used to compute Value at Risk, though there are numerous variations within each approach. The measure can be computed analytically by making assumptions about return distributions for market risks, and by using the variances in and covariances across these risks. It can also be estimated by running hypothetical portfolios through historical data or from Monte Carlo simulations.

We will describe and compare the different approaches.

The Variance Covariance method

This approach is also called the model-building approach. The idea behind is that the return distribution is normally distributed, therefore we can match the wanted confidence level with a certain number of standard deviations. For example a 99% confidence level tells you that the investment should not move more than 2,33 standard deviations.

The basic form of the model is:

$$VAR = N\ \sigma\ \alpha\ \sqrt{t}$$

Where

N= nominal
σ= volatility of the returns
α= confidence level
t= time horizon

For several assets will be needed to assess the variance covariance matrix of the assets returns. When working with large portfolios, the number of variance covariance calculation could too big, therefore it is common used to match the exposures to certain risk factors.

However, there are other problems associated to this approach. The main one is that variances and covariances across assets change over time. This nonstationarity in values is not uncommon because the fundamentals driving these numbers do change over time.

In this sense, a lot of research has been done about how to compute Value at Risk with assumptions other than the standardized normal.

One of the simplest approaches is to incorporate jump diffusion models in order to account for large negative events, i.e. through a Poisson distribution. Hull and White suggest ways of estimating Value at Risk when variables are not normally distributed. Their approach requires the transformation of the distribution and assumes that the new variables are multivariate normal distributed. This and other papers like it develop interesting variations but have to overcome practical problems because estimating inputs for non-normal models can be difficult to do.

Other important critique against the variance-covariance estimates of Value at Risk is that it is designed for portfolios where there is a linear relationship between risk and portfolio positions. Consequently, it can break down when the portfolio includes options, since the payoffs on an option are not linear.

In an attempt to deal with options and other non-linear instruments in portfolios, researchers have developed Quadratic Value at Risk measures. These quadratic measures, sometimes categorized as delta-gamma models (to contrast with the more conventional linear models which are called delta-normal). It takes the form

$$\delta P = \Delta\delta S + \frac{1}{2}\Gamma(\delta S)^2$$

Where

δP is the value change of the portfolio in one day.

Setting

$$\delta x = \frac{\delta S}{S}$$

Then

$$\delta P = S\Delta\delta x + \frac{1}{2}S^2\Gamma(\delta x)^2$$

The variable δP is not normal. Assuming that δx is normal $N \sim (0, \sigma)$, we can calculate the moments

$$E(\delta P) = \frac{1}{2}S^2\Gamma\sigma^2$$

$$E(\delta P)^2 = S^2\Delta^2\sigma^2 + \frac{3}{4}S^4\Gamma^4\sigma^4$$

The first two moments can be fitted to a normal distribution. A further step is to use the three first moments with the Cornish Fisher expansion that allows us to estimate the q^{th} percentile of the distribution δP as

$$\mu_p + w_q\sigma_p$$

Where

$$w_q = z_q + \frac{1}{6}\left(z_q^2 - 1\right)\varepsilon_p$$

z_q is the q^{th} percentile of the standard normal distribution and ε_p is the skewness of the probability distribution of δP.

Historical Simulation

Historical simulations represent the simplest and most popular way for practitioners of estimating the Value at Risk. It involves using past data in a very direct way as a guide to what might happen in the future.

In this approach, the Value at Risk for a portfolio is estimated by creating a hypothetical time series of returns on that portfolio, obtained by running the portfolio through actual historical data and computing the changes that would have occurred in each period. The main weakness of this approach is that the past is not always a good guide of the future.

While all three approaches to estimating Value at Risk use historical data, historical simulations are much more reliant on them than the other two approaches.

Some of the main weaknesses of the general approach are:

- Using historical data where all data points are weighted equally. Some model tries to overcome this problem applying a bigger weight to the most recent data observations.
- New assets or market risks. How to deal with new risks and assets when there is no historic data available to compute the Value at Risk

Once more, Hull and White suggest a different way of updating historical data for shifts in volatility. For assets where the recent volatility is higher than historical volatility, they recommend that the historical data be adjusted to reflect the change.

Monte Carlo Simulation

The aim of this approach is to generate the probability distribution. The Value at Risk will be calculated as the appropriate percentile of the probability distribution.

We specify probability distributions for each of the market risk factors and specify how these market risk factors move together .The estimation of parameters is easier if we assume normal distributions for all variables, the power of Monte Carlo simulations comes from the freedom we have to pick alternate distributions for the variables. In addition, we can bring in subjective judgments to modify these distributions.

The main limitation of this approach is computational due to the large amount of data to process. As the number of market risk factors increases and their comovements become more complex.

The strengths of Monte Carlo simulations can be seen when compared to the other two approaches for computing Value at Risk. Unlike the variance-covariance, this approach does not need to make unrealistic assumptions about normality in returns.

4.4. Conclusions and other alternative risk measures

Every Value at Risk measure makes assumptions about return distributions, which, if violated, result in incorrect estimates of the Value at Risk.

With delta-normal estimates of Value at Risk, we are assuming that the multivariate return distribution is the normal distribution, since the Value at Risk is based entirely on the standard deviation of returns.

With Monte Carlo simulations, we get more freedom to specify different types of return distributions, but we can still be wrong when we make those judgments.

Finally, with historical simulations, we are assuming that the historical return distribution (based upon past data) is representative of the distribution of returns looking forward.

Although these approaches on their simplest forms are not the most accurate tools for assessing the risk of a hedge fund, we have showed how certain modifications allow them to departure from the normality hypothesis and therefore to be adapted for the evaluation of the hedge fund risk. This technology has limitations therefore the results have to be understood in the context of the selected strategy and the inherent risks. In chapter VI we open the door for a new risk management approach identifying the risk factor exposures assumed by the each hedge fund.

Nonetheless, the risks faced in a possible hedge fund investment are diverse and any reductionist approach has to be properly contextualized. López and Cuellar (2010) propose a complementary system for evaluating the inherent risks of each hedge fund through a radar visualization of strategy exposure. They listed some of the possible risks that investors face in the financial markets.

Accounting risk	Fiduciary risk	Political risk
Bankruptcy risk	Hedging risk	Prepayment risk
Basis risk	Horizon risk	Publicity risk
Call risk	Iceberg risk	Regulatory risk
Capital risk	Interest rate risk	Reinvestment risk
Collateral risk	Knowledge risk	Rollover risk
Commodity risk	Legal risk	Spread risk
Concentration risk	Limit risk	Systemic risk
Contract risk	Liquidity risk	Taxation risk
Currency risk	Market risk	Technology risk
Curve construction risk	Maverick risk	Time lag risk
Daylight risk	Modelling risk	Volatility risk
Equity risk	Netting risk	Yield curve risk
Extrapolation risk	Optional risk	

Therefore the complexity and the variety of the assumed risks lead to the need of using several risk measures as appropriate. We propose some measures in order to asses leverage or liquidity.

Leverage measures

Gross on-balance sheet leverage	Total on-balance sheet assets/Equity
Net on-balance sheet leverage	(Total on-balance sheet assets – Matched book assets)/Equity
Gross accounting leverage	(Total on-balance sheet assets + Total on-balance sheet liabilities + Gross off-balance sheet transactions)/Equity
Gross economic leverage	(Risky assets + Risky liabilities + Gross off-balance sheet otional)/Equity
Net economic leverage	(Risky assets – matched book assets + Risky liabilities – matched book liabilities + Gross off-balance sheet notional – hedges)/Equity
VaR leverage	VaR/Equity

Liquidity measures

Absolute liquidity Cash
Cash + Borrowing capacity
Relative measures Cash/Equity
(Cash + Borrowing capacity)/Equity
VaR/(Cash + Borrowing capacity)

Sources: Managed Funds Association (2005) and Financial Stability Forum (2000).

Market risk, leverage and liquidity risk may interact among each other, so a vulnerability analysis should ideally seek to identify possible combinations and concentrations of high volatility, high leverage, higher funding risks.

CHAPTER V

5. INCORPORATING HEDGE FUND IN THE PORTFOLIO CONSTRUCTION

5.1. The Capital Asset Pricing Model (CAPM)

There is an extent literature regarding equilibrium models. The simplest form of an equilibrium model and the first one developed was the standard or one factor *Capital Asset Pricing Model* (CAPM). The authors were Sharpe, Lintner and Mossin.

The basic assumptions on this model, as defined by Edwin, Martin, Stephen and William (2003), are:

1. No transaction cost. There is no cost of buying or selling any asset.
2. Assets are infinitely divisible. This means that an investor could take any position in an investment.
3. Absence of taxes. The implications are that individuals are indifferent to the form in which the return of the investment is received.
4. Individuals can not affect the price of a stock by his buying or selling actions.
5. Investors are expected to make decisions solely in terms of expected values and standard deviations of the returns in the portfolio.

6. Unlimitated short sale allowed.
7. Unlimitated lending and borrowing at the riskless rate.
8. Investors are assumed to be concerned with the mean and the variance of returns.
9. All investors are assumed to have identical expectations.
10. All assets are marketable

They have been object of numerous critiques due to their distant from reality.

