Gregor Gawron

Tail risk of hedge funds: an extreme value application

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Tail risk of hedge funds: an extreme value application

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Chapter 1

Introduction

1.1 Problem description

Investors seek to maximise returns and to minimise risk. As risk is manageable but returns are not, these objectives can best be achieved through risk measurement/management techniques. In this regard, the concept of diversification plays a central role in modern portfolio theory. It follows that investors' welfare can be improved by allocating wealth among a large number of different assets. Ideally, any poorly performing asset can eventually be compensated by for positive performance from other assets in the portfolio. To put it differently, the idiosyncratic risk of a single asset can be diversified away leading to lower portfolio risk and thus a higher risk adjusted portfolio return. Obviously, a necessary condition for risk diversification to work is that asset returns do not depend on each other. Under the assumption of normally distributed returns, a standard assumption in finance, risk and dependence can be expressed by volatility and correlation respectively.

Low volatility and low correlation with other assets offers diversification benefits to investors. These two features, together with historically good performance may explain the increasing attractiveness of hedge funds among institutional and retail investors in recent years. In the last decade the hedge fund industry has been the fastest growing asset class in the financial sector. Despite the decade-long bull market in the 1990s and liquidity/credit crises in the late 1990s, hedge fund investing has been gaining popularity among various types of investors. HFR (2007) estimates that the total net assets in hedge funds are approximately USD 1.4 trillion as of the fourth quarter 2006.

As a result of this growth, an increasing number of studies describing the various hedge fund characteristics, performance comparison with other asset classes, and their overall contribution in institutional portfolios has been produced. Some of the early works are the monographs of Lederman and Klein (1995), Crerend (1998), Jaffer (1998), Lake (1999) as well as the studies of Ackermann, McEnally, and Ravenscraft (1999) and Fung and Hsieh (1997). Other monographs such as Jaffer (2003) focus entirely on the properties of fund of hedge funds.

The risk and diversification benefits of hedge funds have been studied in many different ways. Two major events at the end of 1990s; the near collapse of Long-Term Capital Management and the Asian crisis, have led regulatory authorities to focus more on studying the risk inherent in hedge fund strategies. Brown, Goetzmann, and Park (1998) examine the involvement of hedge funds in the Asian crisis of 1997-1998, and the Report of the President's Working Group on Financial Markets (1999) deals extensively with the Long-Term Capital Management incident in 1998 and highlights the potential risks of excessive use of leverage. The general role played by hedge funds in financial market dynamics has been studied in Eichengreen, Mathieson, Sharma, Chadha, Kodres, and Jansen (1998).

The investment risk of hedge funds, their unique risk properties stand alone as well as in portfolio context have been analysed with standard risk management tools typically assuming implicitly or explicitly normally distributed returns. For example, Edwards and Liew (1999) show that adding hedge funds to traditional portfolios increases the Sharpe ratio of those portfolios. Purcell and Crowley (1999) show that hedge funds outperform traditional assets in times of down markets. Diversification benefits of adding hedge funds are also found in Crerend (1998) and Agarwal and Naik (2000) as well as in Géhin and Vaissié (2005). In these studies a significant upward shift of efficient frontier and reduction in risk measures is observed.

However, hedge funds pose a challenge to standard risk measures based on normally distributed returns. Recent evidence (see e.g. Schmidhuber and Moix 2001, Brooks and Kat 2002) casts doubt on the validity of volatility and correlation as appropriate risk measures for hedge funds. Indeed, the returns of hedge fund indices are not normally distributed and have exhibited unusual levels of skewness and kurtosis. The asymmetric properties of hedge fund returns are investigated in Anson (2002a), Ineichen and Johansen (2002), and Ineichen (2002). These characteristics are consistent with the complex trading strategies used by hedge funds which present option-like payoffs (see e.g. Fung and Hsieh 1997, Fung and Hsieh 2001, Mitchel and Pulvino 2001, Fung and Hsieh 2002c, Agarwal, Fung, Loon, and Naik 2004).

Clearly, volatility and correlation do not provide sufficient information about risk and dependence when the normality assumption is violated. As a consequence, applying symmetric measures on hedge funds may lead to erroneous conclusions. One potential solution to overcome the problem of non-normality in hedge fund returns is to apply methods that take the asymmetry in return distribution into account. For instance, Bacmann and Pache (2004) apply downside deviation, Keating and Shadwick (2002) make use of the Omega function and Favre and Signer (2002) propose the use of a modified Value-at-Risk based on Cornish-Fisher expansion.

In this thesis, the use of *Extreme Value Theory* (EVT) is advocated. This area of statistics enables the estimation of tail probabilities regardless of the underlying distribution of hedge fund returns. The fact that it focuses on the tail returns rather than their means, makes modelling of the whole time series of returns unnecessary. Consequently, the estimation of Value-at-Risk and Expected Shortfall can be done under fairly general types of distributions.

This thesis contributes to the growing literature on risk associated with hedge funds in two main directions. Firstly, it carefully examines the tail risk of individual hedge fund strategies and of portfolios built with stocks, bonds and hedge funds using EVT. Consequently, the first objective is to evaluate the size of return asymmetry in order to quantify a potential tendency for extreme losses among various hedge fund strategies. The second objective follows the first one as it attempts to quantify eventual benefits of the inclusion of hedge funds in a traditional portfolio (stocks and bonds) depending on the initial composition of the portfolio and on the type of hedge funds added. Several papers (Lhabitant 2001, Blum, Dacorogna, and Jaeger 2003, Gupta and Liang 2003) have already used Value-at-Risk derived from EVT in the context of single funds or hedge fund indices. Bacmann and Gawron (2005) evaluates portfolio risk by allocating fund of hedge funds only.

Secondly, the thesis further measures the dependence between hedge funds and traditional investments in periods of distressed markets. In such periods, correlation breaks down and investors' ability to diversify diminishes because the asset dependence is much higher than in periods of market quiescence. For this purpose the main objective is to test explicitly the existence of asymptotic dependence among hedge funds as well as between hedge funds and traditional investments.

1.2 Disposition

This work is organised as follows: Chapter 2 introduces risk measurement techniques especially for assessing risks for non-normal return series; Chapter 3 reviews statistical methods (e.g. EVT) for measuring risk and dependence for asymmetric return distributions; Chapter 4 covers specific characteristics of hedge funds that distinguish them from traditional investments as well as reasons for their asymmetric return distribution; Chapter 5 empirically examines tail properties of hedge funds and compares them with traditional investments; Chapter 6 analyses how hedge funds, stocks and bonds fit together with respect to tail risk; Chapter 7 examines dependence in the tails between hedge funds and traditional investments is examined in Chapter 7; and finally Chapter 8 summarises the thesis conclusions.

Chapter 2

The notion of risk

Since this chapter is concerned with formal financial theory, a general summary of some of the basic ideas in risk management is presented. With this foundation, the discussion of Value-at-Risk and Expected Shortfall in analysing hedge funds becomes more meaningful and clear.

2.1 Risk measurement

Describing risk is a particularly difficult task as no commonly accepted definition exists. In the financial community, risk is usually viewed as exposure to uncertainty or the danger posed to future outcomes by a decision made today. In order to quantify this uncertainty, the different possible outcomes are associated to specific probabilities. Analysing the whole range of probabilities, i.e. probability distribution, is not feasible in practice. This is why simple statistical measures are used to assess the magnitude of risk. The most widely used measure to achieve this task has been the variance (or standard deviation) of returns. Variance describes the variability of returns or dispersion of returns around their mean return. Thus, the higher the variance, the more uncertain the return, and therefore the greater the risk. The vast popularity of variance is largely due to the impact of Modern Portfolio Theory on finance, which dates back to the seminal paper of Markowitz (1952). This theory explores how risk averse investors construct portfolios in order to optimise expected returns for a given level of market risk, from a mean-variance framework. In this regard, this approach views risk as the uncertainty of an investment decision.[1] Nevertheless, the introduction of the mean-variance approach has had significant implications on the development of theory and practice in finance, including that on risk measurement related to the uncertainty of capital requirement decisions. One of these implications is the consideration of distributional assumptions in measuring risk, which is briefly presented below.

Let X denote a random variable, which represents a quantity whose outcome is uncertain. The distribution of X is defined by the probabilities of all events which depend on X. This probability distribution is uniquely specified by the (cumulative) probability distribution function.[2]

$$F(x) = P(X \leq x), \quad -\infty < x < \infty. \tag{2.1}$$

If $F(x)$ is a continuous function of x whose first derivative exists and is continuous, then $F(x)$ can be written as

$$F(x) = \int_{-\infty}^{x} f(t)dt \tag{2.2}$$

where $f(x)$ is called the probability density function of the random variable X and t is used as the variable of integration. A distribution function $F(x)$ is often represented by moments that characterise its main features. Thus, the rth moment of X (or of the distribution of X) is defined by

$$E[X^r] = \int_{-\infty}^{\infty} x^r f(x)dx. \tag{2.3}$$

The first moment is the mean or expected value which specifies the location of the centre of the distribution and it is often denoted by μ. Its central moment of order r is defined as

$$\mu_r = E[(X-\mu)^r] = \int_{-\infty}^{\infty} (x-\mu)^r f(x)dx. \tag{2.4}$$

Hence, μ_2 is the variance which measures the dispersion around the mean of X. The positive square root of variance is called the standard deviation of

[1] See for example the monograph of Moix (2001) for a thorough discussion of these issues.

[2] See Medenhall, Wackerly, and Scheaffer (1990) or any other standard text on statistics for the properties of $F(x)$.

X. Its third and fourth moments are skewness and kurtosis. The former is a measure of asymmetry in the distribution whereas the latter describes the shape of the distribution. A useful distribution often applied in finance is the normal (Gaussian) distribution. It is a bell-shaped distribution which is symmetric with respect to its mean. As this distribution is fully described by its first and second moments, its variance is the adequate measure of risk. Hence, the appropriateness of variance as a risk measure depends strongly on the degree of non-normality of the returns data.[3]

A cornerstone in the mean-variance approach is the quantification of diversification benefits. Markowitz (1952) shows that in attempts to reduce portfolio risk (variance), investors must avoid investing in securities with high covariances among themselves. This means that measuring the degree of dependence between securities is crucial in determining the magnitude of risk where more than one asset is involved. Consequently, in addition to the first two moments of each asset, to construct a properly diversified portfolio, Markowitz's model also requires the expected correlation of each component with every other component. Correlation is a standardised covariance that traditionally has served as a measure of dependence. It is obvious that correlation is strongly related to the variance of the individual assets. Thus, its adequacy as a measure of dependence must be evaluated under the same assumptions as those of variance.

Critics of variance point out that it implies the same sensitivity in both upside and downside movements in return, while investors only dislike downside movements. This very strong assumption has been challenged by the emergence of the Prospect Theory (Kahnemann and Tversky 1979). In that framework, the investor is more affected by a drop in his wealth than by an increase. Moreover, there is strong empirical evidence that asset returns are not symmetric around the mean which rules out the normality assumption. This evidence goes back to Mandelbrot (1963), who argued that volatility

[3] Besides the normality assumption, a second justification for the use of variance as a risk measure comes from the Markowitz (1952) approach. It is well known that this approach is appropriate for investors having quadratic preferences. In that case, investors' expected utility is only a function of the first two moments of the distribution, and thus the variance is the adequate measure of risk.

is time varying and large returns are much more frequent than predicted by the Gaussian distribution.[4] Consequently, the variance and correlation of returns do not provide sufficient information about risk and dependence.

Therefore, risk measures that emphasise the downside risk only have been proposed. In this regard, one considers the concept of Lower Partial Moments.[5] Within this framework risk is measured in terms of probability weighted deviations below some specified target rate of returns q while allowing a more general set of assumptions regarding investors' preferences. A Lower Partial Moment of order n below a specified target level q is computed as:

$$LPM_{n,q} = \int_{-\infty}^{q} (q - x)^n f(x) dx \tag{2.5}$$

where $n = 2$ refers to target semi-variance. For the purpose of capital requirements, risk measures that focus solely on the lower tail of the distribution have been designed. In this context, the most widely used measures are various generalisations of Value-at-Risk and Expected Shortfall (see e.g. Jorion 1997, Moix 2001). Within this framework, risk is assessed in terms of predetermined probability of losing a portfolio value over a certain holding period.[6]

Given the empirical findings of asymmetric return distributions, the use of correlation as a measure of dependence has been challenged in a similar fashion as variance. More general, empirical evidence has shown that correlation changes dramatically in periods of financial distress, making diversification less valuable.[7] This has led to a development of correlation measures either conditional on time or on the size of the returns (Campbell, Forbes, Koedijk, and Kofman 2003). The former make use of the famil-

[4] Mandelbrot (1963) advocated the use of Lévy-stable distributions in fitting speculative price changes. These allow fat tails and imply that the second moment might not be finite. This family of distributions includes Lévy, Cauchy and Gaussian distribution, for which closed form formula exist. See Weron (2001) for more details.

[5] Moix (2001) is a formal treatment of Lower Partial Moments and its relation to other risk measures, whereas Persson (2000) offers an empirical case study.

[6] Section 2.4 and Section 2.5 deal with these measures, respectively.

[7] See for example the work of Longin and Solnik (2001), Karolyi and Stulz (1996), and Ang and Chen (2002). Zimmermann, Drobetz, and Oertman (2002) offers a comprehensive overview on this topic.

iar (multivariate) GARCH modelling, while the latter approaches focus on tail correlation by utilising the extreme value approach (Longin and Solnik 2001, Poon, Rockinger, and Tawn 2003), or the closely related concept of copula (Embrechts, McNeil, and Straumann 2002).[8]

2.2 Types of financial risks

Financial institutions such as banks, hedge funds, and (re)insurance companies are exposed to several types of financial risks. Generally, they are classified into market risks, credit risks, liquidity risks, operational risks and legal risks. In a broader perspective, however, each of these corporations faces more general risks too, such as business risks and strategic risks. However, the daily business of financial institutions is concerned with managing an enormous number and variety of financial transactions and thus the financial risks are of key interest to the financial industry. The following description summarises the characteristics of the various financial risks

Operational risk. This risk results from mistakes or failures in internal operations. It covers a wide area that can be divided into human/technology errors such as management failure, fraud, flawed system implementation, conducting business in an unethical or risky manner, and risks that are outside the control of the firm such as natural disasters and political or regulatory regime changes (Allen, Boudoukh, and Saunders 2004).

Credit risk. This risk arises when a counterparty may fail or might be unwilling to meet its obligations and thus causes the asset holder to suffer financial loss. This class includes: downgrade risk, which refers to the risk that a counterparty might be downgraded by a rating agency; sovereign risk, which refers to the default of a country; and settlement risk, which arises when there is non-simultaneous exchange of value (Bustany 1998).

[8] See Mari and Kotz (2001) for a thorough treatment of the various state-of-the-art dependence measures, including a historical background of the dependence concept. Section 3.5 presents extremal dependence.

Legal risk. This risk is related to the legal uncertainties arising when a counterparty does not have the regulatory authority to enter financial transactions. It could also include activities that contravene government regulations, such as market manipulation and insider trading (Jorion 1997).

Liquidity risk. This risk consists of market/product liquidity risk and cash flow/funding liquidity risk. The latter relates to the inability to raise the necessary cash to roll over debt, or to meet the cash, margin, or collateral requirements of counterparties. Market/product liquidity risk is related to trading risk and arises when a financial institution is unable to execute a transaction in the prevailing market conditions. It may occur during market turmoil when liquidity dries out and the bid-ask spread increases dramatically. This risk is difficult to quantify and varies across market conditions (Crouhy, Galai, and Mark 2001).

Market risk. This risk arises from financial transactions and can be defined as the risk resulting from adverse movement in market prices. There are four major types of market risk (Basle Committee on Banking Supervision 1996):

- *Interest rate risk.* It is divided into specific risk that refers to an adverse movement in the price of an individual security owing to factors related to the individual users and general market risk that refers to the risk of loss arising from changes in market interests rates.

- *Equity risk.* As with debt securities, it is expressed in specific risk that refers to characteristics specific to the firm and can be eliminated through portfolio diversification, and general market risk which can not be diversified and refers to the sensitivity of an instrument or portfolio to a change in stock market indices.

- *Foreign exchange risk.* Due to macroeconomic relations the major sources of foreign exchange risk are fluctuations in international interest rates and their imperfect correlations with currency prices.

- *Commodity price risk.* The risks associated when holding or taking positions in commodities are generally more complex and volatile than the previous risks. Changes in spot positions are the major source of commodity risk. Additional risks such as basis risk, the risk of change in the cost of carry and forward gap risk may also fit into this type of risk.

Understanding, identifying and controlling each of the risks above calls for a measurement system that can quantify the exposure to each type of risk. The so-called *Value-at-Risk* (VaR) measure has become a popular framework for this purpose. It calculates the total market risk associated with a firm's trading book in terms of a probable loss at a given confidence level and summarises it in a single monetary figure. In a similar fashion, the VaR framework has been adopted to quantify the exposure to credit and operational risks. Liquidity risk is more difficult to quantify in a single number.[9]

Before formalising the VaR concept, however, it is worthwhile to reflect upon the general needs for risk management, which lie at the foundation of developing such a measure as VaR.

2.3 Historical evolution

From a historical point of view, one can distinguish several factors that have had an influence on the process leading to the introduction of risk management systems. Perhaps the starting point of this process is the breakdown of fixed foreign exchange rates regimes in the early 1970s. As a consequence, the increased volatility in exchange rates forced financial institutions to look for instruments that could protect them from the increasing exposure to foreign exchange risk. This development led to the introduction of financial derivative instruments (Jorion 1997). A few years later, the oil-price shocks, starting in 1973, and the resulting inflationary pressure in major economies in conjunction with floating exchange rates led to instability in interest rates. The market response to the increased interest rates volatility was to create a wide range of new derivative instruments to trade these risks (Crouhy, Galai, and Mark 2001). Further deregulations and globalisation of financial

[9]See the monographs of Crouhy, Galai, and Mark (2001) and Allen, Boudoukh, and Saunders (2004) for a more detailed description on the applications of VaR concept to these risks.

markets and changing monetary regimes forced financial institutions to pay more attention to the financial markets and the linkages between them. The unpredictability that had arisen by means of volatility increased awareness of the need to address financial risks.

Moreover, the increased competition among banks and customers' demands for more sophisticated and complicated solutions to reduce their risk exposure have, along with technological changes, contributed to the rapid development of derivative instruments. This growing activity in derivative markets and the dynamic nature of these instruments, including the potential for leverage, exposed banks to various risks associated with these trading activities. Additionally, these instruments did not appear on balance sheets which precluded the possibility of disclosing the true risk of banks. The dramatic disasters attributed to derivative losses such as the fall of Barings bank in 1995 and the near bankruptcy of Metallgesellschaft in 1993 highlighted the needs for a proper risk management tool.[10]

In such situations, regulatory authorities have been forced to establish a new safe and sound financial system that will ensure banks remain capable of meeting their obligations and act as a cushion against potentially disastrous losses. This would prevent destabilising effects on the economy. The first attempt in this direction was set up by the Basle Committee on Banking Supervision (1988), a body of the Bank for International Settlements (BIS). The co-called 1988 BIS Accord established international minimum capital guiding principles in order to assess capital required to cover the banks' risks and came into force at the end of 1992. The exposure of each asset position is calculated according to a risk-weighting scheme and then the necessary capital is set to be equal to at least 8 percent of the total risk-weighted assets of the bank.

Although this Accord took off-the-balance engagements into account, it essentially focused on credit risk only and ignored exposure to market risks. Moreover, it did not acknowledge the effects of diversification across issuers, industries and geographical locations that may reduce credit risk substantially. Nevertheless, the Accord and the role of the BIS has been

[10]See Jorion (1997) for details on these and other disasters.

seen as important milestone in forcing banks to quantify risks, evaluate risks and monitor risks.

Aware of these drawbacks and in view of the increasing volume of trade in derivatives, a new solution had to be sought for the construction of capital adequacy. In April 1993, the BIS[11] came forth with a standard model approach that extended the initial Accord to incorporate market risks. This building-block approach required banks to hold additional regulatory capital against market risk in their trading book. The ongoing industry consultations led to the introduction of the "1996 Amendment"[12] that permits banks the use of proprietary in-house risk measurement models to determine their capital charge, as an alternative to the standardised measurement framework. It was implemented at year-end 1997. The foundation of the proposed alternative is based on the Value-at-Risk framework.

Recently, BIS developed a revised framework, the so called BIS II[13] which is based on three pillars: minimum capital requirement, supervisory review, and market discipline. It is a result of many consultation proposals and quantitative impact studies that were circulated to supervisory authorities worldwide since 1999.[14] The main objectives behind this approach were to further strengthen the safety and soundness of the international banking system by defining more risk sensitive capital requirements while eliminating competitive inequalities among internationally active banks. Regarding the minimum capital requirement, the major changes are related to credit risk assessment and incorporation of operational risk. There are, however, no changes in treatment of market risk from the "1996 Amendment". It is intended that the BIS II framework will be available for implementation as of year-end 2006.

[11] Basle Committee on Banking Supervision (1993)

[12] Basle Committee on Banking Supervision (1996)

[13] Basle Committee on Banking Supervision (2004)

[14] See www.bis.org/publ/bcbs107.htm for a historical overview of the consultative process and related literature.

2.4 Value-at-Risk and internal models

VaR was originally identified by the Group of Thirty (1993), a working group of academics, end-users, lawyers, dealers and financiers, whose major recommendation was to value positions on mark-to-market principles. It became popular in 1994 as the US investment bank J.P. Morgan made available to the public their own risk measurement system, called RiskMetrics (J.P. Morgan 1996). Jorion (1997, p.19) gives the following definition of VaR:

> VaR summarises the expected maximum loss (or worst loss) over a target horizon within a given confidence interval.

Its great advantage stems from its reporting simplicity, i.e. it can be expressed in a single monetary number. For example, a one-day VaR with 95% confidence of value \$10 means that, the amount we can lose by holding this asset one day is \$10 or more. Equivalently, the probability of losing more than \$10 by holding this asset for one day is 5%.
Using statistical language, it follows naturally that VaR_p can be expressed as the upper quantile $p \in (0, 1)$ of the loss distribution F.[15] It turns out that VaR_p is defined as

$$VaR_p = x_p = F^{-1}(p) \tag{2.6}$$

where F^{-1} is the inverse of loss distribution F.
In general, one can distinguish between two types of VaR models: parametric and nonparametric VaR. Parametric VaR, also referred to as the variance/covariance method, assumes that underlying risk factors follow the normal or some other specified distribution. The RiskMetrics method, for instance, uses this approach. It assumes that the returns on assets are multivariate normally distributed. The great advantage of this method is that VaR can be expressed as a function of the standard deviation (volatility) of the returns. We are then concerned about calculating the one-sided confidence interval. Hence, VaR can be expressed as

$$VaR_p = \mu + \sigma\Phi^{-1}(p) \tag{2.7}$$

[15] typically the value of p is 0.95 or 0.99 denoting the desired confidence level.

where $\Phi^{-1}(p)$ is the inverse of the standard normal distribution function, and σ together with μ denote the standard deviation and mean, respectively. By choosing an appropriate level of confidence we can decide the proportion of time when VaR will be exceeded. For example, if one wishes to measure VaR with one-sided 99% confidence interval the $\Phi^{-1}(0.99)$ will be equal to 2.33 and the calculation of VaR is reduced to estimating mean and volatility of the returns. At this point, the volatility can be estimated either using the unconditional or the conditional approach. The conditional approach, as used in the RiskMetrics method, recognises that the returns exhibit volatility clustering phenomenon. However, the simplicity of this approach has its drawbacks, most notably the distributional assumption of normality that ignores fat tails, a characteristic common to financial return series. Fat tails in distribution imply that large losses occur more frequently than the normal distribution would lead us to believe. Obviously, symmetric risk measures become inappropriate when used with non-symmetric distributions. As a consequence, the assumption of normality will typically understate the level of risk.

As an alternative to the parametric approach, one can apply the historical simulation method, also called the nonparametric approach. Using this method we do not need to infer a probability distribution and the only assumption regarding the stochastic nature of the returns is that they should be independent and identically distributed (*iid*) (el Jahel, Perraudin, and Sellin 1998). Hence, at least to some extent it accounts for any non-normal characteristics of returns such as skewness or fat tails. The current portfolio is revalued using changes in the risk factors derived from historical data. Keeping the weights at their current values gives us a set of hypothetical portfolio returns for which the hypothetical distribution is constructed. VaR is then obtained by simply reading off the sample quantile from the histogram at the desired confidence level. However, since only one sample path is used, it means that the trends of past changes will continue in the future. Therefore, the number of observations constructing the historical data is a critical input to this method. It is clear that calculating VaR at high levels such as 99% is only possibly provided that such an extreme return is present in our sample length (Ridder 1997). Including or excluding a few observations in the beginning of the sample may cause large fluctuations of the VaR estimate. Consequently, we are faced with a trade-off problem between long and short sample size (Hendricks 1996). Longer samples might no longer be relevant to the current market conditions and any regime changes or mean reversion tendency potentially violates the *iid* assumption. On the other hand, due to lack of data short samples reduce the statistical precision of the VaR estimates. Furthermore, the VaR may change dramatically from day-to-day.[16]

Both methods have their strengths and weakness, and their application is strongly dependent on the specific composition and complexity of the portfolio and the data bank resources that risk managers possess. For instance, a great number of derivative instruments in the portfolio would support the use of the historical method in preference to the variance/covariance method. Conversely, lack of distributional assumptions make it impossible to extrapolate beyond the range of the data. This is a significant drawback since the essential interest for risk managers is to look for the presence of extreme returns, and hence making predictions regarding tail probabilities. Large, unpredicted events are relatively common in financial markets. As a matter of fact, neither method is able to tackle this issue properly.[17] This suggests looking for a semi-parametric approach that addresses fat tail properties, in the sense that a probabilistic argument concerning the behaviour of rare events is combined with the historical simulation method.

The so-called extreme value theory (EVT) provides a statistical methodology to deal with rare events. One advantage of EVT is the fact that it focuses on the extreme returns rather than their means. As a consequence, modelling the whole time series of returns is not necessary. Additionally, EVT uses limiting distribution for extreme returns, regardless of the original distribution. This means that one does not have to make any assumptions about the distribution function of our portfolio returns in order to assess extreme quantiles and event probabilities.

[16] Allen (1994) offers a discussion of the advantages of the historical simulation approach over the parametric approaches

[17] A comprehensive empirical comparison of the various VaR models can be found in van den Goorbergh and Vlaar (1999) or Zucchini and Neumann (2001)

EVT in general and the so-called peak-over-threshold method in particular have received a great deal of attention in financial applications. Longin (1996) showed that the tails of stock returns belong to the Fréchet class[18] and he initiated the use of EVT for capital requirements purposes too. Danielsson and de Vries (1997) and McNeil (1998), McNeil and Frey (2000) as well as Longin (2000) give a demonstration of different EVT approaches for VaR estimation. Embrechts, Resnick, and Samorodnitsky (1999) provide a summary of general EVT results with applications to finance and insurance. EVT itself, however, is not a recent innovation. For many years, it has been successfully applied in the area of environmental design. The estimations of extreme behaviour of sea levels, rainfalls, air pollution etc, belong to the most important applications (e.g. Smith 1989, Davison and Smith 1990, Coles 1991). Other fields where EVT plays an important role are modeling of insurance losses (e.g. Hogg and Klugman 1984, McNeil 1997, McNeil and Saladin 1997) and teletraffic data (Resnick 1997) as well as survival analysis. An up to date summary of the EVT theory and various applications is to be found in Kotz and Nadarajah (2000) and Coles (2001).

2.5 Expected shortfall

One of the shortcomings of VaR as a risk measure, as emphasised by Danielsson (2002) and Embrechts, McNeil, and Straumann (2002), is that it only provides a point estimate of the loss distribution. It does not say anything about the size of losses given that the loss above VaR has occurred. In other words, VaR measures the probability of default only, but not the average loss in case of default. Thus, VaR ignores important information regarding the tails of the underlying distribution. For example, if the 95% VaR is \$10, we are not able to state whether the maximum possible loss is \$15 or \$1000. What one obtains from VaR is that in 5% of worst cases the loss will be higher than \$10. Thus, the definition of VaR as a maximum expected loss is obviously wrong (see e.g. Acerbi, Nordio, and Sirtori 2001, Jaschke 2001). According to Acerbi, Nordio, and Sirtori (2001), the correct version of VaR delivers the answer to the question: what is the minimal expected loss of 5%

[18]This distribution represents the fat tail family of distributions in EVT

worst cases? In situations where both the normal and EVT VaR produce the same number, the information about the shape of the tail beyond that loss is especially important.

Banking supervision should try to minimise the expected loss in the event of bankruptcy. However, interpreting the BIS' three zone approach it follows that a model that has many small exceedances will be rejected whereas a model with few very high exceedances will be accepted.[19] This is precisely the opposite of what banking supervision seeks to achieve. Furthermore, Artzner, Delbaen, Eber, and Heath (1999) have shown that a quantile based risk measure, such as VaR, is not coherent for non-normal data because it fails to be subadditive. Consistent with the authors a risk measure $\rho(.)$ is coherent if it satisfies the following properties:

- translation invariance $\rho(X + a) = \rho(X) + a$
- subadditivity $\rho(X + Y) \leq \rho(X) + \rho(Y)$
- positive homogeneity $\rho(\lambda X) = \lambda \rho(X)$ for all $\lambda \geq 0$
- monotonicity $\rho(Y) \leq \rho(X)$ for all X and Y with $Y \leq X$

The subadditivity property plays an especially important role in practical applications. A risk measure is subadditive when the risk of the total position is less than or equal to the sum of the risk of individual portfolios. Clearly, subadditivity is a highly desirable property which requires that risk is reduced due to portfolio diversification effects. Violation of this property implies that the VaR of a portfolio may be larger than the sum of VaRs of the individual assets. This would cause a number of problems when aggregation of risks across different units is considered as well as for capital requirements and portfolio optimisation. The references cited above give several examples of practical difficulties in cases when subadditivity is not satisfied.

[19]This three zone approach serves a test of model accuracy. Depending on the number of violations a corresponding penalty factor is added, leading to a higher capital requirement.

There is, however, a measure that is subadditive and considers loss beyond VaR level. Artzner, Delbaen, Eber, and Heath (1999) have proposed the use of *expected shortfall* (ES) to overcome the problems associated with VaR. It is defined as

$$ES_p = E[X|X > VaR_p]. \tag{2.8}$$

The relation to VaR can be expressed by (McNeil 1999):

$$ES_p = VaR_p + E[X - VaR_p|X > VaR_p] \tag{2.9}$$

where the second term is the mean excess function which describes the fatness of the tail in EVT.[20] Consequently, by using EVT we can easily estimate the ES and the drawbacks of VaR discussed above can simply be adjusted for by adding an appropriate factor. Hence, ES summarises the tail of the loss distribution into a single number, conditional on loss being beyond the VaR level. Clearly, assuming for example a 95% confidence level, the ES tells us the expected loss given that we actually get a loss in the 5% tail. Finally, despite VaR's drawbacks as risk measure, as can be seen from equation (2.9), a good forecast of ES requires an accurate measure of VaR.

[20] A detailed description of mean excess function is given in Section 3.3. See also (Moix 2001) for the relation of VaR and ES to Lower Partial Moments.

Chapter 3

Extreme Value Theory

This chapter will give an explanation of the statistical theory that justifies the use of extreme value theory in calculations of Value-at-Risk and Expected Shortfall. Besides the derivations forming the peak over threshold approach, a description of the extremal dependence in the bivariate context will be provided.

3.1 Classic Extreme Value Theory

Assuming $X_1, X_2, \ldots, X_n$ as a sequence of *iid* random variables with common distribution F we are especially interested in a possible distribution or classes of distributions of the maximum $M_n = max\{X_1, X_2, \ldots, X_n\}$ as the sample size n increases to infinity. In other words, we are looking for limiting forms for the distribution function of M_n given as (Leadbetter, Lindgren, and Rootzén 1983):

$$\begin{aligned}
\Pr\{M_n \leq x\} &= \Pr\{X_1 \leq x, X_2 \leq x, \ldots, X_n \leq x\} \\
&= \Pr\{X_1 \leq x\} \Pr\{X_2 \leq x\} \ldots \Pr\{X_n \leq x\} \\
&= F^n(x).
\end{aligned}$$

The issue of finding a limiting distribution for the sample maxima is similar to the concept of central limit theorem when the unknown distribution of sums leads to the normal distribution (Beirlant, Teugels, and Vynckier 1996). As for the central limit theorem one seeks a sequence of normalising constants $a_n > 0$ and b_n such that $(\frac{M_n - b_n}{a_n})$ converge in distribution, so that

$$\begin{aligned}\Pr\left\{\frac{M_n - b_n}{a_n} \leq x\right\} &= \Pr\{M_n \leq a_n x + b_n\} \\ &= F^n(a_n x + b_n) \Rightarrow H(x) \qquad (3.1)\end{aligned}$$

where H is a nondegenerate distribution function. Then, as $n \to \infty$, from the so-called *extremal types theorem*[1] it is known that H must be one of the three fundamental types of extreme value limit laws:

$$\begin{aligned}
\text{Type I (Gumbel)}: \quad & \Lambda(x) = \exp\{-e^{-x}\}, \quad x \in \mathbf{R} \\
\text{Type II (Fréchet)}: \quad & \Phi_\alpha(x) = \begin{cases} 0, & x \leq 0 \\ \exp\{-x^{-\alpha}\}, & x > 0 \end{cases} \quad \alpha > 0, \\
\text{Type III (Weibull)}: \quad & \Psi_\alpha(x) = \begin{cases} \exp\{-(-x)^{\alpha}\}, & x \leq 0 \\ 1, & x > 0. \end{cases} \quad \alpha < 0,
\end{aligned}$$

In other words, the limiting distribution for sample maxima follows one of the three distributions specified above, whatever the parent distribution F. The expression (3.1) holds if and only if,

$$\lim_{n \to \infty} n(1 - F(a_n x + b_n)) = -\ln H(x). \qquad (3.2)$$

If the condition (3.2) is satisfied one says that the unknown distribution F is in the maximum domain of attraction of H, $F \in \text{MDA}(H)$. The parameter α is called the shape parameter and gives an indication of the heaviness of the tails, the lower the α the heavier the tail. The importance of this theorem for modelling sampling maxima is comparable to that of the central limit theorem in modelling averages. While the normal distribution is a limit law for sums of *iid* random variables the three extreme value limit distributions are limit laws for maxima of *iid* random variables.[2]

Since the Fréchet distribution is the only limit law that reveals the heavy tail behaviour it is, naturally, of special interest in financial applications. Heavy tailed distributions are expressed by using the concept of regular

[1] See e.g. Leadbetter, Lindgren, and Rootzén (1983)

[2] The domain of attraction problem, i.e. how to find a suitable sequence of a_n and b_n in order to achieve convergence of F to H is of probabilistic nature and will not be discussed here. See the monographs of Leadbetter, Lindgren, and Rootzén (1983), Resnick (1987), and Embrechts, Klüppelberg, and Mikosch (1997) for derivations and proofs.

variation which means that the tail of the distribution function F decays like a power function at infinity:

$$1 - F(x) = x^{-\alpha}\mathcal{L}(x), \tag{3.3}$$

where $\mathcal{L}$ is slowly varying, that is, $\lim_{t\to\infty} \mathcal{L}(tx)/\mathcal{L}(t) = 1$ for $x > 0$ and $t \to \infty$. According to Gnedenko (1943), a distribution F having a tail $1 - F(x)$ which is regularly varying with index $-\alpha$, $\alpha > 0$, is the only necessary and sufficient condition for a distribution function F to belong to the domain of attraction of the Fréchet distribution.

Consequently, the regular variation defines the tail fatness of a distribution and any distribution with a tail behaving as that of the Fréchet distribution is called a Fréchet type distribution. The class of distributions of this type includes the Pareto, Burr, Cauchy, Stable laws with exponent $\alpha < 2$, log-gamma, log-hyperbolic, log-logistic and t-distributions. The properties and the accompanied slowly varied functions of these distributions can be found in Beirlant, Teugels, and Vynckier (1996). The class of distributions in the domain of attraction of the Gumbel type characterises an exponentially decreasing tail and includes the normal, exponential, gamma, and log-normal distributions. Distributions with a finite upper bound, like the uniform in (0,1) and beta distributions, belong to the domain of attraction of the Weibull type.[3] Figure 3.1 illustrates extreme value distributions with shape parameter $\alpha = 2$ for Fréchet and Weibull distributions.

For convenience, the three types of extreme value distribution may be combined into the single *Generalised Extreme Value*(GEV) distribution $H_{\xi;\mu,\sigma}$:

$$H_{\xi;\mu,\sigma}(x) = \begin{cases} \exp\left[-\left(1+\xi\frac{x-\mu}{\sigma}\right)^{-1/\xi}\right], & \xi \neq 0 \\ \exp\left(-e^{-(x-\mu)/\sigma}\right), & \xi = 0 \end{cases} \tag{3.4}$$

with scale, location and shape parameters σ,μ and $\xi = 1/\alpha$ respectively. In the literature, the shape parameter is also termed tail index. The case $\xi > 0$

[3]The necessary and sufficient conditions as well as the choice of norming constants for the domain of attractions of the two remaining extreme value distributions can be found in Resnick (1987), Leadbetter, Lindgren, and Rootzén (1983) or Embrechts, Klüppelberg, and Mikosch (1997).

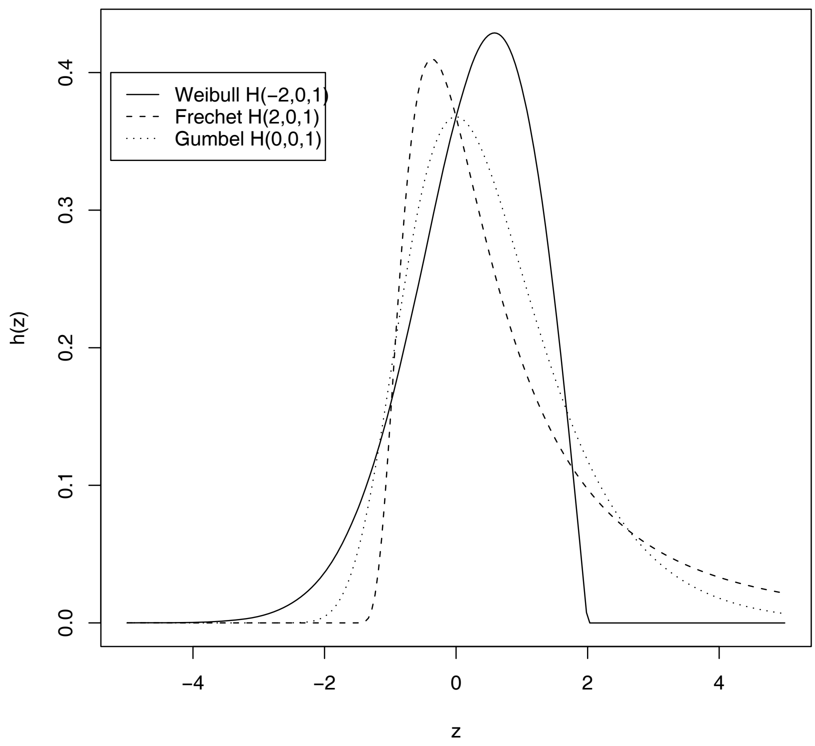

Figure 3.1: *Extreme value distributions with shape parameter $\alpha = 2$.*

corresponds to the Fréchet distribution with shape parameter $\alpha = 1/\xi$, the case $\xi < 0$ gives the Weibull distribution with shape $\alpha = -1/\xi$, and finally $\xi = 0$ gives the Gumbel distribution. The mean of this distribution exists if $\xi < 1$ and the variance if $\xi < 1/2$, more generally, the k'th moment exists for $\xi < 1/k$.

3.2 Peak over threshold

Modelling extreme events by means of the aforementioned extreme value distributions requires a sample of maxima collected in certain blocks or subperiods. A more efficient use of data is offered by the *peak over threshold* (POT) method, in which all observations exceeding a (high) pre-specified threshold are considered. Conditional on the event that the random variable X is larger than the threshold u and denoting these exceedances by y, one is interested in estimating the distribution function F_u called the *conditional excess distribution function*:

$$F_u(y) = P(X - u \leq y \mid X > u), \qquad 0 \leq y \leq x_F - u \tag{3.5}$$

which can be written as

$$F_u(y) = \frac{F(u+y) - F(u)}{1 - F(u)} = \frac{F(x) - F(u)}{1 - F(u)} \tag{3.6}$$

where $x_F \leq \infty$ is the right endpoint of F.
Given that the parent distribution F is in the MDA of GEV, Pickands (1975) has shown that the limiting distribution for the exceedances over a sufficiently high threshold is well approximated by the *generalised Pareto distribution* (GPD), $F_u(y) \approx GPD_{\xi,\sigma}(y)$, for $u \to \infty$. The GPD is expressed as

$$GPD_{\xi,\sigma}(x) = \begin{cases} 1 - \left(1 + \frac{\xi}{\sigma}\, y\right)^{-1/\xi}, & \xi \neq 0 \\ 1 - e^{-y/\sigma}, & \xi = 0. \end{cases} \tag{3.7}$$

The choice of threshold must be high enough for the limit theorem to be valid but not too high in order to have efficient estimation. As with the GEV distribution, the mean exists if $\xi < 1$, and the variance if $\xi < 1/2$.
Redefining the GPD as a function of x with $x = u + y$, i.e. $GPD_{\xi,\sigma}(y) = GPD_{\xi,u,\sigma}(x)$, and using the expression (3.6) one can derive the model to build a tail estimate of $F(x)$ (McNeil and Saladin 1997):

$$\widehat{F(x)} = (1 - F(u))GPD_{\xi,u,\sigma}(x) + F(u). \tag{3.8}$$

F_u now is replaced by GPD and the $F(u)$ can be estimated by $(n-k)/n$, where n is the total number of observations and k the number of observations exceeding the threshold u. This turns to

$$\widehat{F(x)} = \frac{k}{n}\left(1 - \left(1 + \hat{\xi}\frac{x-u}{\hat{\sigma}}\right)^{-1/\hat{\xi}}\right) + \left(1 - \frac{k}{n}\right) \tag{3.9}$$

and by inverting for a given probability $p > F(u)$ one obtains the quantile (VaR) estimation

$$\widehat{VaR}_p = \hat{x}_p = u + \frac{\hat{\sigma}}{\hat{\xi}}\left(\left(\frac{n}{k}(1-p)\right)^{-\hat{\xi}} - 1\right). \tag{3.10}$$

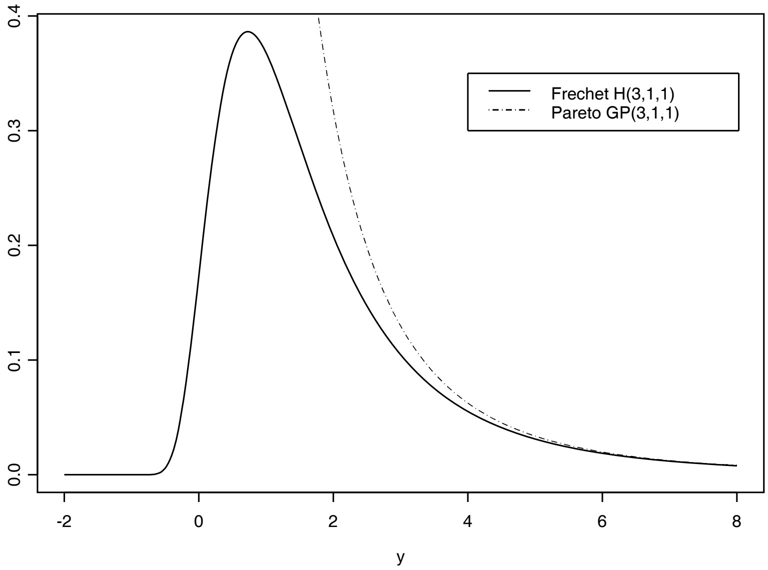

Figure 3.2: *Pareto and Fréchet density with shape parameter $\alpha = 3$.*

For different values of the shape parameter ξ the parametrisation of GPD, and likewise GEV, can be outlined within three submodels corresponding to that of extreme value distributions. Each single GPD is in the MDA of the comparative extreme value distribution and the density has an upper tail similar to that of an extreme value density.[4] The mathematical relation between extreme value and generalised Pareto models is: $GP = 1 + \log(EV)$. Figure 3.2 illustrates the tail equivalence between Pareto and Fréchet distributions.

3.3 Mean excess function

The concept of *mean excess function* is a useful tool in implementation and estimation of EVT as well as in the derivation of the expected shortfall. It is often handled as a diagnostic tool with the intention of exploring the heavy-tailedness assumption and to assist in selecting the appropriate threshold (Davison and Smith 1990). Assuming that $E(X) < \infty$ the mean

[4]See e.g. Reiss and Thomas (1997) for broader description.

excess function $e(u)$ of X is given by

$$e(u) = E\left(X - u | X > u\right) = \frac{\int_u^\infty (1 - F(x))dx}{1 - F(u)} \ . \tag{3.11}$$

It is the mean of the excess distribution function above the threshold u expressed as a function of u. Investigating the shape of the mean excess function reveals information about the tail behaviour of the distribution.[5] For instance, the theoretical $e(u)$ of the exponential distribution is constant for all $u > 0$. For a thinner-tailed distribution one observes a decreasing function $e(u)$, while a heavier-tailed distribution displays a linearly increasing $e(u)$. Thus plotting the mean excess function against u helps to visually decide the threshold.[6] The slope of the empirical $e(u)$ should change from horizontal to a positive trend at the level where the Pickands' theorem comes to be valid. Following Davison and Smith (1990), it can be shown that the mean excess function for the GPD takes on the following form

$$e(u) = \frac{\sigma + \xi u}{1 - \xi}. \tag{3.12}$$

As it has already been pointed out, one of the major objectives for risk management is to obtain a measure that reveals the average expected loss given that the VaR is exceeded. The linearity of the mean excess function implies that once we find that GPD is valid at a threshold u, then it should be valid at all thresholds greater than u with the same shape parameter, but a different scaling. This property allows us to calculate the losses beyond VaR. Bearing in mind the definition of expected shortfall and using the expressions (3.12), one can show that ES for the GPD distribution is (McNeil 1999):

$$\widehat{ES}_p = \frac{\widehat{VaR}_p}{1 - \hat{\xi}} + \frac{\hat{\sigma} - \hat{\xi} u}{1 - \hat{\xi}}. \tag{3.13}$$

[5]Any continuous distribution function is uniquely determined by its mean excess function; see the monographs of Embrechts, Klüppelberg, and Mikosch (1997) and Beirlant, Teugels, and Vynckier (1996) for a large sample of mean excess functions and their derivations.