The basic form of the model states:

$$R_i = R_F + \left(\frac{R_M - R_F}{\sigma_M^2}\right)\sigma_{iM}$$

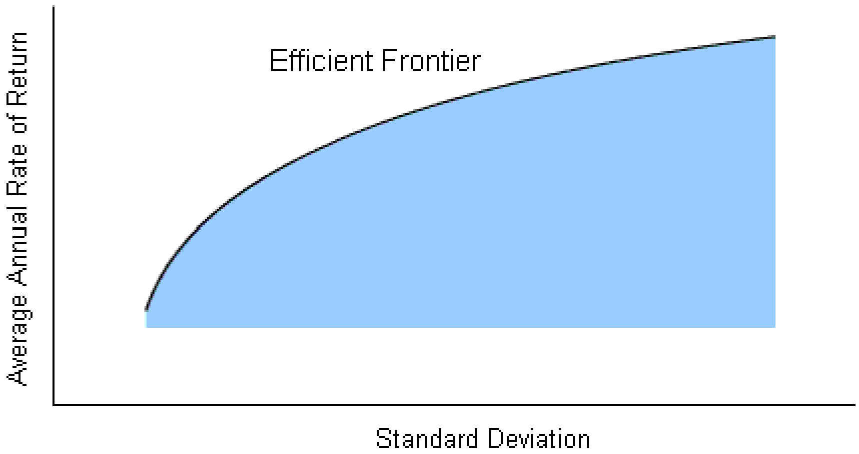
$$R_i = R_F + \beta(R_M - R_F)$$

Where

R_i is the asset return
R_F is the risk free rate
R_M is the market return
σ_M^2 is the variance of the market return

This relation is usually called the security market line. We can state that the equilibrium return on any security is equal to the price of time plus the market price of risk times the relevant definition of risk for the security. The line shows that return is an increasing function of risk.

Figure 8. Shape of the Efficient Frontier



It's clear that for any given value of standard deviation, you would like to choose a portfolio that gives you the greatest possible rate of return; so you always want a portfolio that lies up along the efficient frontier, rather than lower down, in the interior of the region. This is the first important property of the efficient frontier: it's where the best portfolios are.

The second important property of the efficient frontier is that it's curved, not straight. This is actually significant; it's the key on how diversification improves the reward to risk ratio.

In statistical terms, this effect is due to lack of covariance. The smaller the covariance between two securities, the smaller the standard deviation of a portfolio that combines them.

$$\sigma_p^2 = E\left[R_p - \overline{R}_p\right]^2 = E\left[\sum_i^n X_i R_p - \sum_i^n X_i \overline{R}_p\right]^2 =$$

$$= E[X_i \sum_i^n (R_i - \overline{R}_i)]^2 = \sum_i^n x_i \sigma_i^2 + \sum_i^n \sum_j^n x_i x_j \sigma_{ij}^2$$

where

σ_p^2 is the portfolio variance
R_p is the portfolio return

In other words, the CAPM model helps us to explain the search of the investment community for uncorrelated assets. An uncorrelated asset will improve the efficient frontier. It will have a marginal, even negative, contribution to the overall portfolio risk, however it might increase the expected portfolio return.

The use of this conceptual structure has certain limitations. It is a valid framework for normally distributed returns, where the standard deviation reflects the inherent asset risk. However, if the asset returns distribution departure from the normality assumption, the CAPM could be a no valid framework and further analysis will be needed.

Therefore, in order to corroborate the validity of the CAPM approach for hedge funds we will study the statistical characteristics of their return distributions.

The term hedge fund is broadly used. However, each hedge fund applies different strategies and investment techniques consequently, it is more rigorous to classify hedge funds in homogenous groups. The most intuitive and broadly used classification method is according with their strategies techniques. We has showed on section 4.1 a study of the return distributions for the most relevant groups.

5.2. The Central Limit Theorem

So far, we have criticised and showed that due to the negative skew and serial correlation showed by most of the hedge fund strategies, the use of the CAPM allocation model approach, ratios or risk measures that take the standard deviation of the returns as the main risk measure, lead systematically to mislead conclusions. We have illustrated and corroborated those studies. However, the challenge to the previous exposure is done by the Central Limit Theorem.

The Central Limit Theorem.

Developed originally by Laplace and DeMoivre, the Central Limit Theorem (CLT) showed that for any distribution the mean of converges to a normal distribution as the number of observation increases.

The law of the large numbers implies that if $\varepsilon_i : \Omega \to \mathbb{R}$ are independent random variables and with the same distribution, then

$$\lim_{n\to\infty} \frac{(\varepsilon_1(w) - \mu_1 + \cdots + \varepsilon_n(w) - \mu_n)}{n} = 0$$

The CLT strengthens this by quantifying the speed of convergence.

Let $\varepsilon_i : \Omega \to \mathbb{R}$ be independent random variables with the same distribution (i.i.d) with $\mu = \mathrm{E}\varepsilon_i < \infty$ and $\sigma^2 = \mathrm{Var}\varepsilon_i < \infty$ then

$$\lim_{n\to\infty} \mathrm{P}\left\{\left(\frac{(\varepsilon_1 - \mu_1 + \cdots + \varepsilon_n - \mu_n)}{n}\right) \in \left[\mathrm{A}\frac{\sigma}{n}, \mathrm{B}\frac{\sigma}{n}\right]\right\} =$$

$$= \frac{1}{\sqrt{2\pi}} \int_{\mathrm{A}}^{\mathrm{B}} \mathrm{e}^{-\frac{x^2}{2}\mathrm{d}x}$$

As inference, the law of the large numbers is routinely used to build investment portfolios which maximize the probability of a return falling into a desired range. The main idea is to diversify the portfolio by including many independent assets. There are two main types of diversification: vertical and horizontal.

Background remark.(Source: Wikipedia)

- *Horizontal Diversification.*

  Horizontal diversification is reached when you diversify between same-type of investments. It can be a broad diversification (like investing in several NASDAQ companies) or more narrowed (investing in several stocks of the same branch or sector).

- *Vertical Diversification.*

  Vertical Diversification is achieved investing between different types of investment. Again, it can be a very broad diversification, like diversifying between bonds and stocks, or a more narrowed diversification, like diversifying between stocks of different branches.

  While horizontal diversification lessens the risk of just investing all-in-one, a vertical diversification goes far beyond that and insures you against market and/or economic changes. Furthermore, the broader the diversification the lesser the risk.

It is important to remember that both, the *law of large numbers* and *the central limit theorem*, require mutual independence of random variables.

Assume that a portfolio that contains n types of assets each characterized by a return $r_1, r_{2,}, \dots, r_n$. Note that r_i is a random variable. If these random variables are independent, the portfolio is called diversified.

Let N_i be the numbers of assets of type i in the portfolio $1 \leq i \leq n_i$. Let

$$N = \sum_{k=1}^{n} N_k$$

Then the average return from our portfolio, if all the assets are equally weighted, is

$$R_n = \frac{1}{N} \sum_{k=1}^{n} N_k \, r_k$$

In the terminology of probability theory, the average return is just the empirical mean of all returns. The expected value of the average return is

$$E(R_{n)} = \frac{1}{N} \sum_{k=1}^{n} N_k \, \mu = \mu$$

The variance is

$$Var(R_{n)} = \frac{1}{N^2} \sum_{k=1}^{n} N_k^2 \sigma_k^2$$

Therefore, we can hope that in the large n limit, we will be getting a guaranteed return μ from our portfolio. R_n strongly converges to μ as $n \rightarrow \infty$.

Non-systematic risk vanishes in the limit of large n, whereas systematic risk converges to the limit equal to the mean covariance for all pairs of assets

(Markowitz law of mean covariation). It is clear that in the presence of mean covariance, the sequence R_n does not converge to μ.

As a result, it is impossible to achieve perfect diversification of the corresponding portfolio. Once more we find the answer to – *why does the investment community search for uncorrelated assets*–.

5.3. Limitations of the Central Limit Theory when applying to hedge funds.

As we have stated the Central Limit Theorem, affirms that the average distribution of an increasing number of independent variables approaches normality if certain conditions are fulfilled.

- The mean and standard deviations or the processes generating the returns should be stationary over time.
- The processes generating the returns should be independent of each other rather than a function of general systematic factors.

Berg and Van Rensburg (2007) state that "*It is fairly obvious that neither of these conditions is strictly true for hedge funds and it is in part for this reason that the "fat-tails" appear in the distributions of hedge fund strategy returns. For example, systematic trend followers depend on the existence of trends in various financial markets so that the returns of managers operating this strategy* *will tend to exhibit a high degree of interdependence and notable time structure"*.

The conventional mean–variance approach is also criticized by numerous other investigations, including Cvitani,Agarwal and Naik, Amenc (2003) and Amin and Kat (2003).

Amenc and Martellini (2002) caution that portfolio optimization procedures are very sensitive to differences in expected returns. They caution that portfolio optimizers typically allocate the largest proportion of capital to the asset class for which the estimation error in the expected returns is the greatest.

Amin and Kat (2003) state the inclusion of hedge funds significantly improves the portfolios mean–variance characteristics. They also, however, found that portfolios constructed of equities and hedge funds do not combine well into truly low risk portfolios as this lower the skewness and increases the kurtosis of the portfolio.

5.4. Our findings

We have already showed that hedge funds showed serial correlation in their returns, this challenges the hypothesis of independent identical distributed random variables (i.i.d.).

In addition, the CLT approach provided in the previous section is based under the hypothesis of a portfolio built from $\mathrm{N_k}$ equally weighted asset. However, the objective searched by any optimization process is maximizing return and minimizing risk. This will lead, as Amenc and Martellini (2002) stated, to allocate the largest proportion of capital to the asset class for which the estimation error in the expected returns is the greatest.