[6]That is, one computes $e_n(u) = \sum_{i=1}^n (X_i - u)^+ / \sum_{i=1}^n 1_{\{X_i > u\}}$ and plots the exceedances over u against u for $X_{1,n} \le u \le X_{n,n}$.

3.4 Shape parameter estimation

There are a variety of shape parameter estimators in the literature, each one with its own drawbacks and advantages depending on the underlying distribution it aims to fit.[7] The fact that financial returns are assumed to be heavy tailed makes distributions with a Fréchet type tail suitable members for the modelling of extreme quantiles. However, as the parent distribution is usually not known prior to estimation, the GPD representation plays an important role. The estimation procedure in this work will consider the main two estimators; the Pareto based Hill estimator and the standard maximum likelihood estimation covering the whole range of ξ in the GPD.[8]

The most common method in statistical estimations is the maximum likelihood method. Its asymptotic properties in an extreme value context has been investigated in Smith (1985, 1987). Assuming that the underlying data is generated by a GPD, the log-likelihood function is given by

$$\ell\left((\xi,\sigma)\right) = -n\ln\sigma - \left(\frac{1}{\xi}+1\right)\sum_{i=1}^{n}\ln\left(1+\frac{\xi}{\sigma}X_i\right). \tag{3.14}$$

For $\xi > -1/2$, it is shown that the maximum likelihood estimate has standard asymptotic first order properties, in particular it is asymptotically normal, unbiased and efficient. Cases for $\xi < -1/2$ are rarely found in financial applications. Estimation of the shape parameter for distributions satisfying the regular variation condition in (3.3) is obtained by means of Hill's (1975) estimator. Using the k upper order statistics in the estimation, the Hill estimator and its scale take on the following form:

$$\hat{\xi}_k = \hat{\alpha}_k^{-1} = \frac{1}{k}\sum_{i=1}^{k}\log\frac{X_{n-i+1}}{X_{n-k}}, \tag{3.15}$$

and

$$\hat{c}_k = \frac{k}{n}X_{n-k}^{1/\xi} \tag{3.16}$$

where X_{n-k} is the kth order statistic taken as a threshold. Provided that the sequence $k \to \infty$ and $k/n \to 0$ as $n \to \infty$ it is shown that this estimator is a consistent estimator of ξ. As its focus is on the case $\xi > 0$ only it is

[7] See e.g. Beirlant, Teugels, and Vynckier (1996) and Reiss and Thomas (1997).

[8] Pareto distribution belongs to MDA of the Fréchet distribution.

most effective for distributions having a Fréchet type tail. Extension to Hill's estimator that covers the whole range of ξ has been proposed by Pickands (1975) and Dekkers, Einmahl, and de Haan (1989) but were found to offer no consistent advantage over the maximum likelihood estimator or the Hill estimator when GPD or Fréchet distributions were considered.[9] Moreover, both Hill and maximum likelihood estimators are the most frequently used estimators in financial applications.

3.5 Multivariate Extreme Value Theory

When estimating benefits of diversification in downturn periods, the central observations are not of much use. For an investor, extreme events that have the largest economic impact are those events that occur simultaneously on different markets. To quantify the diversification in the tail of the distribution one is primarily interested in looking at joint exceedance probabilities and the respective dependence function. Consequently, a logical approach is to extend the univariate EVT for applications in the multivariate context.[10]

In particular, in this work most of the interest concerns the measurement of extremal dependence for bivariate random variables (X, Y) by studying the behaviour of the conditional probabilities of one variable given that the other is extreme, i.e.

$$\chi = \lim_{t \to \infty} \Pr\{X > t \mid Y > t\} \tag{3.17}$$

where χ measures the degree of dependence. If $\chi > 0$ one says that X and Y are *asymptotically dependent*, in which case the largest values of both variables tend to occur together. In the case $\chi = 0$ the variables are said to be *asymptotically independent* (Coles, Heffernan, and Tawn 1999). In this case the probability that X is large given that Y is large converges to zero as more extreme levels are considered. Examples of distributions for which the asymptotic independence holds are provided by Johnson and

[9] Besides the cited references, a more thorough discussion and comparison of estimators' performance under different conditions is to be found in Reiss and Thomas (1997) and Falk, Hüsler, and Reiss (1994).

[10] Description limits to the case of bivariate only.

Kotz (1972). One such distribution is the bivariate normal with a correlation coefficient $|\rho| \neq 1$. Hence, for a bivariate normal distribution the probability of observing two extreme observations simultaneously is zero.

There are numerous representations of bivariate extreme value (BEV) distributions, however the most common and convenient form is due to Pickands (1981).[11] It follows that any BEV distribution $G(x, y)$ may be written as:

$$G(x,y) = \Pr\{X \leq x, Y \leq y\} = \exp\left\{-(x^{-1} + y^{-1})A\left(\frac{x}{x+y}\right)\right\} \qquad (3.18)$$

where $A(w)$ is called Pickands dependence function. Thus, modelling BEV distributions is achieved by separating $G(x, y)$ into univariate margins represented by one of the three univariate extreme value distributions and the dependence function $A(w)$.[12] The estimation of $G(x, y)$ is then reduced to estimating the dependence function $A(w)$. Various parametric and non-parametric estimation procedures for $A(w)$ have been proposed.[13] Due to its tractability and estimation convenience, by far the most popular model is the logistic (Gumbel) dependence model (Tawn 1988):

$$A(w) = [(1-w)^{1/\alpha} + w^{1/\alpha}]^{\alpha} \qquad (3.19)$$

which leads to the bivariate logistic (Gumbel) distribution

$$G(x,y) = \exp\left\{-(x^{-1/\alpha} + y^{-1/\alpha})\right\}^{\alpha} \qquad (3.20)$$

where α characterises the strength of the dependence between X and Y. Perfect dependence is obtained in the limit as $\alpha \to 0$ and exact independence is given by $\alpha = 1$. Exploring the expression (3.17) by making use of the survivor function $\bar{G}(x, y)$, the estimation of χ reduces to $\chi = 2(1 - A(1/2))$. Consequently, for the bivariate logistic distribution $\chi = 2 - 2^{\alpha}$, and this distribution is therefore asymptotically dependent with $\alpha < 1$. Furthermore, except for the special case of exact independence $\chi = 0$, all BEV

[11] See Johnson and Kotz (1972) for an overview of alternative representations and Resnick (1987) for limiting conditions and introduction to the subject.

[12] Different marginal distributions have been assumed in the literature. The representation in (3.18) assumes margins to be Fréchet, i.e. $F(z) = \exp(-1/z)$.

[13] Tawn (1988) provides different parametric models and Smith, Tawn, and Yuen (1990) and Kotz and Nadarajah (2000) offer an overview of both methods.

distributions are asymptotically dependent. This implies that asymptotically independent distributions are not well modelled using this approach. As noted by Coles, Heffernan, and Tawn (1999), applying models for which $\chi > 0$ to asymptotically independent data leads to the overestimation of probabilities of joint extreme events.

Ledford and Tawn (1996, 1997) address the problem by providing a model that is able to characterise the extremal dependence including the cases of asymptotic independence and asymptotic dependence. Within this model one is able to describe the degree of dependence even though the random variables are asymptotically independent. In their work, they show that the joint survivor function of a bivariate random pair (X, Y) with unit Fréchet margins which satisfies:

$$\Pr\{X > t, Y > t\} \sim \mathcal{L}(t)\{\Pr(X > t)\}^{-1/\eta} \quad \text{for large } t \tag{3.21}$$

where $\mathcal{L}(t)$ is a slowly varying function and $\eta \in (0, 1]$ is the *coefficient of tail dependence*. The parameter η characterises the nature of the tail dependence, and $\mathcal{L}(t)$ its relative strength for a given η. Based on this model Ledford and Tawn (1997) identify four classes (A-D) of joint tail dependence. Classes B, C, and D each exhibiting asymptotic independence.

Class A: Asymptotic dependence, $\eta = 1$ and $\mathcal{L}(t) \to c > 0$

Class B: Positive association, $1/2 < \eta < 1$

Class C: Near independence, $\eta = 1/2$

Class D: Negative association, $0 < \eta < 1/2$.

When exploring the joint survivor function with a BEV distribution with Fréchet margins and logistic dependence model as in expression (3.19) it can be shown that $\eta = 1$, and $\mathcal{L}(t) = 2 - 2^{\alpha}$. Hence, $\chi = \lim_{t\to\infty} \mathcal{L}(t)$ if $\eta = 1$. For a bivariate normal distribution $\eta = \frac{1+\rho}{2}$ which falls into the class of asymptotically independent distributions.[14] Broadly speaking, the higher the value of the coefficient of tail dependence η the stronger the association

[14]Heffernan (2000) provides a derivation example of η and $\mathcal{L}(t)$ and reports a large number of distributions with their respective values of η and $\mathcal{L}(t)$.

in the tails between X and Y. Based on these results Coles, Heffernan, and Tawn (1999) propose the following expression

$$\bar{\chi} = \lim_{t\to\infty} \frac{2\log \Pr(X > t)}{\log \Pr(X > t, Y > t)} - 1, \quad -1 \leq \bar{\chi} \leq 1 \tag{3.22}$$

as a measure of asymptotic independence. With some calculations and using the expression (3.21) it can be further simplified so that $\bar{\chi}$ reduces to

$$\bar{\chi} = 2\eta - 1. \tag{3.23}$$

This quantity measures the rate at which $\Pr(X > t|Y > t) \to 0$ and is useful to asses the degree of dependence at finite levels of t. The values $\bar{\chi} > 0$, $\bar{\chi} = 0$, and $\bar{\chi} < 0$ correspond to the case when the random variables (X, Y) are positively associated in the extremes, exactly independent, and negatively associated, respectively. Additionally, in the context of bivariate normal, it follows immediately that $\bar{\chi}$ is equal to the correlation coefficient. Consequently, as noted by Poon, Rockinger, and Tawn (2003) since $\bar{\chi} = 1$ if $\eta = 1$ and $\chi = \lim_{t\to\infty} \mathcal{L}(t)$, the estimation of η and $\chi = \lim_{t\to\infty} \mathcal{L}(t)$ provides the basis for estimating χ and $\bar{\chi}$. In practice, the test of the hypothesis $\bar{\chi} = 1$ provides a diagnostic check for membership of the bivariate extreme value class. Rejecting this hypothesis can be interpreted as asymptotic independence, $(\chi = 0, \bar{\chi} < 1)$, and $\bar{\chi}$ serves as a measure of extremal dependence within the class. In the contrary, failure to reject the null signifies asymptotic dependence, $(\chi > 0, \bar{\chi} = 1)$ in the data and the parameter χ serves as measure of extremal dependence within the class. In this work, it is of primary interest to determine if hedge funds and traditional assets are asymptotically dependent or if their dependencies drop to zero at a certain rate.[15]

[15] If (X, Y) are transformed to uniform margins on the interval $[0, 1]$, then the expression (3.20) can be viewed as a Gumbel copula. Thus, extremal dependence can also be explained as a limiting property of a copula. Then, testing for $\bar{\chi} = 1$ implies a test for Gumbel dependence in the tail. See Heffernan (2000) for mathematical link of tail dependence and copula.

To carry out the parametric inference of η and $\lim_{t\to\infty}\mathcal{L}(t)$, Ledford and Tawn (1996) note that $\Pr\{X > z, Y > z\} = \Pr\{\min(X,Y) > z\}$ and thus the estimation of the joint survivor function can be reduced to examining the survivor function of a univariate variable. Defining Z as a structure variable $Z = \min(X,Y)$ and treating the slowly varying function as a constant d over a threshold u, $\mathcal{L}(z) = d$, leads to $\Pr(Z > z) = dz^{-1/\eta}$. It follows that the estimation of η is equivalent to ξ of Hill's estimator in expression (3.15). Consequently, the estimator $\bar{\chi}$ and its variance is given by

$$\hat{\bar{\chi}} = 2\hat{\xi} - 1 \quad \text{and} \quad \mathrm{Var}(\hat{\bar{\chi}}) = \frac{(\hat{\bar{\chi}}+1)^2}{2}. \tag{3.24}$$

Furthermore, if the null, $\bar{\chi} = 1$, cannot be rejected one estimates χ under the assumption that $\bar{\chi} = \eta = 1$ which follows immediately from the associated scale parameter d in expression (3.16)

$$\hat{\chi} = \frac{ku}{n} \quad \text{and} \quad \mathrm{Var}(\hat{\chi}) = \frac{u^2 k(n-k)}{n^3}. \tag{3.25}$$

Chapter 4

Hedge funds

4.1 Alternative investment strategies

There are many reasons for the growth of alternative investment strategies, however, the single unifying element of the strategies has its origin in the modern portfolio theory. This theory tells us that diversification, i.e. low correlation to other assets, should improve returns and reduce volatility over the long term at the total portfolio level. The growing demand for alternative investments is explained by the fact that alternative investment funds are assumed to generate absolute returns and maintain low correlation with traditional asset classes. A fund that targets absolute returns is one that aims to achieve a positive return in all market environments, irrespective of movements in the equity and bond markets. Two decades ago, by spreading risks over different countries or sectors, investors could achieve large diversification benefits. Today, due to different aspects such as increasing globalisation, new technologies and the introduction of the common European currency an increasing correlation in the financial markets is limiting the universe for diversification possibilities within the traditional asset classes.

Hedge funds are just one of many types of alternative investment strategies. Despite the large number of heterogeneous strategies, there is no clear classification of what comprises an alternative investment, as evident by the diverse definitions found in the literature. Miller (1998) defines alternative investment strategies to include:

- private, non-traditional, illiquid investments, such as distressed debt, emerging market equity and debt, international private equity, leveraged buy-out funds, mezzanine financing, oil and gas programmes, real estate, economically targeted investments, timberland, and venture capital;

- dynamic non-traditional liquid investment strategies involving securities, derivatives of physicals in liquid markets, such as managed futures, commodities, currencies or hedge funds; and

- investments involving longs and shorts and leverage.

In the foreword to the above cited monograph, the editor also includes the following investments: asset backed securities, such as collateralised loan and bond obligations and insurance,- and credit-derivative linked notes. Alternative investments have typically been private equity and real estate investments. The key point that distinguishes hedge funds from private equity and real estate is liquidity. To the greatest extent, private equity and real estate investments are committed outside the public markets. Hence, the empirical diversifications benefits are just estimations based on internal opinions of value. In contrast, hedge funds differ from private equity and real estate by trading in public markets, exploiting inefficiencies and imbalances in the markets and prices of securities, bonds, currencies and commodities. However, hedge funds are far from being perfectly liquid. They might not be publicly traded or might be closed to new investors. Additionally, most of them actively control risk by hedging via one or more methods and constantly seek new and alternative market opportunities. For that reason, hedge funds are often quoted as skill based investment strategies with capital preservation as a key focus (White 1995).

4.2 Defining hedge funds

There is no standard legal definition of a hedge fund, and most of them differ in one way or another. The term hedge fund need not mean that a particular fund is hedging. It rather refers to the way the fund is organised and operates. Perhaps the best way to define a hedge fund is to describe the characteristics that distinguish it from a traditional investment.

Return focus. The key difference between hedge funds and traditional funds is the return objective. Hedge funds seek to deliver positive returns regardless of the prevailing market conditions (Fung and Hsieh 1999b). The focus is on absolute returns and capital preservation. The success in this regard is dependent on the skill of the manager trying to exploit market inefficiencies. This contrasts with traditional managers who are seeking relative returns and their success is measured by how they perform relative to selected benchmarks regardless of whether these fall or rise. Consequently, hedge fund managers are less dependent on market performance, whereas traditional mangers are more dependent on market performance due to their benchmarking.

Short selling and leverage. A distinguishing features of hedge funds that is generally not available to traditional funds is the ability to buy on leverage and to sell short. Short selling is accomplished by selling shares they do not own in order to buy them back at a lower price in the future. Leverage allows hedge funds to invest more than the capital of the fund by borrowing money. These techniques are implemented to control risks or to enhance returns. The degree to which they are used varies between strategies and within managers.

Regulation. Hedge funds are commonly organised as limited partnerships or limited liability companies open to "qualified investors", meaning those with substantial assets and sophisticated understanding of financial markets (Fung and Hsieh 1999b).[1] Beyond that restriction and certain disclo-

[1]This refers to US legislation only. Provided the number of US clients is less than 14, there are no requirements to register with the Securities and Exchange Commission,

sures and reporting requirements, hedge funds, unlike traditional managers enjoy freedom from regulatory control. This control may limit fund leverage, short selling or the concentration of assets. Hence, hedge funds managers are free to use any strategy a manager chooses. This may account for hedge funds' tendency towards exotic securities or derivatives, and holding concentrated positions about which the manager has conviction rather than overly diversified positions often found in long-only portfolios (White 1995).

Transparency. As a result of lesser regulatory control, hedge fund mangers provide low transparency regarding their trading positions when compared to traditional funds. The performance of hedge funds is ultimately dependent on the manager's skills in exploiting market inefficiencies. Disclosure of positions might result in short squeezes, spread compression or duplication of trades eliminating the profit opportunities (Ineichen 2000). Therefore, in order to protect the profitable trading ideas hedge fund managers are unwilling to share their positions with the public.

Fee structure. In contrast to traditional managers, compensation is related to investment performance. This compensation encourages managers to limit assets under management in order to focus on positive returns rather than on asset growth. Traditional managers, on the other hand, are rewarded for attracting more clients and more assets. Most frequently, performance fees are 20% of investment profits above a hurdle rate or a high watermark (Crerend 1998). The hurdle rate might be fixed or variable. The high watermark means that if a manager loses money in one year the fund has to make up the losses before it can charge performance fees. Performance hurdle rate and high watermark are seen as additional incentives that oblige managers to focus on capital preservation and absolute returns.

regardless of the level of assets under management. In Europe, the regulation with respect to retail investors is heterogeneous, with some countries allowing direct investment in single hedge funds (i.e. Sweden, UK), some in fund-of-funds only (i.e. Switzerland, Germany), and countries where distribution of hedge funds is prohibited (i.e. Belgium, Greece). Distribution is subject to the granting of a licence by a local regulator and usually linked to some minimum investment requirement. For a detailed country specific description see PCW (2005).

Capital commitment. Most hedge fund managers have a significant portion of their wealth invested in the fund they manage. This commitment gives investors additional confidence, ensuring that investor's and manager's interests are closely aligned (Lee, Marber, and Willoughby 1999).

Investment lockup. Hedge funds may invest in less liquid securities which creates the need for longer lock up periods and special requirements on redemption conditions. Lhabitant (2002) states that an initial lock up period of one year with a quarterly redemption is typical. In addition, investors are required to give an advice notice of 30-90 days before redemption.

4.3 Historical evolution

The origin of hedge funds dates back to 1949, when a sociologist and journalist named Alfred Winslow Jones established the first hedge fund in the US. Jones introduced a new approach to managing an equity portfolio. His objective was to generate positive returns through superior stock picking while reducing some of the downside risk by utilising short sales and enhancing returns through leverage. During bull market periods, the fund made profits higher than the market in long positions and lost less in short positions. Conversely, in bear market periods, it made profits in short positions and lost less than the market in long positions. The equity portfolio was thus more dependent on his ability to select right stocks than on general market conditions. Reducing market risk in this manner is called "hedging", which explains the name hedge fund. A detailed description of Jones' model is to be found in Caldwell (1995, p.7) where the following description is given:

> He [Jones] took two speculative tools, short sales and leverage, and merged them into a conservative investing system. His goal was to shift the burden of performance from market timing to stock picking (...).

Another unique element of his fund was the incentive fee structure. The reward to fund manager was based on performance in excess of an agreed upon benchmark, fixed or variable (such as the Dow Jones). He settled on a straight 20% of realised profits (Caldwell 1995). Moreover, by keeping his own capital in the fund he introduced the concept of managers' capital commitment. It means that fund managers contribute with a significant part of their personal wealth in the fund they manage on the same conditions as external investors. This alignment of interests adds to credibility and makes investors and fund managers strive towards the same goal; high return at low risk regardless of market directions. This set up became a model for the hedge fund industry and the strategy he employed, has been named *equity long/short*.

For almost seventeen years he operated in complete secrecy. In 1966, an article in Fortune described Jones' model to have returns that outperformed the best mutual funds at that time. This publication created a stir among money managers and by 1968 approximately 200 new hedge funds had been started (Tremont Partners/TASS 1999). Two equity bear markets between, 1969-1970 and 1973-1974, however, put most of the newly founded hedge funds out of business. It appeared that the majority of them were not hedging at all. In fact, supported by the bull market of the mid-late 1960s they were long only, attracted by the lucrative performance fee structure in combination with leverage. Caldwell (1995) notes that among the prudent managers that survived were Alfred Jones, George Soros and Michael Steinhardt. The latter two are among the most successful money managers in history and founders of the well known Quantum Fund and Steinhardt Partners, respectively.

In the following decade, just a few new hedge funds were established. Still, most of the funds in existence employed Jones' classical long/short equity model. Around this time, another group of skill based strategies called *managed futures* or *commodity trading advisers (CTA)* began to emerge for the first time.[2] Fung and Hsieh (1999b) note that these are structured in a similar way to hedge funds but operate primarily in commodity markets utilising futures contracts. Yang and Faux (1999) name the prevailing economic conditions and difficulties in equity markets as the major reasons for

[2]Although most of the literature regarding hedge fund history does not consider managed futures in their description; nowadays it is well accepted to treat managed futures as a subgroup next to other hedge fund strategies.

the growth of this industry. The 1970s witnessed high inflation and large upward price movements in agricultural and metal markets that provided attractive profit opportunities in commodity futures markets.[3]

In the 1980s the hedge fund industry became an exclusive club of wealthy individuals. Since most of them were not regulated by the SEC and were prohibited from advertising, raising assets under management was based on a word-of-mouth basis. Moreover, they were organised as limited partnerships, allowing only 99 investors. Consequently, the minimum investment amount was high. Yet, in 1984, when Tremont Partners began to track hedge fund managers, they were able to identify 68 managers (Tremont Partners/TASS 1999). Nevertheless, the freedom of hedge fund managers to operate across all markets, capital markets globalisation and the innovation of new financial instruments, resulted in a heterogeneous development in trading strategies. Some managers evolved into *global macro* players. That is, the long/short strategy was replicated on a worldwide basis with an occasional use of derivatives to give them more hedging opportunities. Julian Robertson was one of these money managers. Once again, a cover story in a financial magazine gave rise to a renewed interest in hedge funds. In 1986, Institutional Investor described the global trades of Robertson's Tiger fund. At the end of the 1980s more than 200 funds were in business.

Another important trend that took place in the 1980s was the expansion of managed futures managers to other markets. Yang and Faux (1999) note that the alleviation of inflationary pressure eroded opportunities in commodity markets, so managed futures managers sought profit opportunities in financial futures such as currency and fixed income markets. At this point they became similar to global macro managers. In due course, however, they began to diverge as managed futures managers turned to more systemic trading strategies whereas global macro managers became more discretionary in their trading strategies.[4] The 1990's are characterised by

[3]In this section, for historical reasons, we distinguish between hedge funds and managed futures. However, in the rest of the thesis the term hedge fund refers to both groups.

[4]This statement is a generalisation. Today, there is still a small percentage of managed futures managers trading on a discretionary basis and global macro managers trading systematically.

a continuously heterogeneous development in hedge fund strategies, giving rise to a large number of different trading methodologies and various sub-strategies. In 1995, according to Nicholas and Nicholas (1995) of Hedge Fund Research these include: convertible arbitrage, distressed securities, emerging markets, macro funds, market neutral, market timing, merger arbitrage, multistrategies, opportunistic, sector funds, and short selling.[5] At the end of the 20th century Hedge Fund Research estimated there were as many as 4000 hedge funds with total assets under management of USD 490 billion (HFR 2005).

The new century has seen the continued strong growth of the hedge fund industry. The dramatic fall in global equity markets between March 2000 and March 2003 together with low interest rates, have provided an additional catalyst for the soaring interest in alternative investments generally and hedge funds especially over the last few years. In closing this section, according to HFR (2007) the current number of hedge funds including funds of funds is close to 9500 with assets under management around USD 1.4 trillion.[6] The growth rate over past five years has averaged 15% a year and the demand is led by institutions, despite them representing only 30% of the investor base. A recent report from Goldman Sachs/Russell (2003) based on a survey of 325 organisations worldwide reveals that roughly 60%-70% of respondents have commitments to private equity and real estate investments. For hedge funds, this number is around 20% in Europe and North America, and 40% for Japanese investors. Moreover, the total commitment and average strategic allocation to hedge funds is expected to grow substantially in all regions.

4.4 Hedge fund strategies

Hedge funds represent a very heterogeneous asset class that is not open to a simple generalisation. There is no agreement about the way in which hedge funds should be classified. The classification and description tend

[5]Section 4.4 deals with the different strategies and also describes their characteristics.

[6]Managed futures represent approximately 10% of the hedge fund industry raising total assets under management to ca. USD 1.5 trillion.

to vary from manager to manager and among data vendors and academics. However, the taxonomy below is believed to be a broadly acceptable classification. Conventionally, at the lowest integration level, hedge fund managers are classified into categories according to their trading strategies. Consequently, hedge funds may be grouped into five trading styles that share similar investment methodologies. Finally, at the highest integration level, they may be grouped into two sectors, directional and non directional. The former is characterised by active positions directed to specific movements in the market, whereas non directional include strategies that are not exposed to any specific market movements. The following description is limited to the characteristics of the most important hedge fund strategies, attempting to emphasise on where and how the returns are generated.[7]

Equity hedged. This style represents the largest segment of the hedge fund industry. It includes hedge funds utilising investment strategies that seek to profit from taking long or short positions in primarily publicly traded equities they estimate to be respectively under- and over-valued in some respect. Managers may have a purely balanced or net long or short exposure. The main strategy in this style is *Equity long/short*. This directional strategy is the most straightforward type of hedge fund techniques. Managers may shift their positions over time without any restrictions on the degree of net or long exposure as market conditions change. Investment decisions are usually made within a discretionary framework based on fundamental quantitative and qualitative valuation analysis. Historically, the managers in this group have a tendency to a net long bias (Ineichen 2000). Most long/short managers tend to specialise in a particular area, sector or geographic region where they believe they possess outstanding knowledge or experience. Risk in this strategy is often attributable to managers' stock picking decisions as well as unexpected and rapid directional market shifts, e.g. September 11, 2001 event.

[7]A summary of these strategies with respect to style and market direction is given in the Table 4.1. The definition of styles follows RMF's internal classification, although the mapping to the strategies is not exactly the same. With exception of managed futures the reference regarding the strategies is HFR, www.hedgefundresearch.com.

Market neutral and *Statistical arbitrage* are non directional strategies characterised by managers that operate with a consistent zero exposure or within tight bands of net exposure. Statistical arbitrage mangers perform their investment decision based on quantitative techniques aiming to profit from short term pricing anomalies. On the contrary, market neutral managers seek to exploit longer term pricing anomalies usually by executing investment decisions based on fundamentally driven analysis (Tomlinson 1998). In general, the focus is less on the market direction than on the value of one stock or group of stocks relative to another. Furthermore, managers are usually invested in highly liquid markets, and the usage of leverage is low because there is no market exposure to leverage or magnify (Anson 2002a). Risks generally arise from model errors and from market periods characterised by low volatility or consistent momentum.

The *Short selling* strategy includes managers that are directional in nature by constantly keeping net short exposure to the market. Managers that sell short attempt to profit from quick declines in the stock price by using either technical or fundamental analysis. Ringoen (1999) lists potential signals that may generate shorting opportunities, these are: company is running out of cash, being near bankruptcy, loss of major client, obsolete product technology, or disclosure of accounting frauds. The risks associated with this strategy arise predominately from bullish markets, and unexpected market events.

Relative value. This style includes hedge funds that apply arbitrage strategies and techniques to take advantage of perceived pricing discrepancies between similar or related securities. Returns are generated by establishing long positions in undervalued assets and being short in overvalued assets, based on the premise that the price discrepancy should disappear over time. Most relative value managers are invested in equities, fixed income instruments and derivatives. These may be listed or over-the-counter. Moix and Scholz (2003) note that relative value managers typically have an edge in pricing contracts and therefore take positions when contract complexity is high or market liquidity is low. Thus, the direction of bond or equity markets is less important to the relative value managers, whose only concern is whether the mispricing or spread between two related securities is increasing or converging. The leverage used by these managers is the highest in the hedge fund industry. Jaeger and Rutsch (2003) quote leverage factors of higher than 10 as not unusual.

The *Fixed income arbitrage* strategy includes managers that seek to profit from interest rate spreads between related fixed income instruments by being long a higher yielding instrument and short another at a lower yield, while reducing the duration and convexity to zero (Fulenwider 1999). Managers might exploit yield differences between different market sectors, e.g. corporate-, mortgage-, and municipal bonds versus treasury yield spreads, or cash versus futures. Some managers specialise in distinct market sectors forming their own substrategy. For instance, the *fixed income: high yield* managers invest in non-investment grade debt and the *fixed income: asset backed* managers aim to exploit mispricings in the credit and prepayment risk. The majority of fixed income managers apply a qualitative analysis in order to explore the cause of the price divergence and to assess the probability of convergence. The risks associated with fixed income include liquidity, credit spreads and the volatility within the yield curve.

Convertible arbitrage managers are usually involved in taking long positions in a convertible bond they view as being undervalued and short positions in an appropriate amount of the underlying equity. Convertible bonds are hybrid instruments that can be viewed as a combination of a bond with an embedded call option on the equity of the issuer of the bond. The strategy often involves exploiting this optionality while not taking any market risk (Tomlinson 1998). For instance, managers may buy low convertible bond volatility and sell the higher volatility of the underlying stock. To a great extent the strategy is implemented using over-the-counter contracts of lower graded companies (Agarwal, Fung, Loon, and Naik 2004). Various option pricing or cashflow-based models are employed to support managers' trading decisions. Risk in this strategy often arise from widening credit spreads, rising interest rates, take-overs and low market volatility.

Event driven. Managers within the event driven style attempt to capitalise on anomalies related to corporate events that may cause a significant change in the future valuation of the company. These events include the sale of assets/business lines, market entries and exits, capital structure changes, acquisitions, mergers, tender offers, liquidations and other corporate reorganisations. Event driven funds profit from an incorrect assessment of the situation by other investors or the uncertainty surrounding the event. The main risk factor is the deal itself rather than the market. This means that performance is largely driven by managers' ability to identify and analyse event specific situations. Nevertheless, a rapid change in the direction of the bond or the stock market may have an influence on the deal outcomes which places this style at the border of the nondirectional strategies.

Merger arbitrage managers usually engage in a simultaneous purchase and short sale of shares of target and acquiring companies, respectively, in anticipation of a merger transaction. Following Paulson (2000), the major factors that are fundamental to the success of a merger arbitrage trade are; assessment of the probability of the transaction, announced conditions remain in place, and a clear estimation of the period of time until the completion of the transaction. Leverage is often employed in order to boost returns. Besides broken deals, risks generally arise from regulatory environment and from the time until deal completion.

The second major strategy within the event driven style is the *Distressed securities* strategy. Managers investing in distressed securities are usually buying or selling short securities or debt of corporations which are either undergoing or likely to undergo reorganisation, liquidation or other distressed situations. Usually, the shares and bonds of companies facing such financial difficulties fall heavily. Ineichen (2000) notes that many traditional investors are prohibited from owning securities downgraded to non-investment grade levels or lack skills to properly analyse the value of a distressed company. As a result, the securities of a distressed company are often traded below its fair value giving rise to profitable trading opportunities. Managers within this strategy may be passive, or be involved in taking an active role in a restructuring. The employed leverage is usually very low or not implemented at all (Jaeger and Rutsch 2003). The risks associated with distressed securities include liquidity risk, default- and recovery rates and legal environment.

Global macro. Global macro is the most heterogeneous style of all hedge funds, including managers that have both directional and/or relative value elements at a global level. Macro mangers implement a discretionary trading approach in order to take advantage of broad macroeconomic trends arising in countries as a result of political or economic changes. Usually, managers employ a top-down analysis and quantitative tools to take views on how global macroeconomic developments will impact financial markets. To exploit these anticipated movements, managers may invest in any markets using any instruments and focusing on any trading strategy (Strome 1999). Typically, this involves a significant net or short exposure to equities, currencies, bonds and commodities with various amounts of leverage. Due to the flexibility of implemented trading strategies, there is generally no distinction between separate strategies within the global macro style. However, mangers primarily focused on investment in securities or the sovereign debt of developing or emerging countries are often grouped into the *Emerging market* strategy. Risks in this style vary according to the investment process and amount of leverage employed. Still, the main sources are country specific risks and political conflicts.

Managed futures. Managed futures managers, also known as Commodity Trading Advisers, trade derivative instruments such as futures contracts, options, forward contracts, and swap contracts, attempting to identify and profitably exploit trends early on. Depending on the prevailing opportunities, the underlying markets include bonds, stocks, currencies, short-term interest rates and commodities. Following Yang and Faux (1999), the main source of profits in managed futures is the occurrence of lengthy, directional price trends, either upward or downward. The vast majority of managers follow a *Systematic trading* strategy. These strategies include long-term trend-following and short-term active trading approaches that make use of historical price data to anticipate future price movements. The trading systems employed are generally sophisticated computer-driven systems to maintain a systematic and disciplined approach. A rather small group of managers follow a *Discretionary trading* approach. These managers rely on their experience rather than system and models to make qualitative investments decisions. Risk in this style generally arises from model errors and from trendless market periods. The style and strategy classification with respect to its market movement is provided in Table 4.1 below.

Table 4.1: *Hedge fund classification.*

Style	Strategy	Direction
Equity hedged	*Equity long/short*	*directional*
	Equity market neutral	*nondirectional*
	Short selling	*directional*
Relative value	*Fixed income arbitrage*	*nondirectional*
	Convertible arbitrage	*nondirectional*
Event driven	*Merger arbitrage*	*nondirectional*
	Distressed securities	*nondirectional*
Global macro	*Macro*	*directional*
	Emerging markets	*directional*
Managed futures	*Systematic trading*	*directional*
	Discretionary trading	*directional*

4.5 Hedge fund indices

At present, there are more than a dozen hedge fund index providers. The lack of standardisation in terms of composition, construction and management of indices leads to a significant dispersion in the number of fund constituents, as well as the rebalancing frequency and weighting scheme among the index providers. Obviously this results in different performance numbers between the indices. Table 4.2 summarises the main characteristics of the various index providers. Among these vendors, Hedge Fund Research (HFR) and Credit Suisse First Boston/Tremont (CSFB/Tremont) index families emerged to be the most recognised reference for hedge fund investing. The analysis in this study will be presented with indices constructed by HFR.[8]

[8] www.hedgefundresearch.com

Table 4.2: *Hedge fund index providers and their characteristics.*

Name	Launch date	Base date	No funds/database	No funds/index	Weighting	Rebalancing frequency	Backfilling
HFR	1994	1990	4000	1600	*equally*	*monthly*	*no*
CSFB Tremont	1999	1994	3300	387	*asset*	*monthly*	*no*
S&P	2002	1998	3500	40	*equally*	*annually*	*no*
MSCI	2003	2002	1800	1500	*equally*	*quarterly*	*yes*
Dow Jones	2004	2002	300	18	*equally*	*quarterly*	*no*
CISDM/MAR	1994	1990	2300	1600	*median*	*monthly*	*no*
Hennessee	1987*	1987	3500	690	*equally*	*annually*	*no*
Van Hedge	1994**	1988	5400	1300	*equally*	*monthly*	*no*
Bernheim	1995	1999	900	18	*NA*	*NA*	*NA*
Tuna	1998	1995	2300	2300	*equally*	*continual*	*yes*
Altvest	2000	1993	2600	2600	*equally*	*monthly*	*no*
Eurekahedge	2002	2000	365	110	*equally*	*monthly*	*yes*
Blue X	2002	2002	350 – 400	30 – 40	*special scheme*	*quarterly*	*no*
EACM	1996	1996	100	100	*equally*	*annually*	*no*
HF Intelligence	2001	1998	3200	2652	*median*	*annually*	*no*
Feri	2001	2002	5000	41	*equally*	*quarterly*	*no*
MondoHedge	2003	2002	720	48	*weighted mean*	*monthly*	*no*
Barclay	2003	1997	2450	2450	*equally*	*monthly*	*no*

*in 1992 for general public. **in 1995 for general public. Non-investable indices. Source: RMF Investment Management (2004).

This data vendor tracks over 4000 hedge funds and is one of the most comprehensive and oldest hedge fund data providers. The indices are equally weighted, comprising 1600 hedge funds both onshore and offshore, and the returns are net of all fees on a monthly basis.[9] The choice in favour of HFR is justified by the fact that HFR has a longer history, starting in 1990, which is an important advantage when applying extreme value theory to return data. Since HFR does not provide a managed futures index, this style is represented by the Stark 300 Trader index from the D.B. Stark & Company.[10] This index is an industry-wide and equally weighted managed futures index containing both systematic and discretionary traders.

In addition to performance differences, hedge fund indices exhibit various statistical biases such as; selection, survivorship, and backfill bias. These biases arise because all hedge fund indices are built on underlying databases that are created on a sample of hedge funds rather than the full universe, and because of the differences in data collection criteria employed by the data vendors. *Selection bias* is created by two different layers. First, in order to be included in the database, funds must fulfill certain selection requirements such as minimum track record and assets under management.[11] Second, as there is no requirement for hedge funds to disclose their performance, the inclusion in the database is voluntary. This may indicate that only those funds with good performance that want to attract new investors report to a

[9] Worth mentioning is that these indices are non-investable. This also applies to the CSFB/Tremont indices as well as the indices of the remaining providers in Table 4.2. However, the analysis here just aims to show the risk-return profile of a hypothetical hedge fund investment in combination with traditional assets. In recent years, some index providers have launched investable indices that do provide more transparency and liquidity to investors however at the cost of a limited universe. These stringent liquidity and transparency requirements disqualify many hedge fund mangers to join an index with the effect that these indices are even less representative than non-investable ones. Especially illiquid event driven managers are under-represented as well as successful closed funds. Additionally, the history is too short to perform a meaningful empirical analysis. See Géhin and Vaissié (2004) for a comprehensive overview of investable and non-investable indices.

[10] www.starkonline.com

[11] These two requirements are not applied by HFR. The only criteria used to include hedge funds in HFR index is a monthly net of all fees return along with their month-end fund asst size in US dollars.

database. Conversely, it is also the case that funds with good track records are closed since they reached the desired assets under management.[12] Fung and Hsieh (2000) claim that positive and negative selection-related bias tends to offset each other. Generally, it is difficult to quantify this bias since the universe of hedge funds is unobservable. Nevertheless, selection bias undoubtedly exists as manifested by the fact that equally weighted indices based on different databases perform differently. *Survivorship bias* arises when a database only includes information on operating hedge funds at the end of the sampling period and excludes defunct or closed funds during the sampling period. Funds that stop reporting due to underperformance, liquidation or bankruptcy generate an upward bias whereas a downward bias occurs when funds choose to do so because of strong performance or asset gathering. It is however typically assumed that this bias is positive. *Backfill (or instant history) bias* arises when there is a difference between the date a fund enters the database and the start of its track record. This happens because hedge fund managers request to be included in databases first when they have generated a satisfactory track record during an incubation period. Adding such funds creates an "instant history" of returns overestimating the performance of the database. Numerous studies have investigated these biases with the attempt to quantify the size of them. The estimated magnitude of these biases varies across the studies and majorally depends on the observation length, database used, and the applied measurement technique. For instance, Fung and Hsieh (2000) performed their study on TASS database for the period 1994-1998 and found evidence for survivorship and backfill bias of the size 3%, and 1.4%, respectively. On the contrary, using HFR database for the period 1988-1995, Ackermann, McEnally, and Ravenscraft (1999) estimated the same biases to be 0.16% and 0.05%, respectively. Liang (2000) compared both databases over the period 1993-1998 with respect to survivorship bias and found evidence for a bias of the size 0.39% for HFR and 2.24% for TASS. According to the author, the main reason behind the

[12]Fung and Hsieh (2000) illustrates that with two examples by citing that Soros's Quantum Fund stopped reporting in 1992 even though it had performed well, and Long-Term Capital Management (LTCM) never disclosed their performance. Hence, neither the positive returns before it collapsed, nor the entire loss were recorded in databases.

lower survivorship bias found in the literature for HFR database is due to the relatively low number of dissolved funds collected by HFR database. Following the overview of Géhin and Vaissié (2004), the average impact on the performance of hedge fund indices due to survivorship bias could be assumed to range between 2% and 3%.

A third proxy to asses the performance characteristics of hedge funds is to evaluate the performance of funds of hedge funds as these are the major hedge fund investors. There are at least three reasons to choose a fund-of-funds (FoF) index as a representative for hedge fund universe. Firstly, more and more institutional investors choose funds of funds as vehicles to invest in the hedge fund world. These are offered to investors because the selection process of hedge fund managers requires specialisation, skills and research capabilities, which may not be available in-house. Secondly, as argued by Fung and Hsieh (2002b) and Amin and Kat (2003b), a FoF index is less subject to the aforementioned biases in hedge fund databases. Since funds of funds invest in hedge funds which are not necessarily listed in any database, they provide a better and larger coverage of the whole sector, thus reducing the selection bias. For example, these indices include the impact of LTCM. Survivorship bias is also mitigated because the track record of hedge funds that ceased operations remain in the performance of the FoF index. Consequently, historical returns of a newly added hedge fund are not included in the track record of a FoF index, thereby reducing the backfill bias. Finally, funds of funds are well diversified portfolios. This implies that a FoF index is less sensitive to operational risk.

4.6 Asymmetry in hedge fund return distributions

Given the above characteristics and the differences to traditional managers, it can be no surprise that hedge funds are not driven by the same factors that drive the performance of other assets. Consequently, the risk/return profile is different. To sell securities short and to buy on leverage are two factors that are common to all hedge fund strategies and have a significant impact on risk and expected return. To a great extent, the anatomy of asymmetric return distribution of hedge funds might be attributed to a combination of these two factors together with managers' propensity to dynamically and rapidly shift trading positions and exposures to risk factors daily or intra-daily.

Ineichen and Johansen (2002) and Ineichen (2002) argue that having equally likely observations around the mean is exactly what absolute return managers want to avoid by design. In contrast to long-only mangers having a return profile similar to the underlying markets, hedge funds are trying to manage volatility by means of hedging techniques. It means that to keep the absolute return focus, hedge funds try to enter strategies and opportunities where there is a high probability of profit and a lower probability of loss. By doing so they try shift more of the distribution mass to the right of the zero return. Such a strategy, when successfully applied, will perform well in extreme up/down markets but achieve poor returns when assets markets exhibit trendless periods. Hence, when the trading approach limits downside losses while potentially achieving very large upside returns, the strategy is sometimes referred to as having a long option profile. Consequently, managing the volatility with a downside protection implies a positive skewness of the distribution. With the intention to mimic a perfect trend follower, Fung and Hsieh (2001) created asset based style factors using lookback options on underlying asset classes. Their results show that managed futures strategies are highly correlated with buying straddles on traditional assets, creating an expected return profile similar to a payout of a long straddle.

While these findings might very well fit the description of the return distribution of the directional strategies, other strategies are more designed to have a return distribution that resembles a short option profile. One says that a strategy exhibits a short option profile if it has a high proportion of limited upside returns and a low proportion of larger downside returns. Such strategies are usually exposed to some form of event risk generating fat tails and negative skewness in the distribution. This is especially the case for merger arbitrage strategies. A successful deal returns the difference between the share price of the target company just after the announcement and the price of it at completion. However, if the take-over fails due to unexpected events, the share price of the target company drops to the pre-announcement level causing a loss that is many times higher than the expected profit. With leverage this asymmetry is exacerbated. In the spirit of Fung and Hsieh's (2001) research, Mitchel and Pulvino (2001) extended the asset based factors to include the merger arbitrage strategy concluding that the returns of this strategy are similar to writing naked put options on the market. Banz and de Planta (2002) provide a detailed example of a payoff from a broken deal and note that this asymmetric payoff might pertain to other nondirectional strategies. In particular strategies with significant credit risk exposure in combination with leverage are considered. Anson (2002a) argues that hedge funds with credit risk exposure should have a distribution similar to fixed income instruments that are also exposed to credit risk. Assets with credit risk are generally characterised by fatness in the left tail as a result of event risks. For instance, an event risk for a distressed fund reflects downgrades, defaults and bankruptcies.[13] For the convertible arbitrage strategy an additional event risk is the redemption risk, i.e. the case when the company redeems the convertible bonds.