It is also, important to remark certain characteristic of the Central Limit Theorem. It allows us to estimate the probability of the return to be in the interval of size $\sim 1/\sqrt{n}$ around the mean value. However, it cannot be used to estimate the probability of a large loss $R_n < -L$ in the limit of large n. Therefore this technology is skipping over all the information embedded in the tails of the distribution. As we have showed in the case of hedge funds is very significant.

The last point to remark is regarding to the treatment of the systematic and non-systematic risk. As we have showed the non-systematic risk is the un-diversifiable part of the portfolio risk due to the correlation between the different assets.

$$\mathrm{\sigma_p^2} = \sum_{\mathrm{i}}^{\mathrm{n}} \mathrm{x_i \sigma_i^2} + \sum_{\mathrm{i}}^{\mathrm{n}} \sum_{\mathrm{j}}^{\mathrm{n}} \mathrm{x_i x_j \sigma_{ij}^2}$$

Therefore an important limitation is that the final portfolio return distribution will depend on the correlation assumptions. Many models treat the correlation as a constant or a linear function, however a more robust approach will be to treat correlation as a stochastic variable.

Assuming that β of a security is constant is easy to assess the changes in correlation as the market volatility changes.

$$\rho = \frac{\mathrm{cov}(r_i, r_m)}{\sigma_i \sigma_m} = \frac{\mathrm{cov}(r_i, r_m)}{\sigma_m^2} \frac{\sigma_m}{\sigma_i} =$$

$$= \beta \frac{\sigma_m}{\sigma_i}$$

Therefore, we just showed that:

- The correlation will depend of a non linear variable as it is the volatility
- Higher market volatility will increase the correlation of our variables, challenging the robustness of the model.

Our findings justify, why in market downturns, when market volatility increases, the assets returns became more correlated. At the same time, we can conclude that the validity of the CAPM or any other linear portfolio building model became compromise when we see changes in the correlation levels.

This is particular true in the case of the hedge funds, as we have showed, where the i.i.d. of the returns is challenge from the starting point due to the serial correlation of their returns.

CHAPTER VI

6. IDENTIFYING RISK FACTOR EXPOSURES AND REPLICATING HEDGE FUND PERFORMANCE

6.1. Assimilating hedge fund strategies trough options

As we have stated, the historical return analysis provides an important source of information for evaluating and understanding hedge funds investment styles. These time series can help us to identify the risk factor exposure of each strategy. If we can replicate the return distribution, we would have replicated the hedge fund exposure.

However, the unavailable question arises, if we are able to replicate, through a low intensive trading approach, the different indexes hedge fund exposure, is it justified the current sector fee structure.

An Option analysis approach.

A new group of researchers have proposed an alternative way for studying hedge funds. The idea is to replicate the non normality and non linearity of the hedge funds returns through an option base approach.

Kat and Miffre (2006) highlighted the importance of non-normality risks and developed an extent analysis trying to replicate the non normality of the returns through a conditional multifactor model. In this field Agarwal and Naik (2000), Mitchell and Pulvino (2001) and Kat and Miffre (2006) try to replicate the non normality of the returns through a conditional multifactor model.

One of the latest publications in this field Camarero y Pascual (2013) proposed through the purchase and sale of plain vanilla options, to assimilate and explain the returns of different hedge fund strategies.

This technology allows us to classify strategies and provide an intuitive explanation of the risk factors behaviour. In addition, this paper opens the door to the study of hedge fund risk trough options based models (as the Quadratic Value at Risk measures that we explained in section 4.3).

Following Camarero y Pascual (2013) paper, our study starts by analysing the risk profile of the different investment strategies to the upward and to the downward movements of the equity market. As previously, the proxies taken for the investment strategies returns are the monthly performance of the HFRI Indexes from June 2007 to March 2011. For the equity market we have taken the monthly performance of the S&P 500 index. All the data has been downloaded from the Bloomberg database.

6.1.1. Arbitrage strategies.

The replication of these strategies resembles the selling of options, so the *arbitrageurs* funds seem to be net sellers of volatility. These hedge funds invest by exploiting relative mispricing in certain securities, looking for negative correlation in the returns of the selected securities. However, as we have showed in section 5.3, in times of market stress the correlation in the markets tend to increase. Therefore these funds are not only consistently short volatility (*vega* and *gamma*), they are also short correlation.

Consequently we would expect for an arbitrage hedge fund to achieve consistent small positive returns, with low volatility; however in times of stress it would suffer large losses, larger than predicted by their historical volatility of the returns.

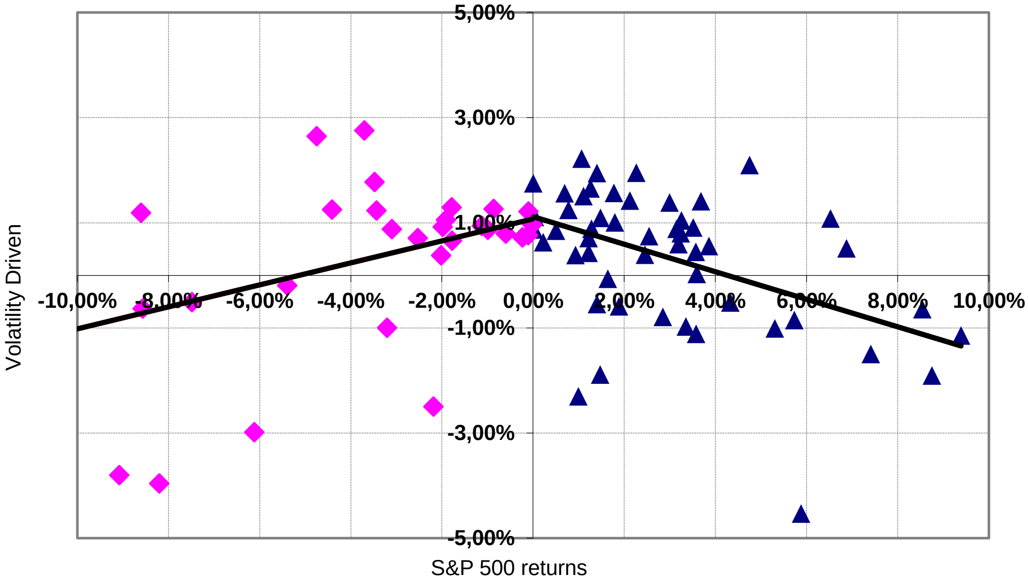
We analyse some of these strategies in further detail.

a) *Volatility strategy.*

These funds trade volatility as an asset class through both listed and unlisted instruments. The instruments used are mainly derivatives or other types of assets with embedded derivatives. The price of these instruments depends on the volatility level; therefore hedging other risk factors, it is possible to isolate the exposure to the volatility.

We observe that the strategy returns assimilates to the selling of a series of straddles, on the equity market returns, with the strikes set around 0%. This means that the HF managers generate the biggest returns when the equity market barely moves. When large equity market movements occurred to either side, their returns decreases.

Figure 9. Volatility Driven index.

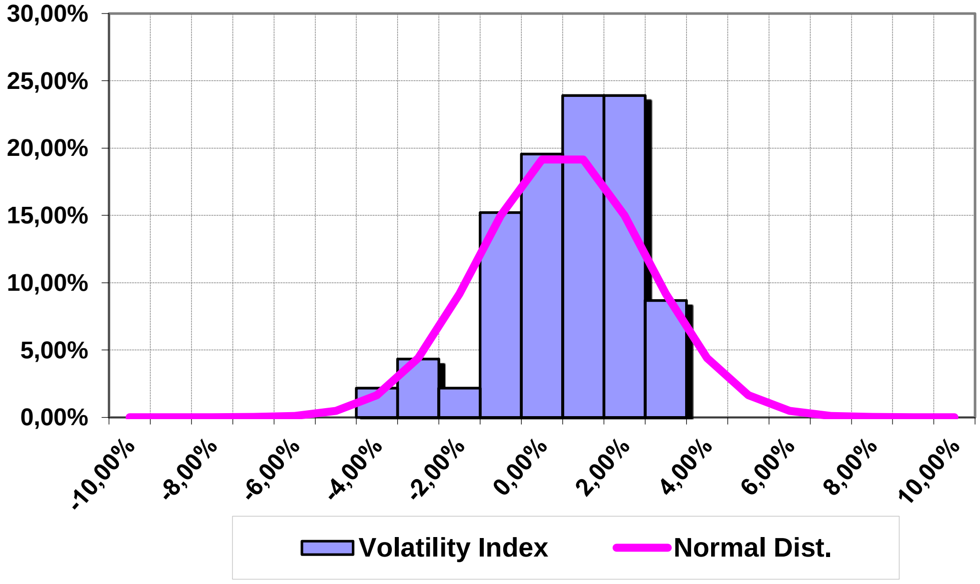


Source Bloomberg

One of the first conclusions that we reach is that these hedge funds are consistently achieving their return for selling volatility to the market. This finding opposes claims, from many volatility hedge fund managers, that they keep a net long volatility position or they have the skills to change from being short volatility to long volatility when the market moves. It is remarkable that the tail risk in this strategy seems to be quite limited.

To this extent, we expect a return distribution for this strategy with a high concentration of small positive returns, low variance and no fat tail.