An additional element having an impact on the return distribution of hedge funds and especially on the nondirectional ones is the flight-to-quality scenario. In a period of market turmoil, the long term expectations behind arbitrage deals deteriorates, driving market prices even further from their fair values. Credit lines are cut quickly forcing managers to liquidate positions at unfavourable prices in order to meet creditor's margin requirements. In such situations managers may run into a liquidity crisis cycle. As stressed by Bookstaber (2000) a further fall in the fund's asset value is to be expected as the forced selling is conducted in too great a quantity or too quickly for market liquidity to bear. Consequently, the rapid decline in a fund's value may lead to yet more liquidations for margin or redemption purposes. Furthermore, this liquidity risk might very well translate into market risk, and as noted by Moix and Scholz (2003), this effect is even more pronounced when leverage is used. Although merger arbitrage managers tend to invest in more liquid positions, the same point can be made for this strategy. Referring to Banz and de Planta (2002), a market crash would typically lead to a massive walkout from takeover bids, eliminating any diversification effect

[13] See Anson (2002b) for a detailed exposition of distressed investing.

that a merger portfolio may have offered under normal market conditions.

Generally, one can say that the directional strategies are exposed to market risk and have a return distribution that resembles a long option profile while the returns of the nondirectional ones can be seen as a compensation for taking credit and liquidity risk with return profile similar to a short option. Two strategies, however, deviate from this generalisation. In contrast to other nondirectional strategies, the equity market neutral strategy attempts to generate positive returns in liquid stock markets by avoiding market risk. As the only determinant is the stock selection, Anson (2002a) argues that this strategy should have a symmetric distribution around a positive mean. An exception from the directional strategies is the emerging market one. Managers within this group have limited hedging possibilities as many emerging market countries do not permit shorting or the necessary instruments do not exist (Goetzmann, Zhu, and Bris 2003). Consequently, as the ability to actively control downside risk is reduced, this strategy is more a long only investment with a return distribution resembling the underlying markets. These markets, as pointed out by Bekaert and Harvey (1997) are highly non-normal exhibiting higher volatility, lower liquidity and a substantial downside risk than the developed countries.[14] Figure 4.1 shows histograms of two typical directional and nondirectional strategies. The directional strategies have larger dispersion of returns and positively skewed longer tails, whereas the nondirectional ones exhibit lower dispersion with negative skewness and fatter tails in the left of the distribution.

Finally, since the pioneering work of Fung and Hsieh (1997) showing that dynamic trading strategies exhibit non linear returns with an option-like payoff, a great number of studies have extended this option based factor approach to other strategies.[15] The common finding in these studies is that the dynamic trading strategy with an asymmetric return payout is an important component in hedge fund performance, in the sense that the option

[14]See additionally the papers of Harvey (2000) and Harvey, Bekaert, and Lundblad (2003) for detailed characteristics of asset returns in emerging markets with respect to the mentioned features.

[15]See e.g. Fung and Hsieh (2002c) for application to fixed income strategies and Agarwal, Fung, Loon, and Naik (2004) for the case of convertible arbitrage. Fung and Hsieh (2002a) and Agarwal and Naik (2004) offer a summary on that topic.

based factors contribute with significant betas and dramatically higher R-squares. This evidence makes two important points that have implications for the rest of the thesis. First, returns of hedge funds have an option like payoff inducing asymmetry. Second, the returns of hedge funds are correlated with market returns in a nonlinear way. Both of these issues imply that the standard mean variance framework is no longer adequate in the context of hedge funds, be it performance measurement, portfolio optimisation or risk analysis.

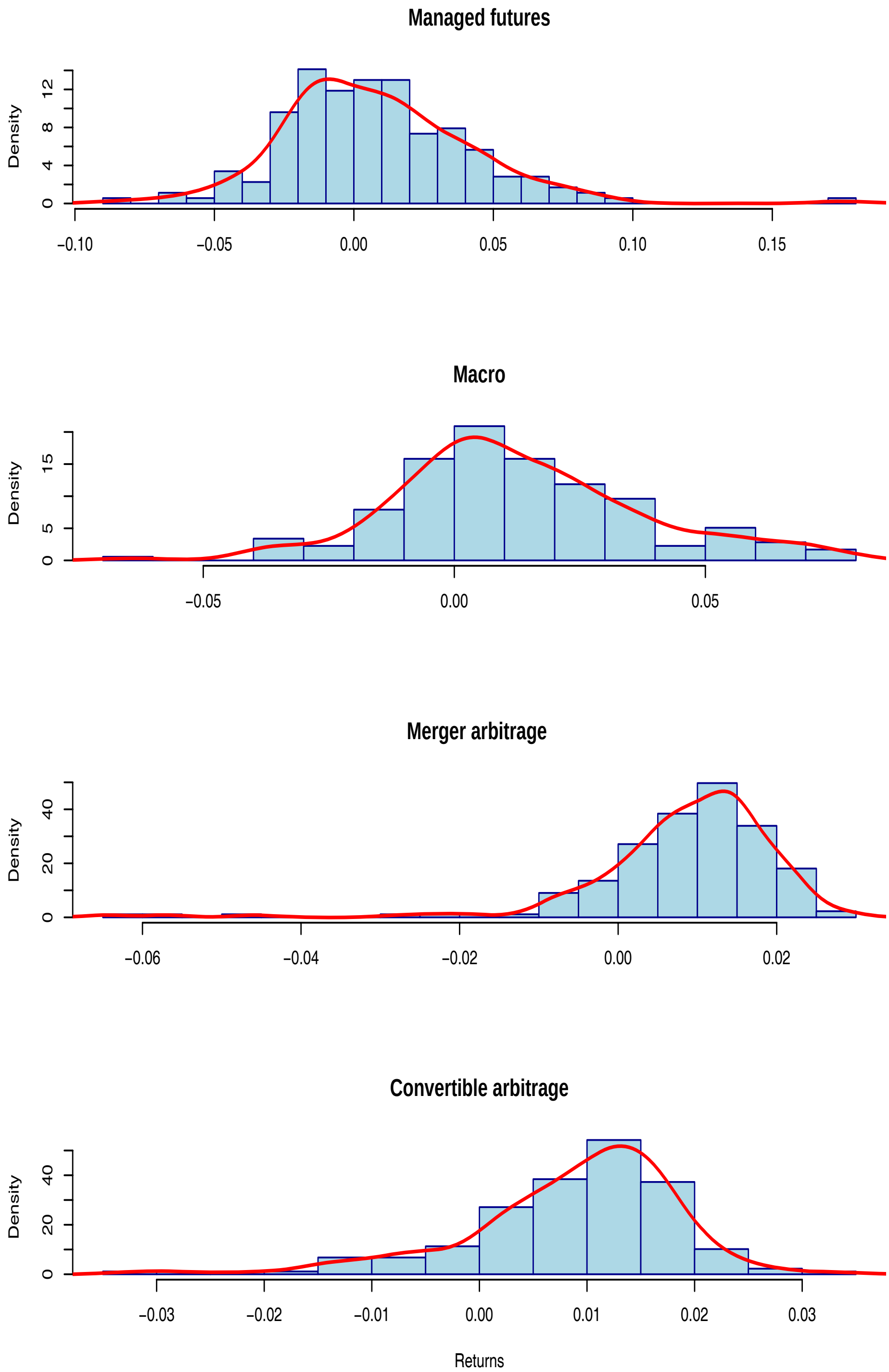

Figure 4.1: *Histograms of selected hedge fund strategies.*

Directional: Managed futures = Stark 300 Trader, Macro = HFRI Macro. Nondirectional: Merger arbitrage = HFRI Merger arbitrage, Convertible arbitrage = HFRI Convertible arbitrage. Sample window (monthly data): Jan 1990–Sep 2004.

Chapter 5

Risk analysis of hedge fund strategies

In this chapter, we first present the data that will be used throughout the rest of the thesis and empirically examine the tail properties of hedge fund strategies. By applying extreme value theory, we calculate the one-month Value-at-Risk and Expected Shortfall at 95% and 99% confidence levels. For the purpose of comparison with traditional assets, stock and bond market data is also analysed.

5.1 Data

To study the risk of the various hedge fund strategies and traditional asset classes, several indices are used as proxies for these assets. The data comprises 10 hedge fund strategy indices and two traditional asset indices. The MSCI World total return index, and Citigroup Government Bond index (all maturities) are used as proxies for the stock market and the bond market, respectively. Hedge funds are represented by the Hedge Fund Research indices (HFRI). The strategies belonging to the equity hedged style are represented by HFRI Equity Hedge (equity long/short strategies), HFRI Equity Market Neutral and HFRI Short Selling. Relative value strategies are proxied by HFRI Fixed Income Arbitrage and HFRI Convertible Arbitrage. The event driven style is investigated using HFRI Merger Arbitrage and HFRI Distressed Securities. As proxies for the global macro strategies, the HFRI Macro and HFRI Emerging Markets indices are utilised. The managed futures style is represented by the Stark 300 Trader index. Together, these indices represent about 80% of the hedge fund industry giving a comprehensive picture of the different characteristics prevailing in hedge fund strategies.

As the demand from investors in the last years has primarily shifted toward diversified hedge fund products, in further steps of the analysis some fund of funds indices will be applied. Besides the HFRI Fund of Funds Composite index that comprises all fund of funds mangers, four additional fund of funds indices provided by HFRI are considered. HFRI offers a classification of these fund of fund indices in four different categories. HFRI FOF Conservative includes funds of funds that exhibit one or more of the following characteristics: seeks consistent returns by primarily investing in funds that generally engage in more conservative strategies such as equity market neutral, fixed income arbitrage, and convertible arbitrage. HFRI FOF Diversified contains funds of funds investing in a variety of strategies among multiple managers. HFRI FOF Market Defensive consists of funds of funds that invest in managers that generally engage in short-biased strategies such as short selling and managed futures. HFRI FOF Strategic includes funds of funds seeking superior returns by primarily investing in managers that generally engage in more opportunistic strategies such as emerging markets, sector specific, and equity long/short.

As the number of monthly returns is rather small when compared to traditional assets, we use the maximum period available, ranging from January 1990 to September 2004. This gives 177 observations for each time series. This number is somewhat small when compared to other EVT applications to financial markets using daily or weekly data. One of the main consequences to expect is large confidence intervals for the different estimates. On the other hand, this data set is large compared to what has been previously used in the hedge fund world. Table 5.1 summarises the descriptive statistics of the data used in the analysis. The descriptive plots in Appendix A display the historical prices and returns along with the histograms and QQ-plots of the investigated indices. Additionally, the mean excess function of the left tail (losses) and the autocorrelation function are plotted. The reported measures and the plots present evidence to suspect a non normal behaviour of hedge fund returns. As expected from the discussion in the previous chapter, the directional strategies are generally positively skewed with a higher volatility than their non directional counterparts. These, on the contrary, are mostly negatively skewed exhibiting high kurtosis, a high first autocorrelation coefficient, and a low volatility. Furthermore, hedge funds tend to outperform stocks and bonds while usually having a lower volatility. Brooks and Kat (2002) use data spanning the period January 1995 - April 2001 and obtain a higher mean return for most of the investigated HFRI indices with the exception of Distressed and Emerging markets strategies. Similarities are found for the estimation of standard deviation as well as the shape of the distribution as indicated by skewness and kurtosis. Finally, the p-values of Shapiro-Wilk's test of normality indicate a non normal behaviour for all funds with the exception of the equity hedged style and the traditional indices.[1] For completeness, Table 5.1 also presents the standard statistics of HFRI funds of funds. These indices show higher mean returns and usually lower volatility than stocks and bonds. Looking at higher moments and the p-values of Shapiro-Wilk's normality test, all fund of funds indices with the exception of the Market Defensive index exhibit a non normal distribution of returns. There is, as well, a tendency of autocorrelation in the non normally distributed fund of funds indices.

5.2 Motivation and methodology

Regardless of the vehicle an investor chooses to invest into hedge funds, the various risk characteristics of hedge fund strategies have to be identified before any allocation to hedge funds can take place. The identification of risks is essential for risk measurement. For a proper risk management, however, an understanding and explanation of the risk sources is equally important. Most of the academic research has been focused on finding statistical evidence of non normality, time dependence or other stylised facts in

[1] Smaller p-values indicate stronger evidence against the null hypothesis (normality), and larger p-values indicate stronger evidence in favour of the null.

Table 5.1: *Descriptive statistics of raw data.*

Index	Mean	Std.Dev	Skew	Kurt	Min	Max	ACF1	S-W test
LS	16.68%	8.99%	0.18	1.22	-7.65%	10.88%	0.16	0.986*
EMN	9.00%	3.21%	0.15	0.19	-1.67%	3.59%	0.08	0.990
SS	4.08%	21.68%	0.13	1.25	-21.21%	22.84%	0.09	0.985*
FI	8.28%	4.37%	-1.68	9.53	-6.45%	4.70%	0.39	0.861***
CA	10.44%	3.41%	-1.13	2.22	-3.19%	3.33%	0.53	0.931***
MA	10.08%	4.30%	-2.63	11.27	-6.46%	2.90%	0.19	0.793***
DS	14.52%	6.15%	-0.66	5.28	-8.50%	7.06%	0.49	0.933***
GM	15.48%	8.51%	0.31	0.36	-6.40%	7.88%	0.17	0.980**
EMG	15.24%	15.04%	-0.79	3.62	-21.02%	14.80%	0.32	0.956***
MF	9.24%	11.61%	0.81	2.79	-8.45%	17.53%	-0.01	0.961***
Stocks	7.32%	14.67%	-0.41	0.31	-13.32%	10.55%	-0.01	0.987
Bonds	7.80%	6.56%	0.23	0.18	-4.28%	5.94%	0.19	0.992
Comp	9.60%	5.66%	-0.24	4.04	-7.47%	6.85%	0.32	0.949***
Cons	8.40%	3.27%	-0.47	3.43	-3.88%	3.96%	0.32	0.950***
Diver	8.88%	6.06%	-0.07	4.02	-7.75%	7.73%	0.32	0.942***
Defen	9.60%	6.01%	0.17	1.19	-5.42%	7.38%	0.13	0.985*
Strat	12.84%	9.15%	-0.36	3.35	-12.11%	9.47%	0.29	0.959***

Mean and standard deviation annualised. *Kurt* = excess kurtosis, *Skew* = skewness. *Min* and *Max* represent the lowest and highest monthly return, respectively. *ACF1* = first order autocorrelation coefficient, *S-W test* = Shapiro-Wilk normality test. Significant evidence against the null hypothesis that the distribution is normal at 10%/5%/1% level is found for values labelled by */**/***, respectively. *Stocks* = MSCI World Total Return, *Bonds* = Citigroup Global Gov. Bond (all maturities), *LS* = HFRI Equity Hedge, *EMN* = HFRI Equity Market Neutral, *SS* = HFRI Short Selling, *FI* = HFRI Fixed Income Arbitrage, *CA* = HFRI Convertible Arbitrage, *MA* = HFRI Merger Arbitrage, *DS* = HFRI Distressed Securities, *GM* = HFRI Macro, *EM* = HFRI Emerging Markets, *MF* = Stark 300 Trader. *Comp* = HFRI FOF Composite, *Cons* = HFRI FOF Conservative, *Diver* = HFRI FOF Diversified, *Defen* = HFRI FOF Market Defensive, *Strat* = HFRI FOF Strategic. Sample window (monthly data): Jan 1990–Sep 2004.

finance and their implications on risk measures (see e.g. Schmidhuber and Moix 2001, Brooks and Kat 2002, Lopez de Prado, M. and Peijan 2004). On the other hand, the practitioner's research put more stress on qualitative and quantitative risk management issues (see e.g. Moix and Scholz 2003, Johnson and Macleod 2003, Banz and de Planta 2002).

Consequently, in order to cope with hedge fund specific return characteristics in risk measurement and management, researchers have proposed new measures or made attempts to adjust the standard tools. For example, the above cited study of Brooks and Kat (2002) recommends an unsmoothing of returns to handle the downward biased volatility resulting from autocorrelation. To capture the risk exposure to systematic risks, Fung and Hsieh (2002a) and Agarwal and Naik (2004) construct option based indices that mimic an asymmetric payoff of hedge fund returns. In order to take the asymmetry of the return distribution into account Bacmann and Pache (2004) advocate the use of Sortino and Price's (1994) downside deviation. However, even though this measure is sensitive to large losses, it does not provide a full description of losses as defined by the extreme quantiles of the distribution. Alternatively, Keating and Shadwick (2002) propose the use of the Omega function when comparing different assets. The Omega function takes into account the entire return distribution allowing ranking of performance and risk profiles over a range of threshold returns, without estimating any moments. Finally, in the spirit of Li's (1999) work, Favre and Signer (2002) and Favre and Galeano (2002) advocate the use of modified VaR based on Cornish-Fisher expansion. However, this kind of approach suffers from an important drawback. It assumes that the first four moments do exist.[2] As pointed out by Dacorogna, Müller, Pictet, and de Vries (2001), the convergence of the fourth moment is not guaranteed for financial data. In other words, a finite variance can be safely assumed but not much more. Moreover, the expected shortfall cannot be derived within the Cornish-Fisher expansion framework. As a consequence, VaR and expected shortfall should be estimated via a more reliable theory, namely extreme value theory.

A few authors have already explored EVT in applications to hedge funds. Their application, however, differ somewhat from ours. Gupta and Liang (2003) study the capital adequacy of almost 1500 single hedge funds concluding that a vast majority of hedge fund managers, 96.3% of the live funds and 88.1% of dead funds, are adequately capitalised. Lhabitant (2001) estimates VaR of single hedge funds by extending Sharpe's style analysis model to include hedge fund strategy indices. A somewhat similar approach to our analysis has been carried out by Blum, Dacorogna, and Jaeger (2003) where the VaR measure is applied. Our analysis, however, extends the estima-

[2] see the discussion on page 23 showing that the k'th moment exist for $k < 1/\xi$.

tion of market risks of hedge funds to also include the concept of Expected Shortfall. It will further attempt to give an explanation of the different magnitudes of risk and its source.

5.3 Estimation and results

The EVT is derived under the assumption of *iid*. However, when viewing the first order autocorrelation coefficients in Table 5.1 and the Ljung-Box statistics in Table 5.2 one can clearly observe a time dependence structure for most of the hedge fund strategies. Actually, only the short sellers strategy is independent for all lags investigated. Nondirectional strategies reveal in general significantly higher autocorrelation numbers than the directional ones. If extreme observations do cluster at high levels there are fewer observations for parameter estimations as is the case for independent time series. Consequently, the presence of autocorrelation can severely bias the estimation of sample variance. In the case of a positive autocorrelation, the estimation of standard deviation tend to be biased downwards. Numerous studies have highlighted the importance of eliminating autocorrelation from the return time series of hedge funds.[3]

As noted by Lo (2001) and Getmansky, Lo, and Makarov (2003), the presence of autocorrelation is a result of managers' tendency to invest in securities that are not frequently traded and with less established market prices. Consequently, the valuation of these positions is complicated and to some extent arbitrarily decided by the manager. In such situations, Brooks and Kat (2002) argue that managers either use the last reported transaction price or an estimate of the current market price, employing a smoothed monthly return time series. This would imply that the location parameter is responsible for serial dependence. While this might be true for emerging market, distressed, relative value and to some extent for long/short

[3]See e.g. Brooks and Kat (2002), Kat and Lu (2002), and Okunev and White (2002). By calculating the so-called extremal index, EVT offers a methodology to test whether the observations cluster at high levels. Unfortunately, this methodology requires a block building of the sample which in the case of hedge funds is not large enough to conduct such a computation.

Table 5.2: *Ljung-Box statistics of raw data.*

Name	LB-Q(1)	LB-Q(3)	LB-Q(6)	LB-Q(9)
Equity long/short	4.92**	6.24	9.30	11.77
Equity market neutral	1.08	7.87**	31.06***	38.44***
Short selling	1.37	2.12	7.44	7.98
Fixed income arbitrage	26.91***	32.32***	34.36***	38.98***
Convertible arbitrage	50.40***	60.61***	62.63***	65.32***
Merger arbitrage	6.62**	9.00**	11.62*	17.55**
Distressed securities	43.99***	47.65***	49.83***	51.72***
Macro	5.27**	5.27	12.33*	14.08
Emerging markets	18.62***	20.28***	22.08***	26.98***
Managed futures	0.02	3.91	12.60*	14.79*
Stocks	0.01	0.71	3.07	5.90
Bonds	6.61**	7.07*	23.71***	31.45***
FOF Composite	18.61***	21.33***	22.31***	25.50***
FOF Conservative	18.58***	27.12***	28.37***	29.99***
FOF Diversified	18.83***	20.83***	24.82***	27.86***
FOF Market Defensive	3.00*	3.51	5.30	8.89
FOF Strategic	15.14***	17.51***	18.83***	23.53***

All hedge funds are represented by the HFRI indices, and managed futures by the Stark 300 Trader index. *Stocks* = MSCI World Total Return, *Bonds* = Citigroup Global Gov. Bond (all maturities). Ljung-Box Q test is calculated for the first order autocorrelation, for a group of the first three autocorrelations, first six, and first nine, respectively. High values indicate a rejection of the null hypothesis that the time series is independent. Significant evidence against the null hypothesis at 10%/5%/1% level is found for values labelled by */**/***, respectively. Sample window (monthly data): Jan 1990–Sep 2004.

strategies with small cap bias, it is difficult to append this reasoning to the presence of serial dependence in equity market neutral and merger arbitrage which are obviously located in liquid markets. Instead, a more plausible explanation might be that arbitrage based funds are locking in positions with a consequence that the returns varies in a narrow bound. Statistically, low variability induces low correlation. This would imply that also the strategy parameter plays an important role for the determination of serial dependence. Additionally, since even bonds which are very liquid exhibit a significant autocorrelation it seems that the location parameter is not solely defined by illiquidity itself. Which of these two parameters dominates the autocorrelation structure and its magnitude is difficult to quantify. However, the highest autocorrelation coefficients are found for nondirectional strategies located in less liquid bond markets (distressed and relative value strategies) indicating that the strategy parameter as well as both components of the location parameter are responsible for serial dependence. These strategies are followed by emerging markets which is exposed to illiquidity only, and finally merger arbitrage with equity market neutral exposed to the strategy factor only. Liquidity risk is also one of major sources having impact on the tails of a distribution which explains why strategies with highest serial dependence, presumably due to illiquid location parameter, also exhibit fat tails.[4]

In accordance with the suggestions in the above cited literature, the return time series are unsmoothed by using the following formula:

$$r_t = \frac{r_t^* - \hat{\rho} r_{t-1}^*}{1 - \hat{\rho}} \tag{5.1}$$

where r_t is the unsmoothed return, r_t^* the observed return, and $\hat{\rho}$ the estimated first order autocorrelation coefficient.[5] After adjusting the data for the first order serial dependence there is no evidence of autocorrelation for longer horizons in the data.[6] Table 5.3 reports the key statistics of the unsmoothed data. As expected, the standard deviation of the positive autocorrelated series has increased, while the indices with a negative autocorrelation coefficient achieved a slightly lower standard deviation. According to the F-test of difference in variance (last column in Table 5.3), this difference is significant for most of the strategies.[7] The effect of unsmoothing on higher moments is neglectful. The signs of third and fourth moments

[4] See the discussion in Section 3.1 on page 52.