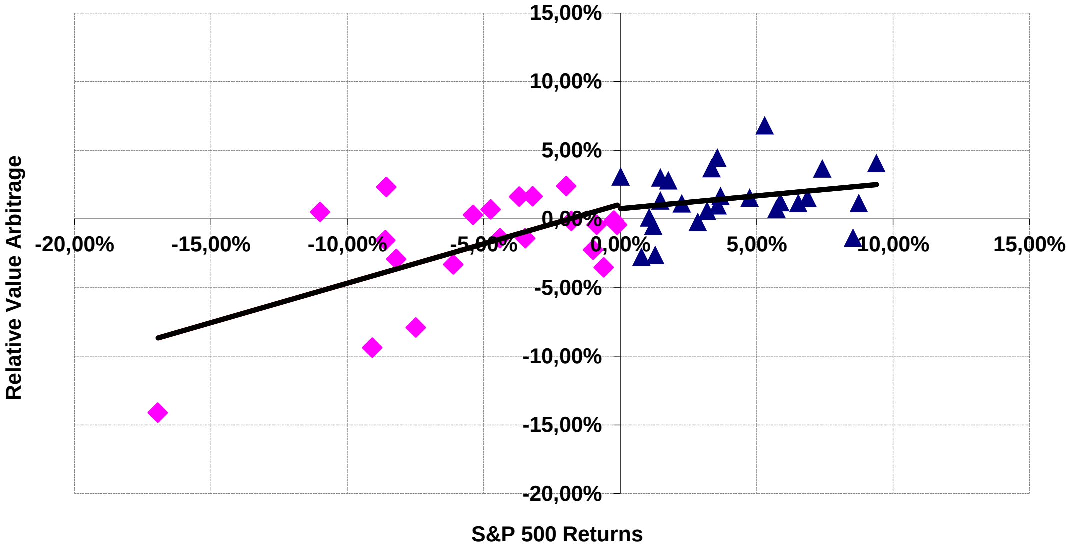
Figure 10. The distribution of Volatility index returns.



b) Relative value strategy.

This type of funds looks for discrepancies in the market price of certain securities. The opportunities could be identified through the use of fundamental, macro models or quantitative analysis. There are no restrictions in terms of the securities used. HFRI includes in this index several sub-strategies.

Figure 11. Relative Value Arbitrage index.

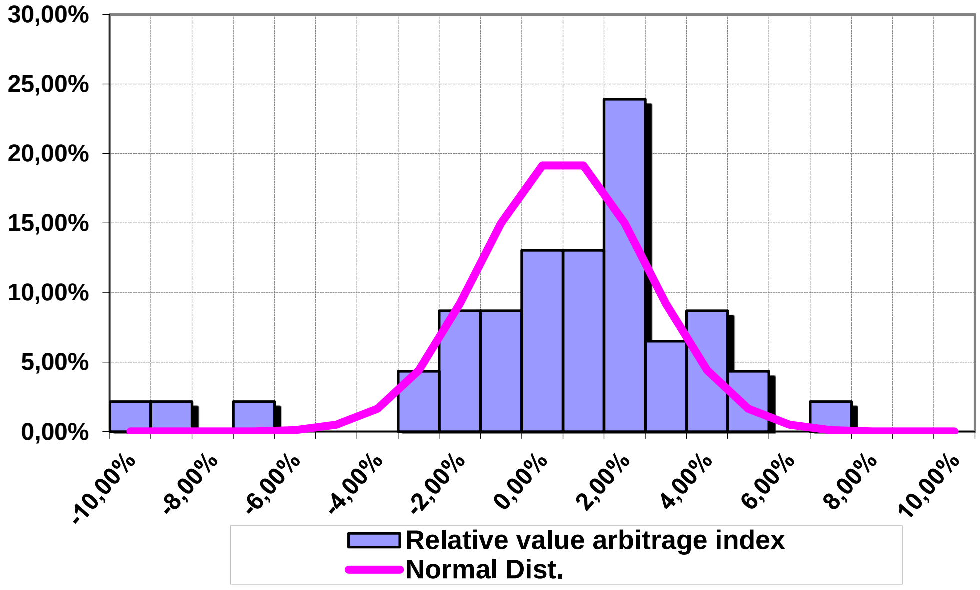


Source Bloomberg

The relative value arbitrage returns are similar to the sale of put options on the equity market. Our results are coherent with the findings of Mitchell and Pulvino (2001). They found that risk arbitrage returns are positively correlated with equity market returns in downturns but uncorrelated in flat or appreciating equity markets.

The strategy returns distribution shows the highest median between the analysed strategies, low variance and a fat tail to large negative returns from the equity market.

Figure 12. The distribution of Relative Value Arbitrage returns.



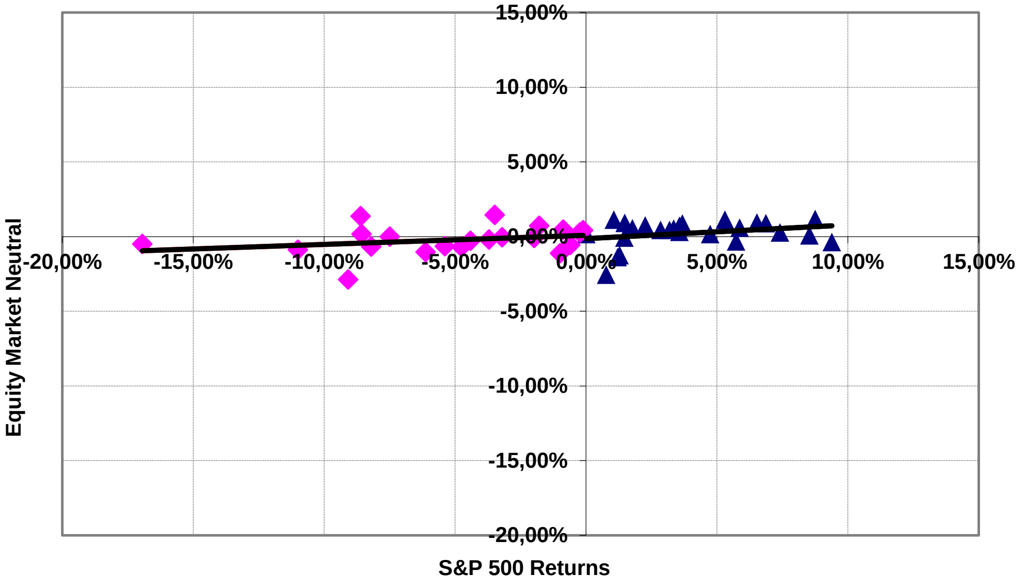
6.1.2. Equity hedge strategies.

This group concentrates the largest number of hedge funds. Their strategy is to take long and short positions in the equity market. The analysis could be performed through quantitative or fundamental analysis. Some of these funds, in addition to equities, use other market securities as; derivatives, Exchange-Traded Funds or Contracts For Differences.

a) Equity market neutral strategy.

The aim of these strategies is to be market neutral in dollar or beta terms through the purchase and sale of securities, usually their net equity market exposure is not greater than 10% long or short. According to HFRI information, they include Factor-based and Statistical/Trading strategies. Factor-based techniques consist of finding factors that have a common effect between securities. Statistical strategies usually apply some type of mean reversion approach between sectors or securities.

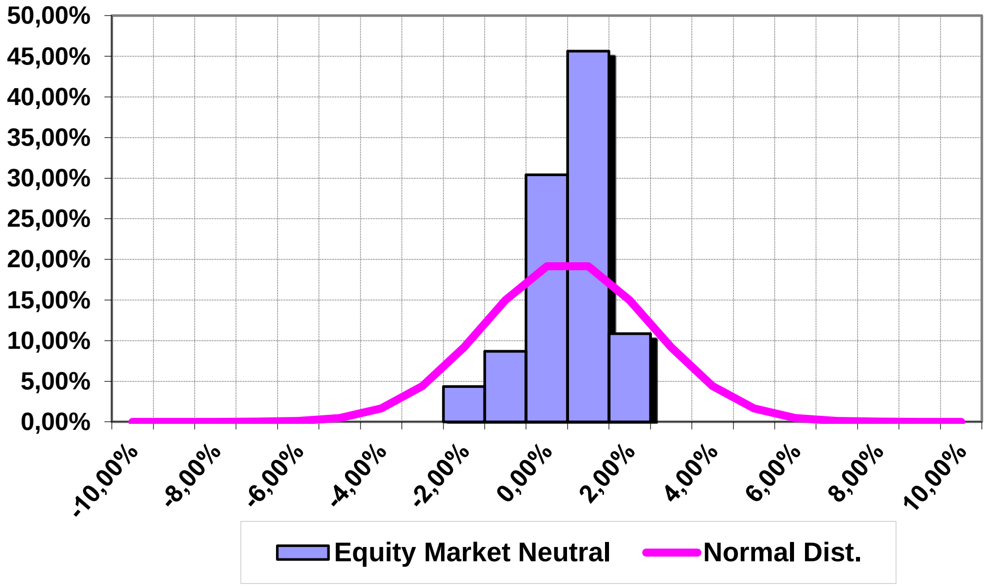
Figure 13. Equity Market Neutral index.



Source Bloomberg

Our results show that equity market neutral returns are correlated with equity returns. The strategy returns are similar to the purchase of call options and the sale of put options on the equity market. This strategy is equivalent to a synthetic long future. It is important to note that the amount of options purchased and sold is small. Therefore we would expect a return distribution with a very concentrated mass around the centre, large number of small positive returns, low variance and no fat tails at either side. This strategy shows the lowest median and variance between the analysed strategies.

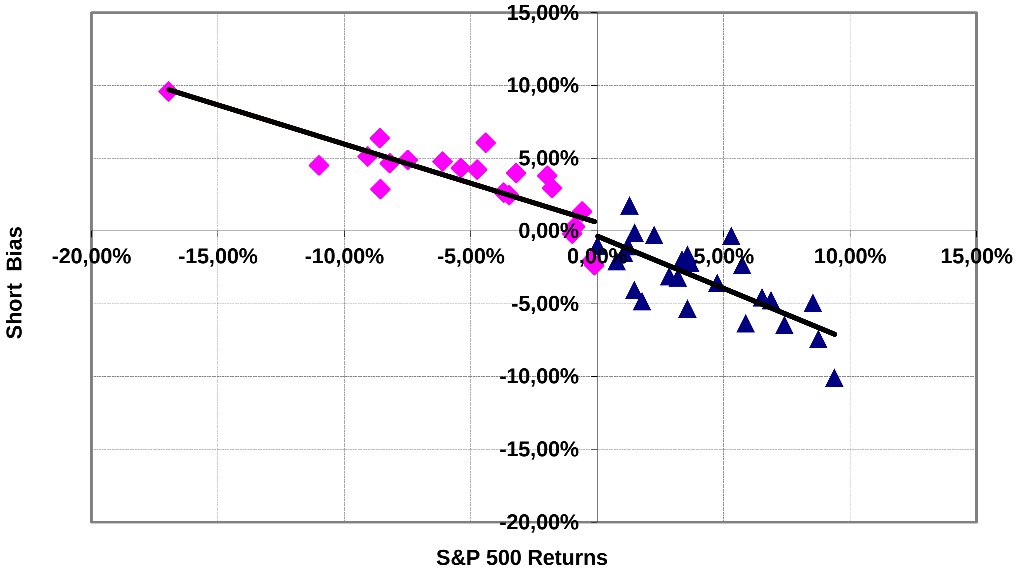
Figure 14. The distribution of Equity Market Neutral returns.



b) Short bias strategy.

These funds have the common characteristic of being net short equity exposure through the sale of overvalued securities. The level of short exposure varies between funds. The aim of the managers is to outperform in a declining equity market and not to suffer in a bullish equity market.

Figure 15. Short Bias index.

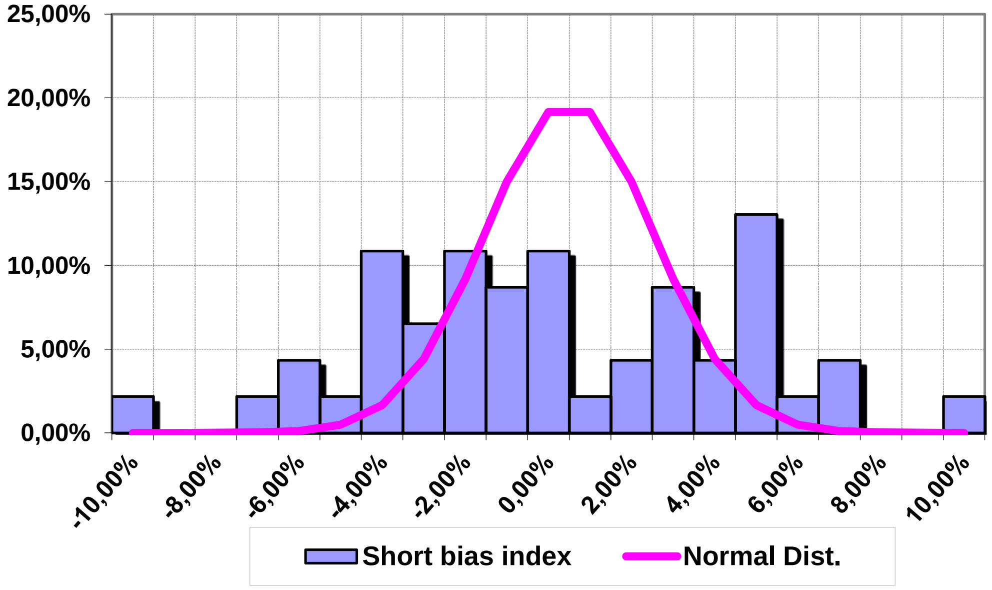


Source Bloomberg

The returns of the short bias strategies resemble the purchase of put options and the sale of call options on the equity market with similar strikes. This strategy replicates the sale of synthetic futures. A more precise analysis indicates that the purchase of puts could be changed to the purchase of put options spreads.

The returns do not seem concentrated around any point of the distribution, we would expect high variance and high fat tails on both sides; therefore we would expect a departure from a normal distribution.

Figure 16. The distribution of Short Bias returns.



6.2. Hedge fund indexes returns versus options portfolios

As stated in Camarero y Pascual (2013), taking the options profiles defined in the previous section, we are going to build a dataset of *Options Portfolios* on a monthly basis that we will compare with the original strategies returns. In order to build the different *Options Portfolios,* we have split the portfolios in two parts; *options* and *cash*.

Options are derivative instruments and therefore unfunded, only premiums are paid or received, usually at the inception of the trade. However margins are demanded, to the option sellers, in order to minimize potential future credit risk exposure. We have assumed; a level of 15% of the option notional is demanded in concept of margins, the rest of the hedge fund cash will be invested in government bonds or lent as deposits. For our purposes we have assumed that the cash is lent at the 3 month Libor rate. This maturity is consistent with the liquidity redemption window of most hedge funds. However, note that many hedge funds invest in illiquid assets, and they are compensated for providing liquidity to the market. This will be equivalent to assuming that part of the cash of our portfolio is invested in long term bonds. The obvious problem is that the funds will have maturity mismatch between their assets and liabilities. Our experience indicates that this situation is very common; this is one of the reasons why many hedge funds have to restrict investors' redemptions in periods of large outflows.

In our portfolios we have calibrated the notional equivalent of each option, consistent with the strategies returns and risks, as a function of the AUM (assets under management). We have used 3 month maturity options in all the portfolios. We have taken as inputs the implied volatility levels for 3 months options and the dividend returns published by Bloomberg. The final *Options Portfolio* returns are adjusted and corrected with the typical level of commission paid to hedge funds; 2% of management fee over the assets under management and 20% of success fees over the profits with high water mark. However, our models have an important limitation, option prices are assumed to be executed to a mid theoretical price, not taking into consideration the bid/offer spreads. Due to the low intensive trading proposed the high liquidity of the options market on the S&P 500 and the fact that we have not considered extra compensation for the asset liability maturity mismatch. We consider our results as conservative and good proxies of real market returns.

a) Volatility strategy.

We have created the *Options Portfolio* by the sale of 104%/96% strangles, each leg with an equivalent notional of 0,6 of the total fund AUM, plus the purchase of 85% put options that will hedge the tail risk to large negative equity moves, the equivalent notional of these options is 0,3 of the total fund AUM.

The results, adjusted by commissions, show that the *Options Portfolio* achieves higher returns and a more efficient return distribution (higher mean, lower volatility and less negative Skew) than the Volatility Index. Although, the number of months with positive returns are lower than in the Volatility Index, the size of the monthly losses are smaller and the size of the profits bigger.

Table 8. Comparison between Volatility and Options strategies distributions

	Volatility Index	Options Strategy
Mean	0,040%	0,051%
Median	0,652%	0,103%
Stand. Desv.	1,704%	1,312%
Skew	- 0,860	- 0,205
Kurtosis	0,494	3,290
Min.	-4,53%	-4,42%
Max.	2,76%	4,04%
N. of positive	56,52%	50,00%
N. of negative	43,48%	50,00%