[5] It is worth noting that the estimation of Ljung-Box statistics is performed under assumption of normality. Hence, unsmoothing non-normal data with a linear coefficient should be interpreted with care.

[6] An alternative method would be to correct the variance only and leave the time series raw. However, when applying EVT one needs corrected data since the variance itself does not matter in estimation of the tail.

[7] Brooks and Kat (2002) do not perform any significance test for difference in standard deviation. However, with exception of equity market neutral all investigated HFRI indices exhibit positive first order autocorrelation and thus the standard deviation increased.

remained the same. The largest changes has been observed for fixed income and merger arbitrage strategies with the implication that these return series became less negatively skewed with a lower kurtosis. Thus, the unsmoothed data is used for the rest of the analysis.

The estimation of VaR and ES based on EVT is conducted by utilising the peak over threshold approach. This involves fitting a generalised pareto distribution to excess returns above a certain high threshold. The main issue in applying this approach is the selection of an appropriate threshold. An accurate estimation of the considered quantile principally depends on the estimation of the shape parameter, which in turn is sensitive to the selected threshold. A threshold too low will lead to biased estimations since the Pickands' condition in (3.7) is not satisfied. On the contrary, a too high threshold leads to a large variance and few observations are left for the estimation. Among various selection techniques, we follow the mean excess function advocated by Davison and Smith (1990) and McNeil (1997). The same authors suggest the use of maximum likelihood in estimations of the shape parameter. This method permits the shape parameter to take positive as well as negative values.

To control the accuracy of the estimation, various diagnostic tools such as QQ-plot, PP-plot, and return level plot of the fitted generalised pareto distribution have been implemented. Noting the degree of agreement among them gives more confidence about the threshold selection, and thus the estimated VaR and ES.[8] Table 5.4 reports VaR and ES results for the hedge fund strategies. This table also contains the 95% confidence intervals for the VaR and ES estimates as well as the estimated shape parameters.

Beginning with the shape parameter, Table 5.4 reveals that with the exception of equity market neutral, the nondirectional strategies seem to be governed by a fat tailed distribution in the left tail. The estimated shape parameter for these strategies reveal strong positive values. This is consistent with the short option profile they exhibit. A notable evidence for a fat tailed distribution is also found for the emerging market strategy. This should not come as a surprise as this strategy is predominately a long

[8] The mean excess function of the unsmoothed time series is to be found in Appendix A together with other descriptive plots.

Table 5.3: *Descriptive statistics of unsmoothed data.*

Name	Mean	Std.Dev	Skew	Kurt	Min	Max	S-W test	F-test
LS	17.04%	10.57%	0.20	0.95	-9.05%	11.95%	0.988	0.72**
EMN	9.00%	3.47%	0.17	0.24	-1.92%	3.82%	0.990	0.85
SS	3.36%	23.61%	0.11	1.34	-23.71%	24.94%	0.984**	0.84
FI	8.04%	6.57%	-0.85	5.79	-9.80%	6.76%	0.919***	0.44***
CA	10.68%	6.15%	-0.51	3.66	-7.52%	7.81%	0.950***	0.31***
MA	10.68%	4.81%	-1.90	7.96	-7.09%	3.94%	0.874***	0.80
DS	14.76%	10.60%	-0.68	6.27	-16.45%	13.17%	0.933***	0.34***
GM	15.72%	10.12%	0.23	0.47	-8.16%	9.52%	0.984**	0.71**
EMG	15.48%	21.06%	-0.99	4.41	-30.86%	18.08%	0.942***	0.51***
MF	9.00%	11.49%	0.84	2.84	-8.20%	17.36%	0.959***	1.02
Stocks	7.68%	14.52%	-0.43	0.35	-13.21%	10.45%	0.986*	1.02
Bonds	7.92%	7.97%	0.16	0.24	-5.65%	7.15%	0.992	0.68**
Comp	9.72%	7.92%	-0.29	3.83	-10.91%	7.77%	0.948***	0.51***
Cons	8.40%	4.57%	-0.54	3.52	-5.90%	4.68%	0.952***	0.51***
Diver	9.00%	8.50%	-0.16	3.70	-11.37%	8.87%	0.941***	0.51***
Defen	9.60%	6.86%	0.04	1.02	-6.28%	7.89%	0.989	0.77*
Strat	13.08%	12.35%	-0.31	3.08	-16.68%	11.90%	0.963***	0.55***

Mean and standard deviation annualised. *Kurt* = excess kurtosis, *Skew* = skewness. *Min* and *Max* represent the lowest and highest monthly return, respectively. *S-W test* = Shapiro-Wilk normality test. */**/*** indicate a rejection of the null hypothesis that the distribution is normal at 10%/5%/1%, respectively. *F-test* = F-test for difference in variance. Null hypothesis is no difference in variance between the raw and the unsmoothed data. Significant evidence against the null hypothesis at 10%/5%/1% level is found for values labelled by */**/***, respectively. *Stocks* = MSCI World Total Return, *Bonds* = Citigroup Global Gov. Bond (all maturities), *LS* = HFRI Equity Hedge, *EMN* = HFRI Equity Market Neutral, *SS* = HFRI Short Selling, *FI* = HFRI Fixed Income Arbitrage, *CA* = HFRI Convertible Arbitrage, *MA* = HFRI Merger Arbitrage, *DS* = HFRI Distressed Securities, *GM* = HFRI Macro, *EM* = HFRI Emerging Markets, *MF* = Stark 300 Trader. *Comp* = HFRI FOF Composite, *Cons* = HFRI FOF Conservative, *Diver* = HFRI FOF Diversified, *Defen* = HFRI FOF Market Defensive, *Strat* = HFRI FOF Strategic. Sample window (monthly data): Jan 1990–Sep 2004.

only investment on markets with a considerable downside risk. Because the inverse of the shape parameter defines the number of moments, Table 5.4 further indicates that only the first two moments are defined for the emerging market and the merger arbitrage strategy. The estimated shape parameter for theses strategies is 0.45 and 0.37 respectively. For the distressed securities strategy this is confined to the first three moments (0.27). This implies that optimisations or VaR estimations with higher moments containing these strategies will not produce reliable results. The shape parameter estimations are similar in sign to the results in Blum, Dacorogna, and Jaeger (2003) with the exception of short selling and global macro which in their study obtain a high positive, and a slight positive value, respectively. That study, however, is based on CSFB/Tremont indices which are capital weighted and hence less comparable to HFRI. Furthermore, their sample window contains 108 observations collected from January 1994 to December 2002. The most likely reason for the difference in the shape parameter of global macro strategies is the composition of CSFB/Tremont global macro index which also includes emerging market hedge funds that exhibit fatter tails.

The lack of liquidity and credit risk exposure is responsible for the fact that the equity market neutral strategy reveals a more normal behaviour. The estimated shape parameter is -0.07. In direct contrast to the other nondirectional strategies, the investments are committed in highly liquid equity markets. From Table 5.4 one may further discern that the shape parameter of the remaining directional strategies is generally negative and close to zero, implying a normal or even a short tailed distribution in the left tail; -0.05, -0.11, -0.10, and -0.05 for the equity long/short, short selling, macro, and managed futures, respectively. Here, also, the trades are mainly committed in liquid equity or futures markets. Sott (2004) points out that these characteristics allow managed futures mangers to change direction relatively quickly making them more flexible in market stress periods, and thus offering a downside hedge. An equivalent statement might be attributed to the global macro and the long/short equity strategies.

While knowledge of the shape parameter is interesting in itself, the question of economic interest is how large extreme returns are. Given the obvious tail fatness of relative value and event driven strategies one might draw a

Table 5.4: *VaR, ES and shape paramter of hedge fund strategies.*

Name	95%		99%		*Shape*
	VaR	*ES*	*VaR*	*ES*	
LS	**3.34**	**4.83**	**5.77**	**7.15**	−0.05
	(2.78; 4.23)	(3.88; 6.34)	(4.57; 7.66)	(5.60; 9.61)	
EMN	**0.80**	**1.29**	**1.60**	**2.03**	−0.07
	(0.61; 1.10)	(0.98; 1.77)	(1.21; 2.19)	(1.54; 2.79)	
SS	**10.85**	**14.65**	**17.08**	**20.28**	−0.11
	(9.18; 13.27)	(12.22; 18.17)	(14.16; 21.29)	(16.72; 25.42)	
FI	**2.24**	**4.14**	**5.08**	**7.87**	0.24
	(1.71; 3.12)	(2.96; 6.10)	(3.58; 7.57)	(5.40; 11.94)	
CA	**1.92**	**3.53**	**4.38**	**6.53**	0.18
	(1.40; 2.71)	(2.55; 5.01)	(3.15; 6.24)	(4.68; 9.31)	
MA	**1.26**	**3.23**	**3.99**	**7.53**	0.37
	(0.80; 2.03)	(2.05; 5.19)	(2.53; 6.42)	(4.77; 12.13)	
DS	**3.13**	**5.50**	**6.62**	**10.29**	0.27
	(2.46; 4.17)	(4.09; 7.71)	(4.86; 9.38)	(7.37; 14.83)	
GM	**3.20**	**4.72**	**5.69**	**6.98**	−0.10
	(2.58; 4.15)	(3.76; 6.21)	(4.50; 7.51)	(5.50; 9.26)	
EMG	**7.87**	**14.20**	**16.06**	**29.22**	0.45
	(6.70; 10.00)	(10.42; 21.02)	(11.52; 24.26)	(19.27; 47.16)	
MF	**3.92**	**5.36**	**6.27**	**7.61**	−0.05
	(3.30; 4.80)	(4.44; 6.68)	(5.15; 7.86)	(6.20; 9.60)	
Stocks	**6.87**	**9.10**	**10.55**	**12.20**	−0.19
	(5.85; 8.36)	(7.69; 11.16)	(8.89; 12.98)	(10.26; 15.04)	
Bonds	**3.06**	**4.02**	**4.65**	**5.31**	−0.24
	(2.63; 3.71)	(3.43; 4.92)	(3.95; 5.71)	(4.50; 6.54)	

Peak-over-Threshold estimates of Value-at-Risk and Expected Shortfall for hedge fund strategies and traditional assets, in percent. *Shape* = the estimated shape parameter ξ from generalised Pareto distribution as defined in equation (3.7). Values in parentheses represent a 95% confidence interval. *LS* = HFRI Equity Hedge, *EMN* = HFRI Equity Market Neutral, *SS* = HFRI Short Selling, *FI* = HFRI Fixed Income Arbitrage, *CA* = HFRI Convertible Arbitrage, *MA* = HFRI Merger Arbitrage, *DS* = HFRI Distressed Securities, *GM* = HFRI Macro, *EM* = HFRI Emerging Markets, *MF* = Stark 300 Trader, *Stocks* = MSCI World Total Return, *Bonds* = Citigroup Global Gov. Bond (all maturities). Sample window (monthly data): Jan 1990–Sep 2004.

conclusion that these bear the highest risk. Turning the discussion toward the risk numbers measured by VaR and ES, it is apparent that at 95% level the lowest values are found among the nondirectional strategies. The risk of large losses measured by 95% VaR and ES is generally lower than that of bonds which are proxied by the Citigroup Government Bond index. The reason is that the low volatility of non directional strategies outweighs the fat tail effect. A similar result has been observed in Schmidhuber and Moix (2001), where a hyperbolic distribution has been fitted to hedge fund data.

Ineichen (2004) points out that as actively managed risks result in low volatility of hedge funds, large losses will have a much higher impact on higher moments, i.e. fatness of the curve, than for the more normal and symmetrically distributed high volatility assets. Additionally, in a simulation study Burghardt, Duncan, and Liu (2003) have shown that the size of the higher moments does not matter for the distribution of drawdowns and maximum drawdowns. However, they found that the higher the volatility the higher the likelihood of drawdowns, and the higher the mean the lower the likelihood of experiencing a drawdown.

In comparison to stocks, represented here by the MSCI World Total Return index, the estimated 95% VaR and ES values of nondirectional strategies are far lower. In all cases the estimated VaR and ES of stocks is above the confidence interval of nondirectional strategies. Among all strategies, the equity market neutral one shows the lowest risk numbers. The directional strategies reveal a rather mixed though not surprising picture. The dimension of risk at 95% level of long/short equity, macro and managed futures is comparable to that of bonds and much lower than stocks. Despite the directional market exposure of these strategies, the lower risk is a direct result of active volatility management that reduces the downside risks. The remaining directional strategies, short sellers and emerging market, reveal higher risk numbers. It should be mentioned that these strategies differ from other directional strategies in the sense that they essentially have net exposure in one direction only, short or long respectively. Hence, they exhibit higher volatility which produces higher risk numbers.

Moving to the higher quantile (99%) the increase of VaR and ES numbers in the tail is largest for the relative value, event driven and emerging market strategies. This shift is expected given the fatter tail of these strategies. The change in their risk measures is generally twofold. Hedge funds with a distribution closer to normal face an increase in their risk measures of roughly 50%. The lowest overall numbers are again obtained for equity market neutral whereas short sellers and emerging market remain the riskiest strategies. Compared to bonds, the risk numbers for all strategies are less attractive as in the 95% case. However, three strategies (equity market neutral, fixed income arbitrage and convertible bond arbitrage) have lower VaR numbers, and equity market neutral even shows a lower ES. Nevertheless, the overwhelming majority of hedge funds demonstrate a much lower risk than that of stocks. The estimated VaR and ES of stocks is above the confidence interval of hedge funds. Short selling and emerging market are, once again, the exceptions to this.

As a diagnostic check and for the purpose of comparison, Table C in Appendix C presents VaR and ES estimated with a historical method. The numbers are within the 95% confidence interval of the EVT based VaR and ES. The differences are larger for the 99% level and especially for the fat tailed distributed indices indicating higher risk with EVT estimation.[9] Additionally, it is important to bear in mind the statistical biases present in hedge fund indices as described in Section 4.5. Hence, the results should be interpreted with care as the impact of survivorship bias in addition to performance might also be significant for higher moments. Using TASS database over the period 1994-2001, Amin and Kat (2003b) had investigated this issue concluding that not taking fund closures into account causes an upward bias in the skewness and downward bias in the kurtosis estimates and thus underestimating the risk. The exact impact on our results is difficult to quantify as the study of Amin and Kat (2003b) does not distinguish between styles in bias estimation of higher moments. The impact of survivorship bias on individual styles has been investigated by Liang (2000), although not for higher

[9]This comparison is for illustrative purposes only as the number of observations is very limited, e.g. only two observations can be used to calculate the 99% ES. Besides that, Blum, Dacorogna, and Jaeger (2003) note two other benefits with parametric estimates over the historical method; estimation of quantiles beyond what is covered by available data, and smoother tail estimates within covered historical data.

moments. However, the author could not find a significant bias in HFRI style indices.[10] On the contrary, significant bias has been concluded for most of the TASS investment styles. As in the study of Amin and Kat (2003b), directional funds with exception of emerging markets are generally showing higher survivorship bias than their nondirectional counterparts. Neglecting for a moment the different windows in investigated periods and assuming that the characteristics obtained from these studies on TASS database are applicable to our HFRI indices, one is tempted to conclude that the impact on strategies exhibiting fat tails is rather negligible. Consequently, a slightly upward adjustment of risk numbers in more normally distributed strategies is to be expected.

Another critical point is the investigated period from January 1990 to September 2004. As with any other statistical analysis, a time window has to be fixed before conclusions can be drown from. Since the investigated period contains both bull and bear equity markets, credit crises in late 1990's, as well as hedge fund debacles it should serve as a reliable and representative set for comparative analyses. Nevertheless, in times of writing the thesis, the last two years (2005 and 2006) have been very profitable for equity investors. Hence, Table B in Appendix B provides descriptive statistics updated for the months up to December 2006. The general picture of this data extension is that most of hedge fund strategies exhibit a lower return and volatility. Strategies with positive skewness and kurtosis tend to display higher numbers in the third and fourth moment whereas the nondirectional ones tend to show a lower skewness and an increase in kurtosis. These changes indicate that in the last two years we have observed a large number of small positive returns. It also means that most of the extreme observations needed to calculate the tail risk measures did occur in the past. Also, the size of maximum and minimum returns remained the same as well as the size of autocorrelation coefficients. Indeed, the upward trending stock markets and the absence of large extreme observations in the left tail for the investigated indices let us believe that the impact of the last two years is infinitesimal on tail risk estimations conducted in this chapter.

[10] Again, this might be due to the fact that HFR collects a lower number of dissolved funds as claimed by Liang (2000). The investigated period over 1993-1998 differs as well.

Consequently, with an increased data set, this would suggest a more robust estimation of the risk measures as the standard errors and thus confidence intervals become smaller.

To sum up, on the basis of VaR and ES estimates hedge funds predominately demonstrate a lower risk of large losses than traditional investments. These low risk numbers are mainly a result of active risk management by implementing dynamic long/short trading strategies that reduce volatility. Figure 5.1 concludes these findings by displaying on the same return range the histograms of stocks, bonds and two hedge fund strategies. Given the smaller dispersion of hedge funds, the extreme losses that generate the fatness in the left tail are rather small in absolute values when compared to equity markets. Thus, the size of the higher moments is less important when assessing risk of hedge funds.

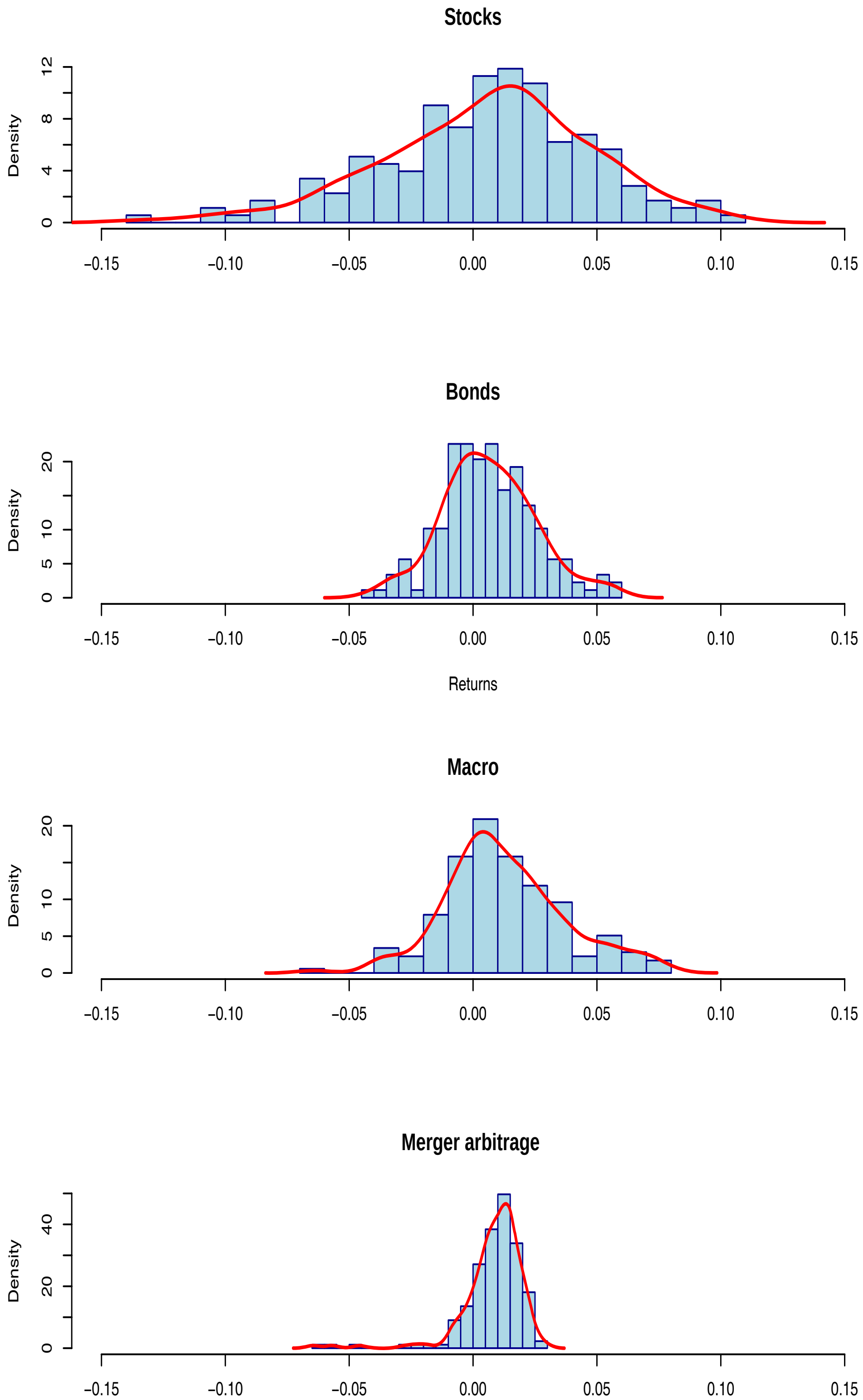

Figure 5.1: *Histograms of traditional investments and hedge fund strategies.*

All histograms plotted on the same scale [-0.15;0.15]. Stocks = MSCI World Total Return, Bonds = Citigroup Global Gov. Bond (all maturities), Macro = HFRI Macro, Merger arbitrage = HFRI Merger arbitrage. Sample window (monthly data): Jan 1990–Sep 2004.

Chapter 6

Portfolio risk of hedge funds and traditional assets

In view of the fact that investors' demand for hedge funds has shifted towards diversified hedge fund products, in this chapter we will no longer consider single strategies but concentrate on the HFRI fund of funds indices. To analyse how hedge funds, stocks and bonds fit together with respect to risk several portfolios are constructed and their evolution of VaR and ES at the 95% and 99% level is computed.