Figure 17. Volatility Index vs. *Options Portfolio* returns distributions

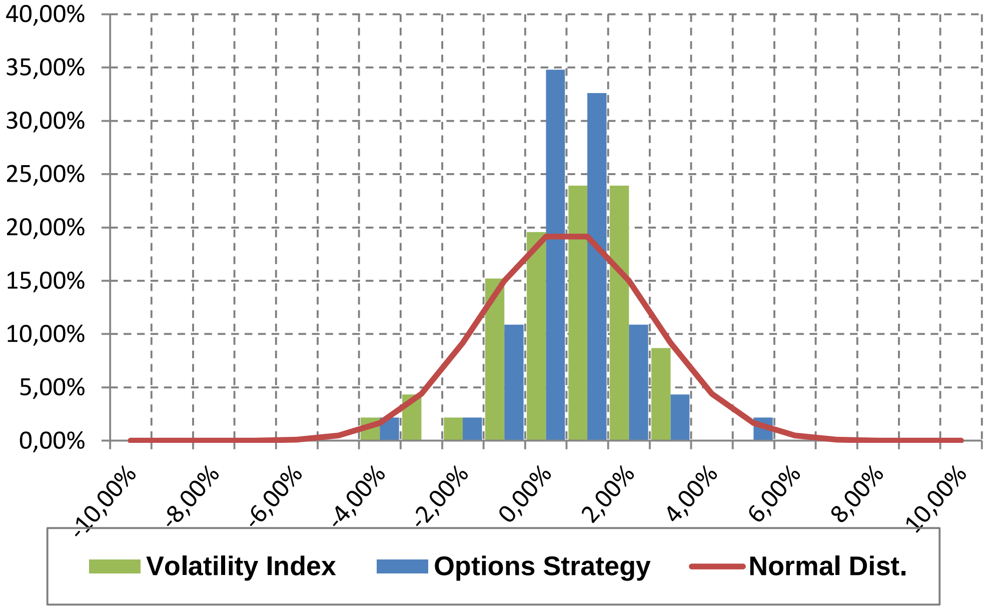
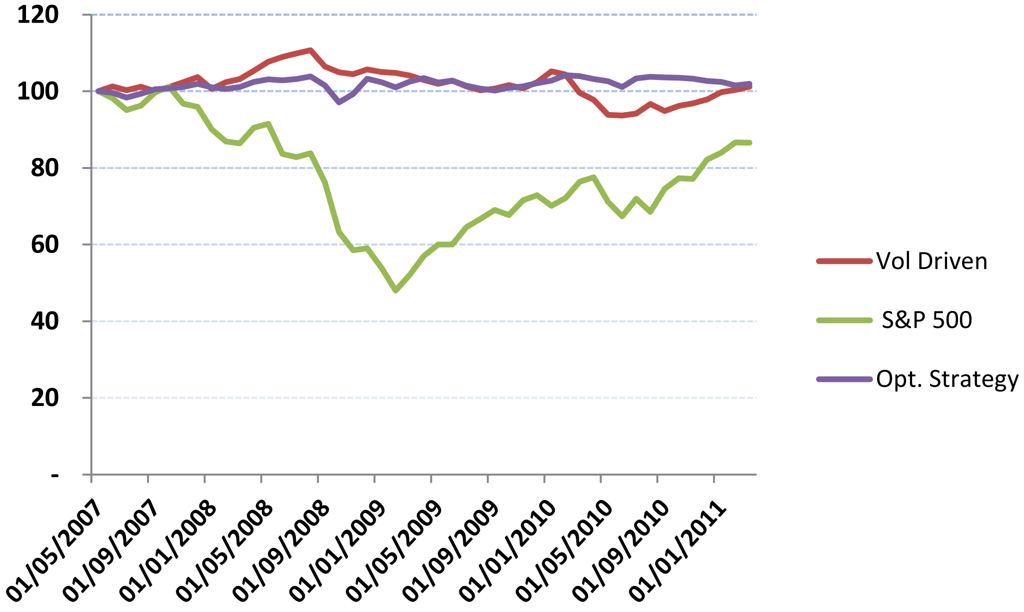


Figure 18. Volatility Index vs. *Options Portfolio* performances (in base 100)



* Note that the S&P 500 returns are not adjusted with the 2/20 commissions

b) Relative value strategy.

In this case our *Options Portfolio* has been built by the sale of ATM put options, the options notional is equivalent to the total AUM level.

Figure 19. Relative Value Arbitrage Index vs. *Options Portfolio* returns distributions

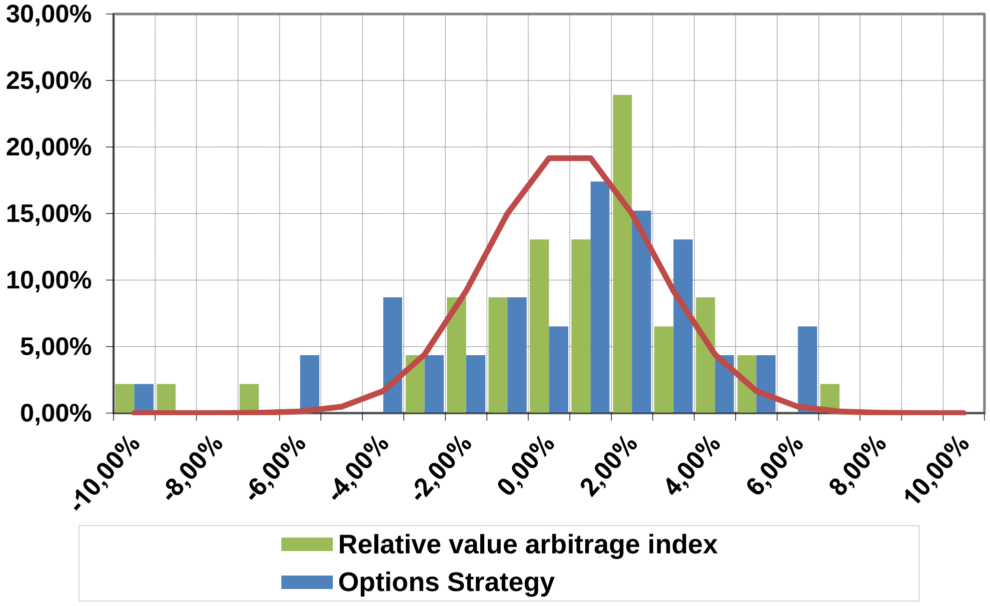
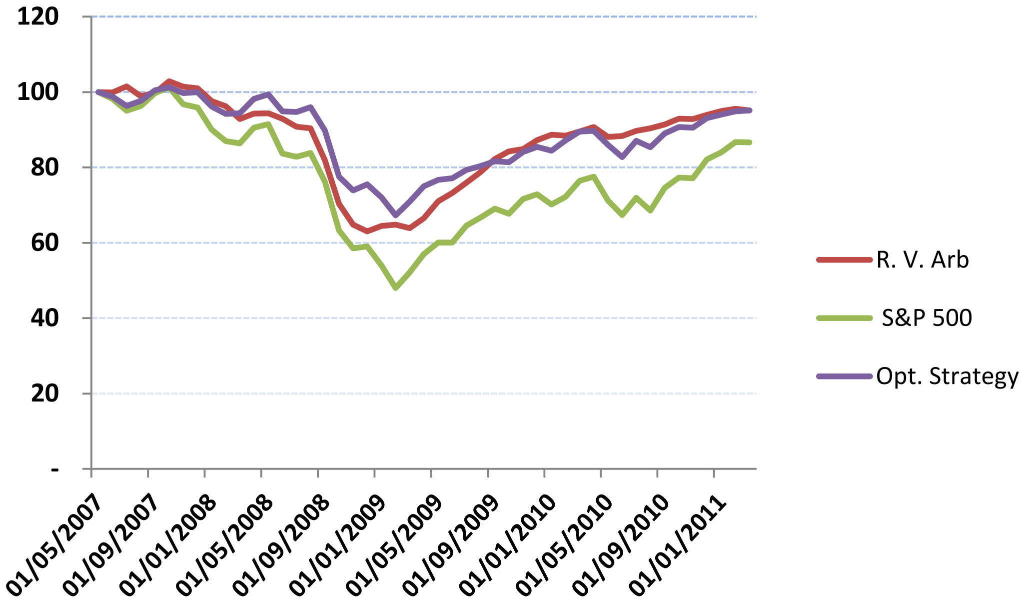


Figure 20. Relative Value Arbitrage Index vs. *Options Portfolio* performances (in base 100)



* Note that the S&P 500 returns are not adjusted with the 2/20 commissions

c) *Equity market neutral strategy.*

We have built this *Options Portfolio* buying ATM calls and selling ATM put options. The notional equivalent of each option is 0.3 of the total AUM level. This is consistent with a low leverage.

The results of the *Options Portfolio* shows lower returns that in the Equity Market Neutral Index, however we achieve lower volatility, less negative skew and lower excess kurtosis.

Table 9. Comparison between Relative Value and Options strategies distributions

	Equity Market Neutral	Options Strategy
Mean	**0,024%**	**-0,059%**
Median	**0,160%**	**0,079%**
Stand. Desv.	**0,923%**	**0,829%**
Skew	**- 1,106**	**- 0,686**
Kurtosis	**1,731**	**0,222**
Min.	**-2,87%**	**-2,44%**
Max.	**1,45%**	**1,33%**
N. of positive	**56,52%**	**52,17%**
N. of negative	**43,48%**	**47,83%**

Figure 21. Equity Market Neutral Index vs. *Options Portfolio* returns distributions