6.1 Data

The HFRI fund of funds (FOF) indices that are used in this part of the analysis have been described in Section 5.1 where the standard statistics of the raw data are also found (Table 5.1). Table 5.3 presents the unsmoothed results and Appendix A provides a historical time series as well as descriptive plots. Normality can not be rejected for the HFRI FOF Market Defensive only. Judging from the skewness and kurtosis, the returns of the remaining FOF seem to obey a fat tailed distribution with an additionally significant first order autocorrelation. All FOF indices have higher mean returns than stocks and bonds. The volatility is lower than stocks whereas two FOF indices, Diversified and Strategic, have higher volatility than bonds. In view of the discussion in the previous chapter, Table 6.1 gives the estimated VaR

Table 6.1: *VaR, ES and shape parameter of funds of funds.*

Name	95%		99%		*Shape*
	VaR	*ES*	*VaR*	*ES*	
Comp	**2.41**	**4.17**	**4.88**	**7.99**	0.35
	(2.03; 3.10)	(3.09; 6.11)	(3.52; 7.36)	(5.39; 12.63)	
Cons	**1.36**	**2.49**	**3.06**	**4.71**	0.23
	(1.03; 1.89)	(1.79; 3.65)	(2.16; 4.54)	(3.25; 7.09)	
Diver	**2.65**	**4.70**	**5.67**	**8.83**	0.27
	(2.06; 3.55)	(3.49; 6.55)	(4.17; 7.97)	(6.37; 12.59)	
Defen	**2.24**	**3.40**	**4.08**	**5.35**	0.06
	(1.86; 2.87)	(2.66; 4.60)	(3.13; 5.62)	(4.01; 7.54)	
Strat	**4.25**	**6.68**	**8.02**	**11.03**	0.13
	(3.42; 5.50)	(5.17; 8.94)	(6.15; 10.84)	(8.32; 15.10)	
Stocks	**6.87**	**9.10**	**10.55**	**12.20**	−0.19
	(5.85; 8.36)	(7.69; 11.16)	(8.89; 12.98)	(10.26; 15.04)	
Bonds	**3.06**	**4.02**	**4.65**	**5.31**	−0.24
	(2.63; 3.71)	(3.43; 4.92)	(3.95; 5.71)	(4.50; 6.54)	

Peak-over-Threshold estimates of Value-at-Risk and Expected Shortfall for fund of funds and traditional assets. *Shape* = the estimated shape parameter ξ from generalised Pareto distribution as defined in equation (3.7). Values in parentheses represent a 95% confidence interval. *Comp* = HFRI Composite, *Cons* = HFRI Conservative, *Diver* = HFRI Diversified, *Defen* = HFRI Market Defensive, *Strat* = HFRI Strategic, *Stocks* = MSCI World Total Return, *Bonds* = Citigroup Global Gov. Bond (all maturities). Sample window (monthly data): Jan 1990–Sep 2004.

and ES along with the estimation parameters. The lowest risk numbers at both confidence levels are found for the Conservative index, whereas the Strategic one reveals the highest values. With the exception of the latter index, the FOF disclose risk estimates significantly lower than those of stocks. At both risk levels, the estimated VaR and ES is below the confidence interval of stocks. The estimated shape parameters indicate a fat tailed distribution in the left tail of the return distribution, although this is less evident for the FOF Market defensive index. It is worth noting that the third and fourth moments are not defined for the FOF Composite index, as is the case for the fourth moment of the FOF Diversified one.

6.2 Motivation and methodology

Modern financial theory usually suggests the use of the mean-variance approach when allocating capital into various assets. Fung and Hsieh (1999a) investigate the appropriateness of this approach in the context of hedge funds and mutual funds. Their results support the use of mean-variance to rank funds as the rankings produced are nearly correct. However, they also conclude that risk assessment can not be done accurately using this approach as it is appropriate only for normally distributed returns. Consequently, the tail risk of negatively skewed assets tends to be underestimated. As shown in the previous chapter, hedge funds exhibit an asymmetric return distribution. Brooks and Kat (2002) argue that the mean-variance framework has a propensity to overestimate the true risk-return profile of hedge funds, which leads to an over-allocation to this asset class. By constructing option based risk factors of the underlying hedge fund indices, Agarwal and Naik (2004) compared the tail losses of portfolios constructed using the mean-variance approach and the mean-expected shortfall framework. The results show that the mean-variance approach substantially underestimates the tail losses and this underestimation is most severe for portfolios with low volatility.

In a recent paper, Amin and Kat (2003a) demonstrate that while hedge funds combine well with stocks and bonds in the mean-variance framework, this is no longer the case when skewness is considered. Adding hedge funds to a portfolio of stocks and bonds improved the mean-variance characteristics but at a cost of lower skewness and higher kurtosis making hedge funds less attractive in a portfolio context. Such an approach, however, suffers from the assumption that the higher moments exist. The shape parameters in Table 6.1 indicates that this might not be the case. Additionally, as the results in the previous chapter shows, the presence of fat tails does not necessary induce higher values of large losses. Thus, the investigation of risk in portfolios with hedge funds should be conducted in terms of absolute return rather than solely relying on distributional moments. Furthermore, contrary to Amin and Kat (2003a), the analysis in this chapter will not rely on an optimisation for at least three reasons. Firstly, any optimisation framework relies on the definition of expected returns, which are particulary prone to errors. As a consequence, the choice of expected returns coming from a model or from a historical perspective influences the optimal weights of hedge funds, stocks, and bonds in the portfolio. Secondly, optimisation methods are very sensitive to errors in the different estimates and tend to exacerbate the impact of the errors on the optimal weights.[1] Finally, the behaviour of institutional investors is not well captured by an optimisation framework. Indeed, institutional investors tend to favour limited investment (between 1% and 5%) when considering the inclusion of a new asset class in their portfolios. Instead, in this chapter, the analysis of risk in portfolios with hedge funds is conducted by measuring the VaR and ES derived from EVT for an incremental addition of hedge funds.

6.3 Estimation and results

In order to analyse how hedge funds, stocks, and bonds fit together, several portfolios are created out of the different asset classes. These different sets of portfolios are constructed by choosing the initial composition between stocks and bonds. Eleven sets are defined, where the allocation to stocks (bonds) ranges from 0% (100%) to 100% (0%) in steps of 10%. In each of the sets, we add different levels of hedge funds (0%, 1%, 5%, 10%, 15%, 20% up to 100% in steps of 5%). When hedge funds are added to the portfolio, the proportion of stocks (or bonds) is kept constant in the traditional part of the portfolio. For example, if a set is built with 20% stocks and 80% bonds, adding 20% hedge funds will decrease the weight of stocks to 20% * 80% = 16% and the weight of bonds to 80% * 80% = 64%. In total, we analyse 242 portfolios for a given fund of funds index which corresponds to 1210 portfolios for the five fund of funds indices. This method provides more information than the standard optimisation framework. As noted in Kat and Lu (2002), forming portfolios itself tends to create autocorrelation. We follow the suggestions therein and perform unsmoothing of the time series after the construction of the portfolios.

In order to simplify the estimations of the large number of portfolios, the threshold u is parameterised as a product of percentile p and the empirical

[1] See e.g. Michaud (1998) in the traditional context of mean-variance.

standard deviation of each portfolio's returns. The percentile p is determined by evaluating the mean excess function as suggested by Davison and Smith (1990). The choice of 70th percentile has been found to be a sound definition of the threshold for the different time series as it generally gives stable results.[2] On average, one obtains 35 observation points, typically ranging from 25 to 45.

The analysis of Figures 6.1, 6.2, and 6.3 shows the different behaviours depending on the composition of the traditional portfolios. The introduction of hedge funds in a traditional portfolio reduces the risk measured by 95% VaR or 95% ES for all the considered cases. The optimal level depends strongly on the initial traditional portfolio composition and on the type of the added fund of funds. For instance, when the traditional portfolios contain mostly stocks, VaR and ES are decreasing to the VaR and the ES of the individual FOF as expressed by a downward sloping pattern in Figure 6.3. This behaviour is expected since all FOF indices have much lower risk than stocks. In other words, these traditional portfolios should contain as much hedge funds as possible.

On the other hand, when the traditional portfolio contains mostly bonds, diversification effects can be achieved. This is apparent from the u-shaped pattern of FOF indices in Figure 6.1. For instance, the FOF Strategic has much higher risks as measured by VaR and ES and still the portfolio risk is significantly reduced up to an allocation of approximately 40% in order to increase again when its addition raises. Looking at all FOF indices, it appears that an optimal composition is found between 50% and 60% in hedge funds and between 40% and 50% in bonds for the overall portfolio. Moreover, the reduction of VaR and ES is statistically significant.[3] For example, the 95% VaR (95% ES) of a bond only portfolio is 3.01% (4.00%). When 50% FOF Composite is added to this portfolio, VaR (ES) drops to 1.42% (2.34%) and the upper limit of the confidence interval is 1.85% for

[2] Alternatively one could have fixed the threshold such that the number of exceedances represents a specified fraction (e.g. 10%) of the data for each portfolio. A graphic evaluation of the mean excess plots, however, indicated that this procedure leads to a less satisfactory choice of threshold.

[3] At 5% significance level.

VaR (3.40% for ES). This observation is valid for an inclusion of the FOF Composite ranging from 25% up to 75%.

For mixed portfolios, in the regions of 40% to 50% stocks, the inclusion of FOF Strategic does not seem to have significant risk reducing properties, when measured by ES.[4] However, including FOF Strategic might still be worthwhile due to return enhancement. Still, adding ca 40% of FOF Strategic does not not change the risk magnitude of the mixed portfolio. This is partially consistent with the evidence from Schneeweis and Spurgin (2000) that generalises hedge fund strategies into risk reducers, return enhancers, and pure diversifiers. Their results show that investors adding long/short equity and global macro strategies into a typical stock/bond portfolio should rather expect return enhancement than risk reduction or diversification.

In general, the characteristics of the fund of funds index added to the traditional portfolio have a strong impact on the risk profile of the blended portfolio. The lowest risk reduction is achieved with the FOF Strategic due to the high risk behaviour of the index. The most important reduction of risk is obtained with the FOF Conservative when the traditional portfolio contains mostly bonds. In the case of the addition of FOF Market Defensive to the traditional portfolio, we find an optimal composition (optimal level of hedge funds) for each traditional portfolio. The level of hedge funds to be added is a function of the composition of the traditional benchmark (between 40% to 70%). In other words, the FOF Market Defensive category provides a different risk profile presenting diversification effects whatever the initial traditional portfolio. This FOF index is overweighed toward managed futures and short sellers. These findings are consistent with Kat's (2004) claim that managed futures reduce substantially the risk of traditional portfolios.[5] From a risk perspective, investor should consider managed futures in their hedge fund portfolio in order to diversify the extreme risk in the traditional portfolio.

[4]See the lower panel of Figure 6.2.

[5]An early application of adding managed futures into traditional portfolios is Lintner (1983), which concludes that managed futures strongly improve the risk/return tradeoff of blended portfolios.

The overall impression gained from the portfolios evaluated at 99% risk level is very similar to that of the 95%, though, the inclusion of hedge funds in bond dominated portfolios indicates an optimal allocation of between 30% and 50%. Stock dominated portfolios benefit most from an allocation to hedge funds, whereas mixed portfolios are again least affected. The ranking of the different FOF is preserved, meaning that the FOF Conservative and FOF Market Defensive contribute with the highest reduction in risk, as measured by VaR and ES. The FOF Strategic has the lowest, and in most cases even no risk reduction character. Judging from the ES figures, this index reduces risk only for stock dominated portfolios. As already pointed out, this FOF has the highest volatility among all investigated indices.

In contrast to the findings and indications in the literature, the results in this chapter clearly show that the contribution of hedge funds in a traditional portfolio has a risk reducing character, and, in most cases, regardless of the initial composition of the traditional one. The magnitude of this effect is dependent on the initial composition of the portfolio and the type of added FOF. There is in general no major difference in VaR and ES with respect to ranking of the individual FOF indices although the optimal allocation is lower when measured by ES.[6] In contrast to Amin and Kat (2003a), the risk reduction is achieved despite the less attractive fat tails properties of the hedge fund indices. Additionally, looking at FOF mean returns, this improvement in terms of risk control does not necessarily come at the cost of lower expected returns. The explanation for this behaviour is the lower volatility of FOF as a result of active risk management. The increased probability of large losses as indicated by negative skewness/large kurtosis or the positive shape parameter does not translate into large losses in absolute values. Finally, there seems to be a diversification benefit in the tail from adding FOF. This finding is especially apparent for bond dominated portfolios as an addition of hedge funds exhibit a u-shape pattern regardless of the magnitude of risk of the individual FOF. An optimal allocation is achieved since hedge fund are exposed to different risk sources than bonds. The issue of tail diversification is examined in more details in the next chapter.

[6]Expected shortfall should be more reliable in estimating diversification benefits since it is a coherent risk measure whereas VaR is not. See the discussion in Section 2.5.

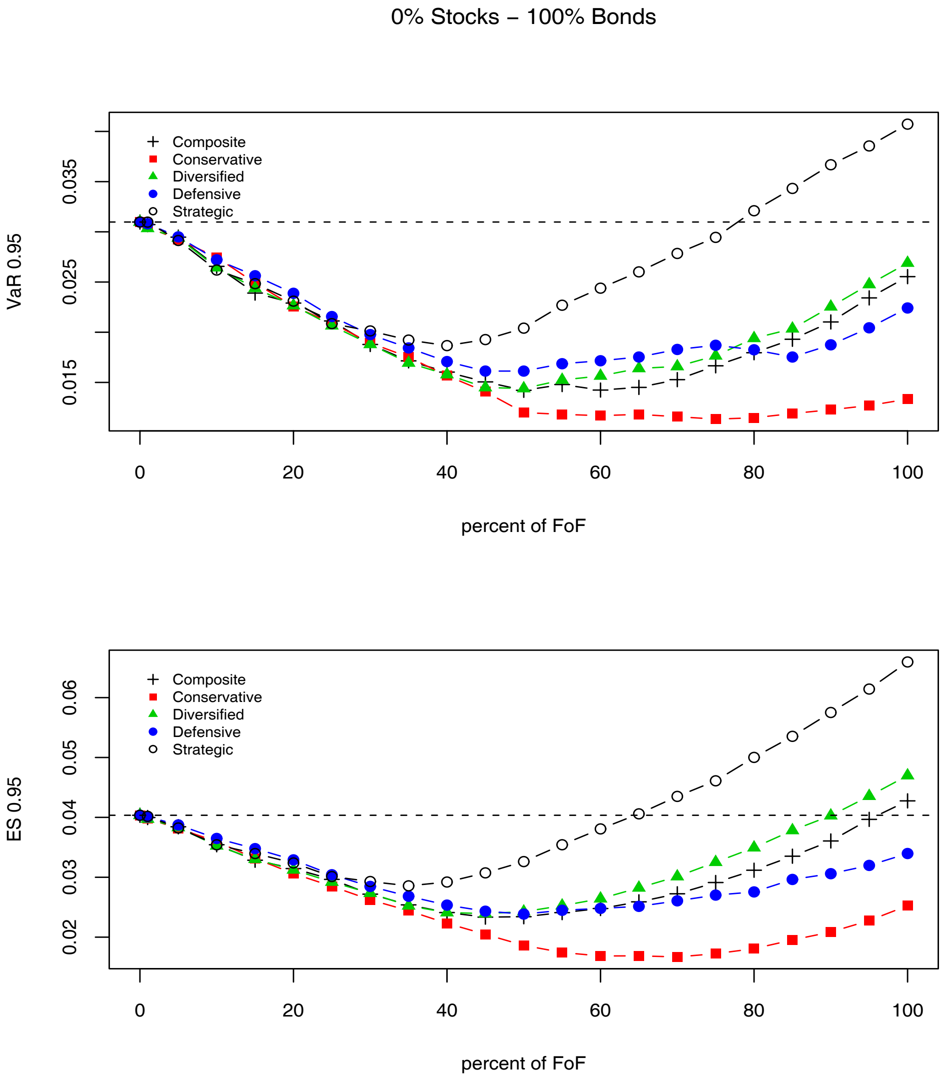

Figure 6.1: *VaR and ES for 0% Stocks and 100% Bonds.*

Evolution of 95% VaR (top) and 95% ES (bottom) when adding hedge funds to traditional portfolios. Horizontal dashed line indicates the initial VaR and ES of the traditional portfolio without hedge funds.

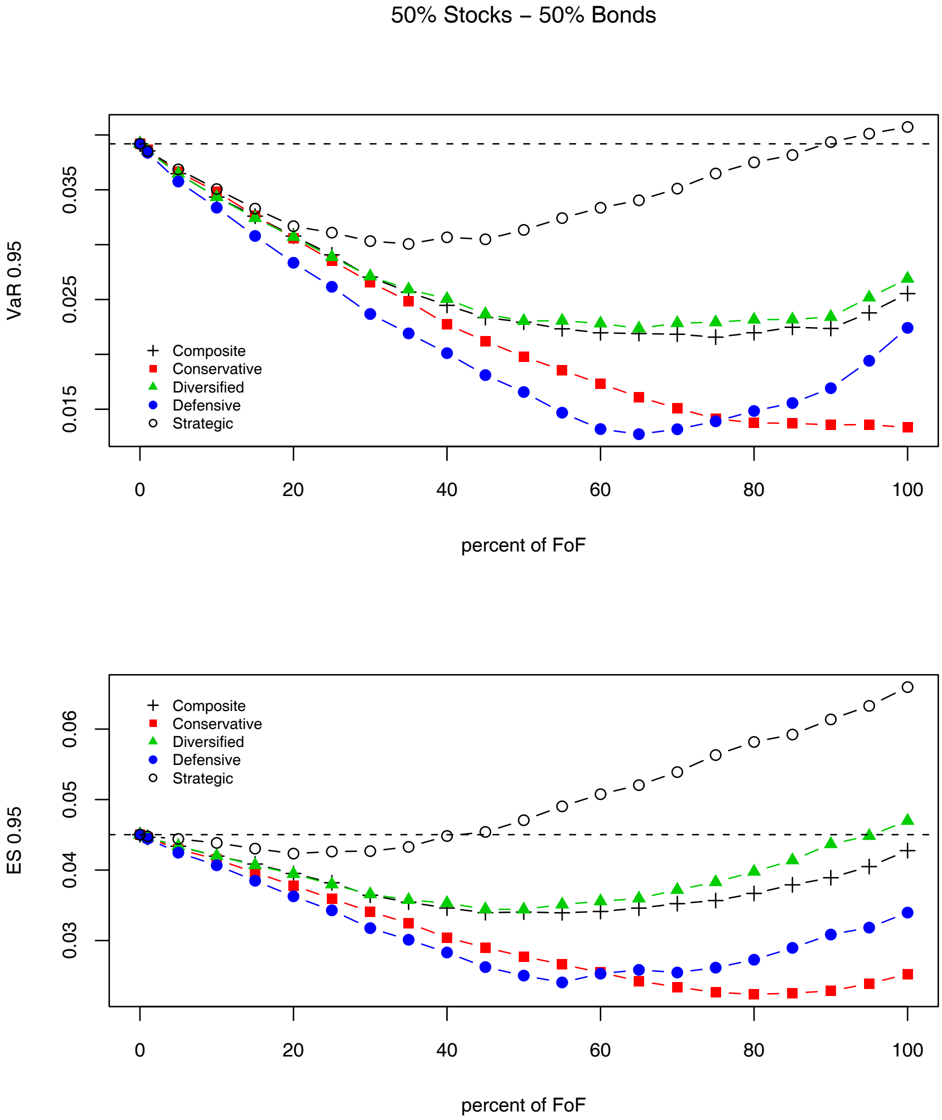

Figure 6.2: *VaR and ES for 50% Stocks and 50% Bonds.*

Evolution of 95% VaR (top) and 95% ES (bottom) when adding hedge funds to traditional portfolios. Horizontal dashed line indicates the initial VaR and ES of the traditional portfolio without hedge funds.

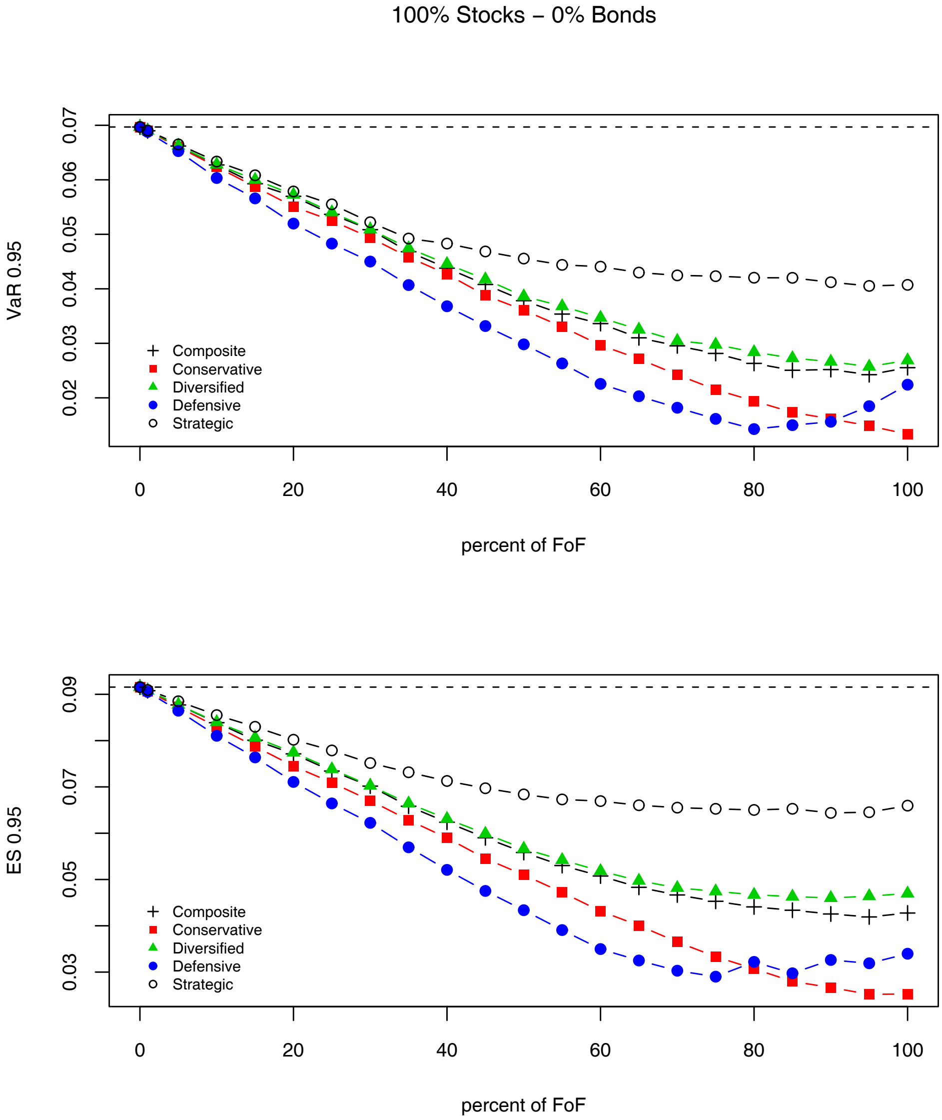

Figure 6.3: *VaR and ES for 100% Stocks and 0% Bonds.*

Evolution of 95% VaR (top) and 95% ES (bottom) when adding hedge funds to traditional portfolios. Horizontal dashed line indicates the initial VaR and ES of the traditional portfolio without hedge funds.

Chapter 7

Extremal dependence

As described in Section 2.1, one of the crucial issues in measuring risks is a realistic approach to the dependencies between asset classes. The previous chapter has shown that hedge funds are able to reduce the risk of different traditional portfolios. However, when building portfolios, the dependence between hedge funds and other asset classes is treated as endogenous. Given the nonlinearities of hedge funds to traditional assets and the apparent asymmetric return distribution, correlation as a measure of dependence is assumed to be of less value. In this chapter, we explicitly evaluate the extreme dependence between the different assets as defined by the multivariate EVT in Section 3.5.