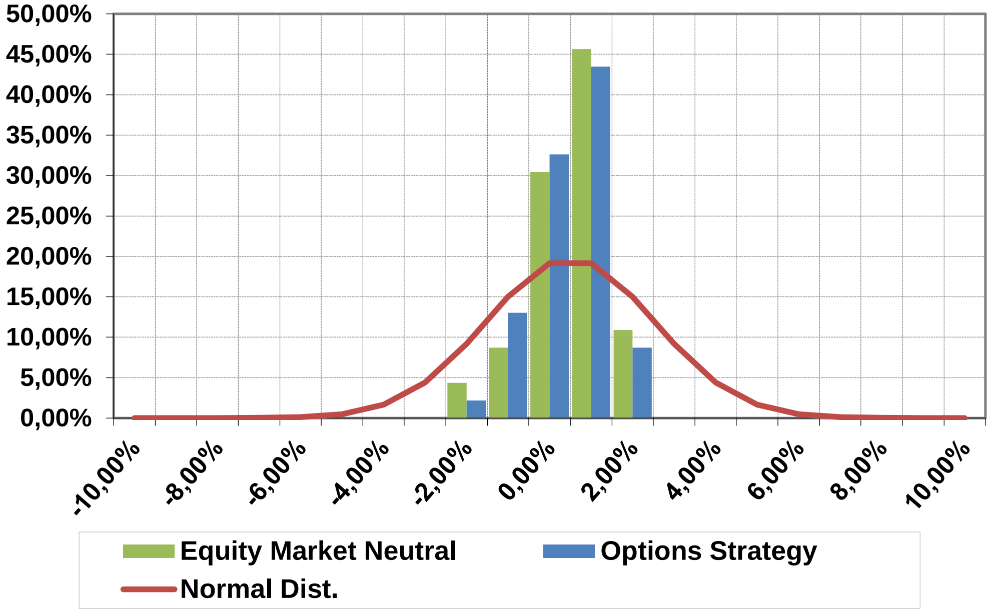
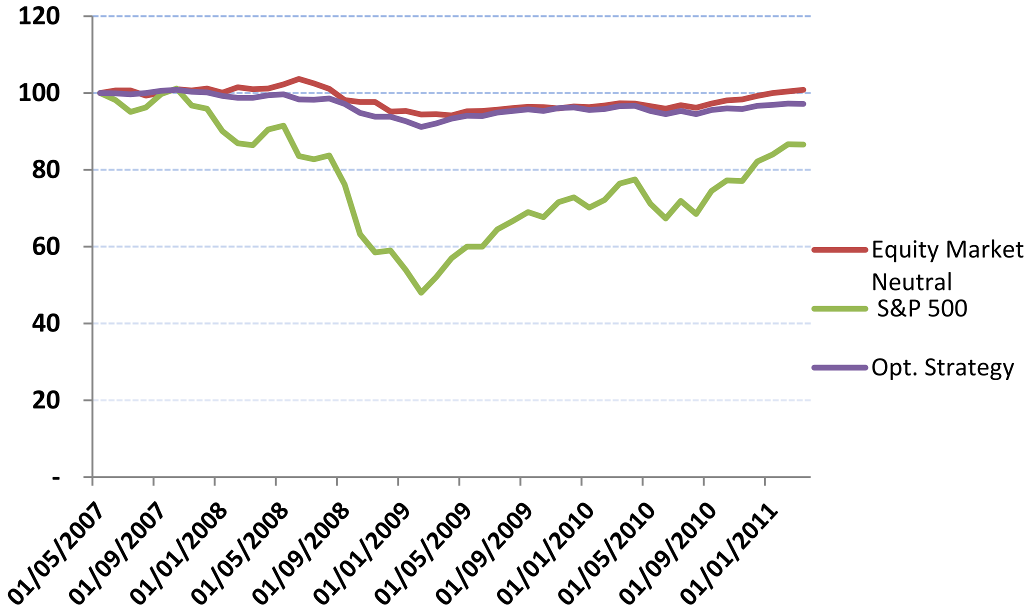


Figure 22. Equity Market Neutral Index vs. *Options Portfolio* performances (in base 100)



* Note that the S&P 500 returns are not adjusted with the 2/20 commissions

d) Short bias strategy.

In this case the *Options Portfolio* is built buying ATM puts and selling ATM calls.

The options notional of each leg is equivalent to 0.75 of the total AUM.

The results show two nearly identical distributions.

Table 10. Comparison between Short bias and Options strategies distributions

	Short Bias	Options Strategy
Mean	**-0,241%**	**-0,239%**
Median	**-0,659%**	**-0,545%**
Stand. Desv.	**4,282%**	**3,972%**
Skew	**0,024**	**0,311**
Kurtosis	**- 0,521**	**- 0,413**
Min.	**-10,09%**	**-7,39%**
Max.	**9,58%**	**9,70%**
N. of positive	**41,30%**	**41,30%**
N. of negative	**58,70%**	**58,70%**

Figure 23. Short Bias Index vs. *Options Portfolio* returns distributions

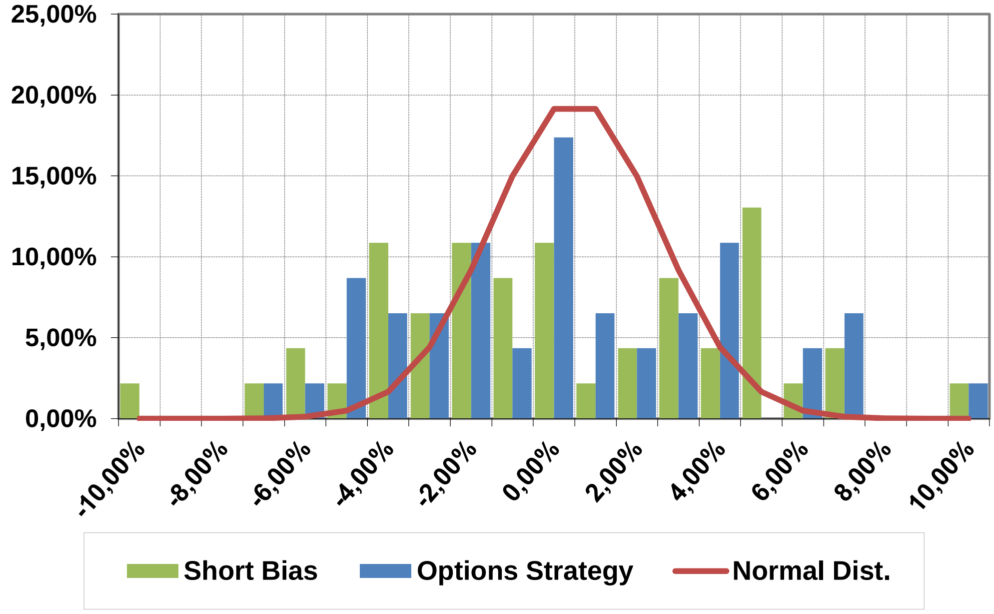
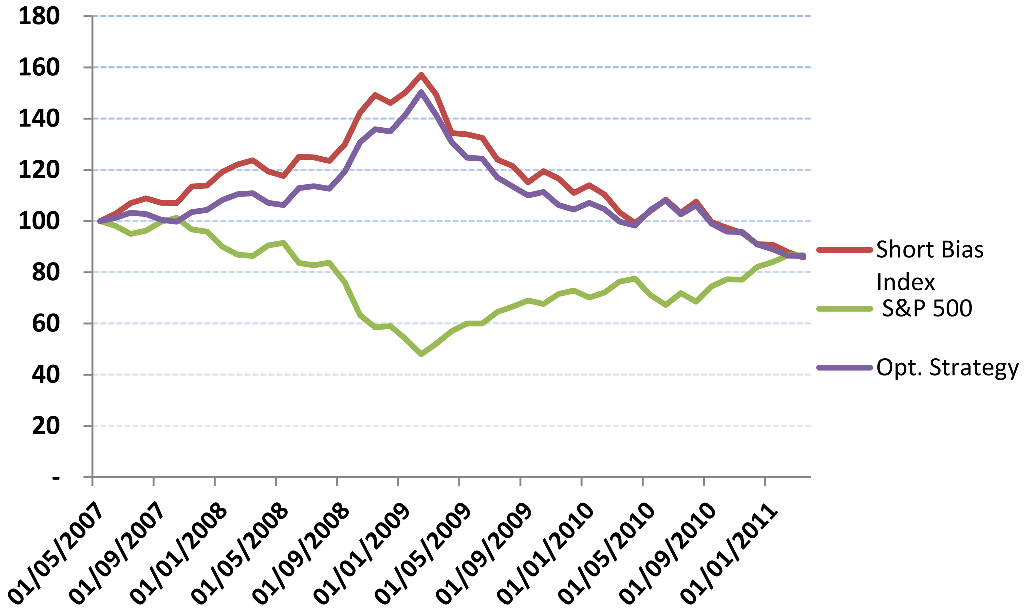


Figure 24. Short Bias Index vs. *Options Portfolio* performances (in base 100)



* Note that the S&P 500 returns are not adjusted with the 2/20 commissions

6.2.1. Formal validation of the analysis

In order to check the validity of our models we find that the original hedge fund strategy returns, as we illustrated, show serial correlation. As we stated, some of the reasons behind the serial correlation of the hedge fund returns could be the aim of the managers to smooth returns and therefore to reduce their reported risk level. This argument becomes reinforced by the fact the serial correlation is reduced when we increased the period length of the returns. Not surprisingly this increase in the return period length also increases the explanatory power and the statistical significance of our model returns when we regress the time series. For consistency with the redemption window assumed in our analysis, we judge 3 months returns to be the right length to consider.

We show the difference of the reported R^2 between the hedge fund and the option strategy returns regressions for 1 month versus 3 month returns.

Table 11. R2 between hedge fund and option strategies as we increased the period length

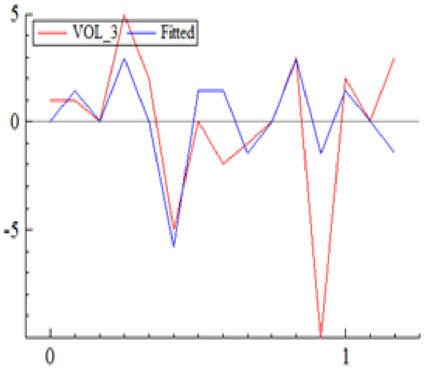
R2	Volatility	Relative Value Arbitrage	Equity Market Neutral	Short Bias
1 month returns	0,05	0,43	0,01	0,86
3 month returns	0,35	0,82	0,55	0,88

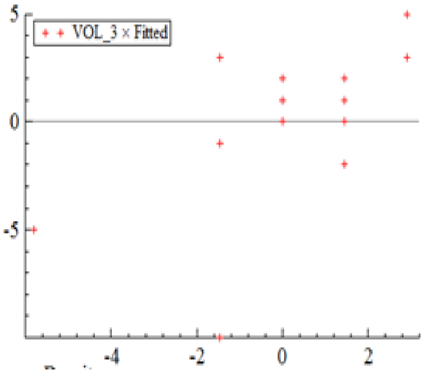
Table 12. Regression of hedge fund and options strategies quarterly returns, fitted model and errors distribution by strategy

VOLATILITY

	Coefficient	Std.Error	t-value	t-prob Part.	R^2
OPC_3	1.45161	0.5207	2.79	0.015	0.3570

sigma	2.89923	RSS	117.677419
log-likelihood	-36.7333	DW	1.79
no. of observations	15	no. of parameters	1
mean(VOL_3)	-0.0666667	var(VOL_3)	12.1956

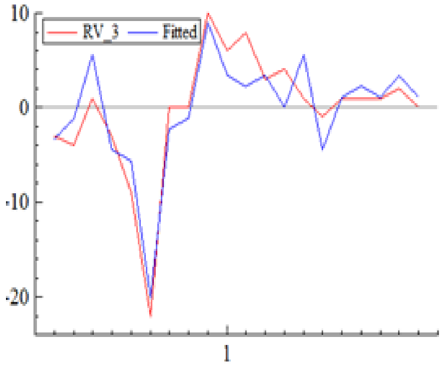


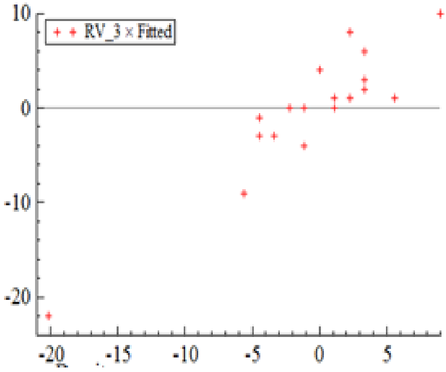


RELATIVE VALUE

	Coefficient	Std.Error	t-value	t-prob	Part.R^2
Opc_3	1.11861	0.1193	9.37	0.000	0.8222

sigma	2.7937	RSS	148.290146
log-likelihood	-48.4132	DW	2.15
no. of observations	20	no. of parameters	1
mean(RV_3)	-0.2	var(RV_3)	41.66

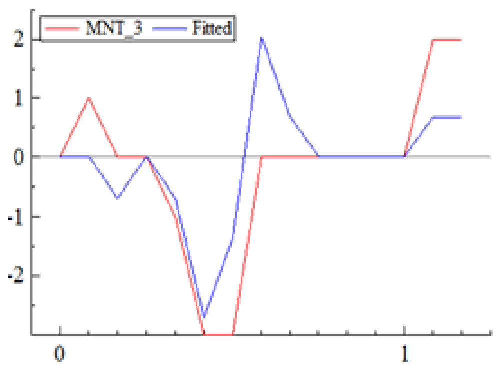


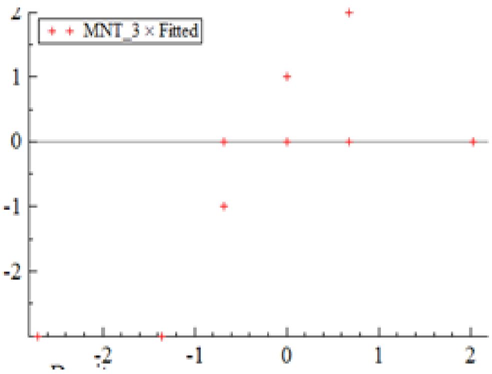


MARKET NEUTRAL

	Coefficient	Std.Error	t-value	t-prob Part.	R^2
OPC_3	0.676471	0.1617	4.18	0.001	0.5557

sigma	0.942685	RSS	12.4411765
log-likelihood	-19.8813	DW	0.618
no. of observations	15	no. of parameters	1
mean(MNT_3)	-0.133333	var(MNT_3)	1.84889

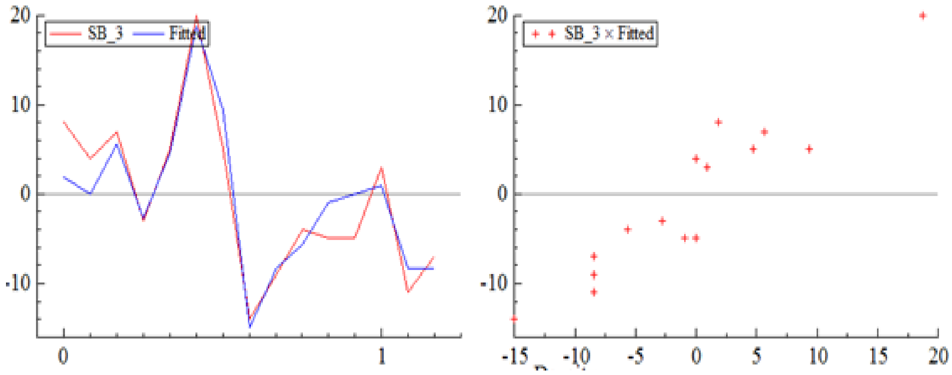




SHORT BIAS

	Coefficient	Std.Error	t-value	t-prob Part.	R^2
OPC_3	0.936994	0.09302	10.1	0.000	0.8787

sigma	3.10057	RSS	134.589559
log-likelihood	-37.7404	DW	1.51
no. of observations	15	no. of parameters	1
mean(SB_3)	-0.4	var(SB_3)	73.84



CONCLUSIONS

To use the returns generated by the different hedge fund investment strategies as input for the classical Markowitz portfolio theory, concludes that the risk-return characteristics of these alternative investment vehicles are a very attractive proposition, thus inferring that hedge funds are a sound investment choice for the investment community. Markowitz' framework, however, omits three very important aspects regarding the performance of hedge funds: these are the existence of statistical moments of higher order (skewness and excess kurtosis), autocorrelation of returns as well as biases. These three factors possess the potential to distort the return data of hedge funds in a way that leads to exaggeration of their return characteristics, and underestimating the inherent level of volatility, hence making the hedge fund investments appear more attractive than they are in reality.

The results obtained prove that hedge funds lose a large part of their attractiveness when considering the combined effects of fat tails, autocorrelation and survivorship bias. Furthermore, their status of being considered return enhancers during bear markets as standalone assets, and as risk diversifiers in a portfolio context due to their alleged low correlation with stocks and bonds is being questioned.

As we saw in chapter IV, the autocorrelation of the hedge fund returns, as in other alternative investments, suggest that some type of smoothing is performed by the managers. The largely unregulated nature of the business makes it particularly vulnerable to misrepresentation and fraud, including the gross overstatement of hedge fund performance and the payment of unnecessary commissions. Therefore we claim that further regulation in this front and proper due diligence of the funds' performance are essential.

Understanding the statistical behaviour of hedge fund strategies is a key factor in order to select hedge fund investments. Study of their historical returns will provide us with a lot of information; however it is important to understand the limitations of the technology used. Performances generated in a specific part of an economic cycle, that seem to have achieved consistent high excess returns could underperform systematically once the business cycle changes, therefore the returns generated by a hedge fund have to be understood in the context of the strategy used and the economic cycle. We showed that from a mathematical point of view many models treat the correlation as a constant or a linear variable, however a more robust approach will be to treat correlation as a stochastic variable.

We have provided a statistical analysis of some hedge funds strategies, and proposed a complementary and easy form of explaining and assimilating their return distributions, through the purchase and sale of plain vanilla options over the equity market. This technology has allowed us to account for the non linearity and non normality of these returns, and to identify relevant risk factors that explain a strategy's returns and risk. Trying to explain strategy return with a linear model might systematically lead us to mistaken conclusions.

Applying our findings we have built a series of Options Portfolios that we have compared with the original strategies. Our results show that with low intensive trading strategies we are able to achieve similar returns and more efficient returns distributions in most cases. Therefore, we challenge the idea that the hedge fund industry is able to generate alpha – excess returns – in a consistent basis. In fact, liquidity risk is behind a significant part of the "excess" hedge fund performance.

Our findings establish that hedge funds are providing exposure to risk factors different to the traditional assets classes - equity, bonds and cash. This conclusion does not demerit the role of hedge funds as a specialized industry that allow, to less sophisticated or with lower resources investors, to access different assets classes, providing them with new management tools. In addition, this industry contributes very decisively to the integration and completeness of the financial market. A statement that must be understood in the context of the risk assumed by leverage funds and the effect that crowed – and leverage – trades might have in liquidity reduction situations. As we proved in chapter V, in mathematical terms, the correlation will depend of a non linear variable, as it is the volatility, and higher market volatility will increase the correlation of our variables. The obvious consequence is that in a downturn market situation, most of the hedge fund strategies – with the exception of contrarian ones - will behave in line with the rest, providing no portfolio diversification benefits and a lack of liquidity at the same time.

In addition, with our technology, we have built portfolios that replicate the different hedge fund time series returns. We have showed that all our Options Portfolios tested, as we showed in chapter VI, will clearly outperform the hedge funds returns strategies if we assume lower commissions. Therefore we see no reason to justify the large fees charged across by most parts of the hedge fund industry. Our conclusion is reached by the hedge fund industry as a whole. This conclusion is not in conflict with the fact that certain hedge fund managers consistently obtain returns for their investors that amply justify the fees charged.

As we explained, this conclusion is not trivial because from our view, an asymmetric and “excessive” fee by the risk assumed leads to the assumption of disproportionate risks, as for example too much leverage, contributing to a non-efficient allocation of resources and increasing market volatility.

We conclude that a new fee structure model is needed in the hedge fund industry in order to support their role as an efficient resource allocator, provider of liquidity and a contributor to the market completeness, trough the exploitation of different investment opportunities not targeted by other market players.

This study does not cover how to set this new fee structure model but we look forward to continuing with our investigation and research in this field, as a continuation of our studies

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