7.1 Data

This part of the analysis makes use of all hedge fund indices investigated so far, i.e. the funds of funds as well as the single strategy indices. All hedge funds are represented by HFRI indices, with the exception of the managed futures strategy which is proxied by the Stark 300 Trader index. The Citigroup Global Government Bond index (all maturities), and MSCI World Total Return index are used as proxies for bonds and equities. Usually, in order to obtain the first impression of diversification potential, the correlation is calculated. Table 7.1 displays the correlation numbers of fund of funds indices with stocks and bonds. Bond markets seem not to be correlated with hedge funds while stocks, with the exception of FOF Market Defensive, appear to have a moderate correlation.[1] Furthermore, the correlation numbers within the fund of funds indices indicate minor diversification benefits. To some extent, this might be explained by the fact that the same strategies are present in many fund of fund indices. The only hedge fund index with moderate correlation is the FOF Market Defensive.

Table 7.1: *Correlation coefficient of funds of funds.*

Name	Stocks	Bonds	Comp	Cons	Diver	Defen	Strategic
Stocks	1.00	0.20***	0.46***	0.48***	0.48***	0.02	0.48***
Bonds	.	1.00	-0.01	0.04	-0.01	0.09	-0.02
Comp	.	.	1.00	0.85***	0.96***	0.66***	0.92***
Cons	.	.	.	1.00	0.77***	0.58***	0.80***
Diver	.	.	.	.	1.00	0.58***	0.83***
Defen	.	.	.	.	.	1.00	0.52***
Strat	.	.	.	.	.	.	1.00

Estimated correlation between fund of funds indices and traditional assets. Values significantly different from 0 at 10%/5%/1% level are marked by */**/***, respectively. *Stocks* = MSCI World Total Return, *Bonds* = Citigroup Global Gov. Bond (all maturities), *Comp* = HFRI FOF Composite, *Cons* = HFRI FOF Conservative, *Diver* = HFRI FOF Diversified, *Defen* = HFRI FOF Market Defensive, *Strat* = HFRI FOF Strategic. Sample window (monthly data): Jan 1990–Sep 2004.

Table 7.2 reports the correlation coefficients of individual hedge fund strategies and traditional investments. With traditional assets and within hedge funds, the highest diversification benefits are obtained with FOF Market Defensive constituents, i.e. short sellers and managed futures, as well as two strategies that belong to the FOF Conservative, i.e. equity market neutral and fixed income. The former two are generally negatively correlated. On the contrary, strategies offering smaller diversification benefits are: macro, long/short equities, distressed, and emerging markets. These numbers are, however, not as high as those within funds of funds.

[1] Brooks and Kat (2002) calculate correlation of FOF Composite to various stock indices and Lehman Gov. Bond index. With S&P500 and DJIA, the correlation is about 0.50 and with bonds slightly negative (-0.05). The effect of unsmoothing on correlation with stocks is negligible whereas the dependence with bonds turned to a positive number (0.11). Remaining HFRI indices showed generally an increased correlation with stocks and bonds.

Table 7.2: *Correlation coefficient of hedge fund strategies.*

Name	Stocks	Bonds	LS	EMN	SS	FI	CA	MA	DS	GM	EM	MF
Stocks	1.00	0.20***	0.62***	0.09	-0.66***	0.06	0.29***	0.40***	0.47***	0.41***	0.68***	-0.14*
Bonds	.	1.00	0.04	0.13*	-0.01	-0.13*	0.05	0.01	-0.06	0.12	0.04	0.25***
LS	.	.	1.00	0.36***	-0.79***	0.06	0.42***	0.43***	0.61***	0.58***	0.65***	-0.04
EMN	.	.	.	1.00	-0.10	0.07	0.09	0.22***	0.16**	0.24***	0.08	0.14*
SS	.	.	.	.	1.00	-0.06	-0.35***	-0.35***	-0.56***	-0.38***	-0.58***	0.21***
FI	.	.	.	.	.	1.00	0.11	0.02	0.19**	0.09	0.20***	-0.06
CA	.	.	.	.	.	.	1.00	0.39***	0.54***	0.36***	0.38***	-0.07
MA	.	.	.	.	.	.	.	1.00	0.52***	0.28***	0.43***	-0.11
DS	.	.	.	.	.	.	.	.	1.00	0.44***	0.60***	-0.20**
GM	.	.	.	.	.	.	.	.	.	1.00	0.60***	0.33***
EM	.	.	.	.	.	.	.	.	.	.	1.00	-0.06
MF	.	.	.	.	.	.	.	.	.	.	.	1.00

Estimated correlation between hedge fund strategies and traditional assets. Values significantly different from 0 at 10%/5%/1% level are marked by */**/***, respectively. *Stocks* = MSCI World Total Return, *Bonds* = Citigroup Global Gov. Bond (all maturities), *LS* = HFRI Equity Hedge, *EMN* = HFRI Equity Market Neutral, *SS* = HFRI Short Selling, *FI* = HFRI Fixed Income Arbitrage, *CA* = HFRI Convertible Arbitrage, *MA* = HFRI Merger Arbitrage, *DS* = HFRI Distressed Securities, *GM* = HFRI Macro, *EM* = HFRI Emerging Markets, *MF* = Stark 300 Trader. Sample window (monthly data): Jan 1990–Sep 2004.

7.2 Motivation and methodology

Correlation as a measure of dependence in the context of hedge funds has been one of the most frequently analysed topics in the literature (see e.g. Lo 2001, Kat and Lu 2002, Amin and Kat 2002). It is often argued that the greatest advantage of hedge funds is the low correlation to traditional assets. Having an additional asset with low or negative correlation permits the diversification of risk in a mean-variance framework. However, the insights gained from Chapter 5 and 6 suggest the need to examine dependence by other means than correlation. Clearly, the nonlinearities of hedge funds and the evidence of not normally distributed returns invalidates the use of correlation as a dependence measure. Numerous authors have already highlighted the asymmetry of dependence in hedge funds returns (see e.g. Fung and Hsieh 1997, Lo 2001, Agarwal and Naik 2004). An often advocated solution is to examine the correlation separately in upwards/downwards environments (see e.g. Fung and Hsieh 1997, Schneeweis and Spurgin 2000). The results usually indicate a higher correlation in turbulent financial markets than in market quiescence. This means that in periods when diversification is most needed, investor's ability to diversify is strongly reduced. However, linear measures like correlation are not applicable when returns are not normally distributed. Longin and Solnik (2001) and Kat (2003) give an illustration of errors that can be made when correlation is conditioned either on returns or volatility.[2] The implication is that one is wrongly concluding higher correlation in down markets than in up markets while by construction it is the same.

This calls for a measure of dependence that is able to address the asymmetry adequately. In other words, the dependence should be measured in such a way that the tail properties of variables are taken into account. In recent years the concept of extremal (tail) dependence has achieved prominence in financial applications. This measure is derived from multivariate extreme value theory which aims to describe the joint tails of multivariate outcomes. The literature on financial applications of multivariate extreme

[2]A general overview of errors that can be made when correlation is estimated for non-normal data is given in Embrechts, McNeil, and Straumann (2002).

value methods has been growing rapidly in recent years. Straetmans (1998) and Stărică (1999) focus on foreign exchange applications, whereas Longin and Solnik (2001), Poon, Rockinger, and Tawn (2003) and recently Heffernan (2004) explore the dependence structure in tails for equities. A first attempt to assess the tail dependence of hedge funds and traditional assets has been undertaken by Blum, Dacorogna, and Jaeger (2003). This study, however, assumes that the dependence structure is well described by elliptical distributions.[3] This assumption might be too strong as the distributions in the hedge fund world are usually asymmetric. As a consequence, in the next section the quantification of tail dependence is applied following the results in Ledford and Tawn (1996, 1997), and Coles, Heffernan, and Tawn (1999). More specifically, the dependence for extreme values is investigated by testing whether the dependence structure is asymptotically dependent or asymptotically independent. By doing so, one is able to quantify the ability to diversify in turbulent market periods, i.e. in periods when large losses occur. Concluding asymptotic dependence means a larger probability of observing large losses simultaneously.

7.3 Estimation and results

The estimation of extremal dependence follows the steps outlined in Poon, Rockinger, and Tawn (2003). It is confined to estimating the pair of dependence measures $(\chi, \bar{\chi})$ that provides the necessary information to characterise both the form and the degree of extremal dependence. The first step is to transform each pair of the original bivariate returns (W, V) to unit Fréchet margins (X, Y). This transformation removes the influence of the marginal aspects of the initial random variables while keeping the differences due to dependence aspects. More specifically, the transformation can be expressed as:

$$X = -1/\log \hat{F}_W(W) \quad \text{and} \quad Y = -1/\log \hat{F}_V(V), \tag{7.1}$$

[3]Elliptical distributions include multivariate normal as well as some fat tailed distributions, e.g. multivariate t-distribution.

where $\hat{F}_W$ and $\hat{F}_V$ are the empirical marginal distribution functions of W and V, respectively. Having transformed the variables, the next step is to construct the structure variable $Z = min(X, Y)$ and estimate the parameter $\bar{\chi}$ for each pair of assets. This reduces to the estimation of the coefficient of tail dependence η by means of the Hill estimator as described in Section 3.5. This coefficient measures the association in the tails between X and Y and $\bar{\chi}$ is a measure of asymptotic independence. By applying the delta method, the following one-sided test of $\hat{\bar{\chi}}$ is next performed.

$$H_0 : \hat{\bar{\chi}} = 1$$
$$H_1 : \hat{\bar{\chi}} < 1.$$

If the parameter $\hat{\bar{\chi}}$ is not significantly less than 1, one cannot rule out the possibility of asymptotic dependence. In this case, it is conservative to examine the tail dependence coefficient χ under the assumption of $\hat{\bar{\chi}} = 1$. The parameter χ is then an appropriate measure of the strength of dependence within the class of asymptotic dependent variables. On the other hand, if the parameter $\hat{\bar{\chi}}$ is significantly smaller than 1, then $\bar{\chi}$ measures the strength of dependence within the class of asymptotically independent variables. These, in turn, based on the estimated size of the coefficient of tail dependence η are classified into positive association, near independence, and negative association, respectively.

Tables 7.3 and 7.4 report the different values for the extremal dependence measures. Since the data set is rather short, the standard errors are large. Despite this fact, several conclusions can be drawn. Firstly, there seems to be no evidence of asymptotic dependence between hedge funds and bonds. The estimated $\bar{\chi}$ values are all significantly smaller than 1. This means that large losses in bond markets do not occur simultaneously with large losses observed in fund of funds indices. These findings are related to the reduction in VaR and ES in portfolios dominated by bonds and hedge funds. The optimal composition found in the previous chapter is a consequence of the absence of extremal dependence between hedge funds and bonds. Looking at the correlation numbers in Table 7.1 one could have suspected this behaviour. However, as the $\bar{\chi}$ is now the correct measure of dependence in the absence of asymptotic dependence, the estimated values of $\bar{\chi}$ indicate a higher dependence in the tails than that computed from the correlation. This means that the association in the tails between bonds and hedge funds is higher than predicted by correlation but not so strong as to be defined by the bivariate extreme value distribution.

Secondly, the picture appears to be less clear regarding the dependence with the stock market. The interpretation of the form of tail dependence relies on the decision rule one chooses. Thus, there is strong evidence (1%) against the null hypothesis $\bar{\chi} = 1$ for the FOF Market Defensive, moderate (5%) for the FOF Composite and the FOF Diversified and weak evidence (10%) against the null for the FOF Conservative and the FOF Strategic, respectively. Setting the significance level to 5% is, however, a well established convention used by statisticians. In this regard, one concludes that the stock market is asymptotically related to the FOF Conservative and the FOF Strategic only. Under the assumption of null hypothesis, the parameter χ measures the strength of dependence. From Table 7.4, the computed values reads 0.47 and 0.43, for the FOF Conservative and the FOF Strategic, respectively. These numbers are interpreted as a probability of jointly negative extreme returns of the stock market and these two funds of funds. The results also imply that in order to diversify the extreme risks, equity investors are better off investing in the other funds of funds which do not exhibit asymptotic dependence. In the context of the FOF Composite and the FOF Diversified, the constituents are well diversified across the strategies covered by hedge funds. It means that these types of funds of funds are exposed to a wide range of risk sources which reduces the link to the stock market. The results obtained with the FOF Market Defensive are consistent with previous findings showing that managed futures provide downside protection to equity markets (see e.g. Kat 2004). Again, this is consistent with the strong reduction of VaR and ES when FOF Market Defensive is added to portfolios containing mainly equities.

Table 7.3: *Estimates of the $\bar{\chi}$ parameters for funds of funds.*

Name	Stocks	Bonds	Comp	Cons	Diver	Defen	Strat
Stocks	1.00	0.26***	0.44**	0.57*	0.48**	0.02***	0.56*
Bonds	.	1.00	0.22***	0.32***	0.23***	0.24***	0.32***
Comp	.	.	1.00	0.80	0.66	0.37***	0.75
Cons	.	.	.	1.00	0.86	0.45**	0.57
Diver	.	.	.	.	1.00	0.37***	0.76
Defen	.	.	.	.	.	1.00	0.33***
Strat	.	.	.	.	.	.	1.00

Estimated $\bar{\chi}$ values of asset pairs. Values significantly smaller than 1 indicate no extremal dependence in large negative returns. One-sided test of $\bar{\chi} = 1$ is performed. Significant evidence against the null hypothesis at 10%/5%/1% level is found for values marked by */**/***, respectively. *Stocks* = MSCI World Total Return, *Bonds* = Citigroup Global Gov. Bond (all maturities), *Comp* = HFRI FOF Composite, *Cons* = HFRI FOF Conservative, *Diver* = HFRI FOF Diversified, *Defen* = HFRI FOF Market Defensive, *Strat* = HFRI FOF Strategic. Sample window (monthly data): Jan 1990–Sep 2004.

Table 7.4: *Estimates of the χ parameters for funds of funds.*

Name	Stocks	Bonds	Comp	Cons	Diver	Defen	Strat
Stocks	.	.	.	0.47	.	.	0.43
Bonds	.	.	.	.	.	.	.
Comp	.	.	.	0.58	0.83	.	0.72
Cons	.	.	.	.	0.50	.	0.55
Diver	.	.	.	.	.	.	0.65
Defen	.	.	.	.	.	.	.
Strat	.	.	.	.	.	.	.

The value of the parameter χ is only reported if the corresponding parameter $\bar{\chi}$ was not statistically smaller than one. In that case there is evidence for asymptotic dependence in the negative returns and the parameter χ measures the degree of this dependence. *Stocks* = MSCI World Total Return, *Bonds* = Citigroup Global Gov. Bond (all maturities), *Comp* = HFRI FOF Composite, *Cons* = HFRI FOF Conservative, *Diver* = HFRI FOF Diversified, *Defen* = HFRI FOF Market Defensive, *Strat* = HFRI FOF Strategic. Sample window (monthly data): Jan 1990–Sep 2004.

Consequently, asymptotic independence justifies the use of $\bar{\chi}$ as a measure of dependence. It ought to be noted that although the estimated numerical values of χ for the FOF asymptotically dependent with stocks (FOF Conservative = 0.47 and FOF Strategic = 0.43) are nearly similar to the $\bar{\chi}$ values observed from asymptotically independent ones (FOF Composite = 0.44 and FOF Diversified = 0.48), the magnitude of their dependence has a different interpretation. The former ones exhibit a dependence structure as defined by a bivariate extreme value distribution with a probability of joint extreme events of ca 0.45, whereas for the latter ones this probability is zero. Instead, other distributions than bivariate extreme value are better suited to describe this dependence, e.g. bivariate normal. Indeed, the computed numerical values of $\bar{\chi}$ for the asymptotically independent fund of funds are nearly identical to those obtained from the correlation.[4]

Bacmann and Gawron (2005) investigated the asymptotic dependence of stocks and fund of hedge funds using data from January 1990 to August 2003. Their results point to a similar conclusion with exception of FOF Composite which was found to be asymptotically related to stocks. As this evidence was close to be rejected, the most likely reason for this dissimilarity is the shorter data that led to larger standard errors making the null hypothesis of asymptotic dependence harder to reject. Furthermore, besides the shorter data frame, the study of Bacmann and Gawron (2005) was based on data that was not unsmoothed.[5]

For investors, the knowledge whether two time series exhibit asymptotic dependence is of great importance since concluding this relationship indicates a probability for joint extreme events and thus implying limited diversification benefits in times of crises. Hence, the estimated χ numbers have a much stronger interpretation than any numbers calculated from correlation. For instance, despite the lower estimated χ value, the presence of asymptotic dependence between stocks and FOF Strategic ($\chi = 0.43$) should

[4] One can easily prove that this might be the case by recalling that the coefficient of tail dependence for bivariate normal is $\eta = \frac{1+\rho}{2}$, and since $\bar{\chi} = 2\eta - 1$ it follows that $\bar{\chi} = \rho$, e.g. $\bar{\chi} = \rho = 0.02$ for FOF Market Defensive and $\bar{\chi} = \rho = 0.48$ for FOF Diversified.

[5] As documented in Chapter 5, unsmoothing the returns led to higher standard deviations among hedge funds. This, together with a larger data set make us believe that the results in this study are more robust.

be more worrying than the estimated correlation of stocks with FOF Diversified ($\rho = 0.48$). Thus, correlation is just a measure of linear dependence for elliptical distributions which does not assume joint extreme events. As noted by Embrechts, McNeil, and Straumann (2002), for $\rho < 1$, regardless of how high a correlation we choose, if we go far enough into the tail, extreme events appear to occur independently in each margin.[6]

Finally, the dependence within hedge funds suggests a strong asymptotic dependence, with FOF Market Defensive as an exception again. In order to get more insights about the constituents that are responsible for this relationship, the pair $(\chi, \bar{\chi})$ is also computed for individual hedge fund strategies. There is, however, an additional interest in performing this calculation. Many countries put restrictions on individuals willing to invest in hedge funds. Usually the only allowed channel is through a fund of fund provider.[7] In response to the growing demand for hedge fund products, many financial institutions have introduced or plan to launch their own fund of fund products. Hence, to obtain a picture of the diversification potentials needed to construct such a fund it is worthwhile to study the tail dependence characteristics that single hedge fund strategies offer.

The estimated values of $\bar{\chi}$ and χ for single strategies are to be found in Table 7.5 and 7.6, respectively. Consistent with the earlier observations, none of the individual hedge fund strategies exhibit asymptotic dependence with bonds. Apart from the short selling strategy, the magnitude of the estimated $\bar{\chi}$ parameters for bonds indicate positive association in the tails that is higher than the correlation coefficients might suggest. This means that the diversification benefits between bonds and hedge funds are usually overestimated when correlation is utilised to measure the dependence. Regarding the tail dependence of hedge fund strategies and stocks, Table 7.5 shows a more heterogenous pattern. The null hypothesis of asymptotic dependence cannot be rejected for long/short equities, merger arbitrage, distressed, and emerging markets. It appears that this dependence is limited to the directional equity based strategies as well as the event driven strategies. The

[6] See also Johnson and Kotz (1972).

[7] See for instance the discussion in McDonald (2003) about reasons for retail investments and the regulatory differences in various countries.

explanation for asymptotic dependence of long/short and emerging market managers is most likely the net long bias to the stock markets. In the case of the event driven strategies, it is explained by the fact that in times of deteriorating market conditions, the debt positions of distressed managers tend to behave like equity which leads to a stronger stock market exposure. For the merger arbitrage managers these periods are characterised by increasing number of broken deals. As pointed out by Mitchel and Pulvino (2001) the returns of this strategy are similar to writing naked put options on the stock market. In combination with a flight to quality scenario, event driven managers are left with fewer possibilities to respond to extreme stock market events. The remaining strategies for which the asymptotic dependence has been rejected show positive association in the tails with exception of managed futures and short sellers that exhibit a negative association.

With respect to funds of funds, stocks have been found to be asymptotically dependent with the FOF Conservative and the FOF Strategic. For the latter, it is now easy to identify the source of this dependence since both long/short equities and emerging markets are asymptotically dependent. This link is however not that obvious for the FOF Conservative as none of its constituents offers evidence of asymptotic dependence with stocks. It appears that fund of fund providers in the FOF Conservative index do not fully succeed in selecting the right managers or providing the right composition of managers in their construction of diversified products.

Table 7.5: *Estimates of the $\bar{\chi}$ parameters for hedge fund strategies.*

Name	Stocks	Bonds	LS	EMN	SS	FI	CA	MA	DS	GM	EM	MF
Stocks	1.00	0.26***	0.78	0.34***	-0.41***	0.40**	0.48**	0.96	0.73	0.32***	0.78	-0.08***
Bonds	.	1.00	0.54**	0.43**	-0.17***	0.09***	0.28***	0.24***	0.37***	0.22***	0.22***	0.42**
LS	.	.	1.00	0.59*	-0.52***	0.47**	0.77	0.71	0.68	0.56*	0.72	-0.07***
EMN	.	.	.	1.00	0.28***	0.11***	0.20***	0.33***	0.30***	0.20***	0.33***	0.17***
SS	.	.	.	.	1.00	0.16***	-0.31***	-0.13***	-0.34***	-0.08***	-0.19***	0.12***
FI	.	.	.	.	.	1.00	0.05***	0.31***	0.23***	0.19***	0.20***	0.01***
CA	.	.	.	.	.	.	1.00	0.39**	0.54*	0.19***	0.27***	0.03***
MA	.	.	.	.	.	.	.	1.00	0.80	0.16***	0.54*	0.05***
DS	.	.	.	.	.	.	.	.	1.00	0.57*	0.51**	0.09***
GM	.	.	.	.	.	.	.	.	.	1.00	0.50**	0.24***
EM	.	.	.	.	.	.	.	.	.	.	1.00	0.13***
MF	.	.	.	.	.	.	.	.	.	.	.	1.00

Estimated $\bar{\chi}$ values of asset pairs. Values significantly smaller than 1 indicate no extremal dependence in large negative returns. One-sided test of $\bar{\chi} = 1$ is performed. Significant evidence against the null hypothesis at 10%/5%/1% level is found for values labelled by */**/***, respectively. *Stocks* = MSCI World Total Return, *Bonds* = Citigroup Global Gov. Bond (all maturities), *LS* = HFRI Equity Hedge, *EMN* = HFRI Equity Market Neutral, *SS* = HFRI Short Selling, *FI* = HFRI Fixed Income Arbitrage, *CA* = HFRI Convertible Arbitrage, *MA* = HFRI Merger Arbitrage, *DS* = HFRI Distressed Securities, *GM* = HFRI Macro, *EM* = HFRI Emerging Markets, *MF* = Stark 300 Trader. Sample window (monthly data): Jan 1990–Sep 2004.

Table 7.6: *Estimates of the χ parameters for hedge fund strategies.*

Name	St	Bn	LS	EMN	SS	FI	CA	MA	DS	GM	EM	MF
Stocks	.	.	0.54	.	.	.	.	0.38	0.47	.	0.48	.
Bonds	.	.	.	.	.	.	.	.	.	.	.	.
LS	.	.	.	0.34	.	.	0.39	0.43	0.54	0.44	0.54	.
EMN	.	.	.	.	.	.	.	.	.	.	.	.
SS	.	.	.	.	.	.	.	.	.	.	.	.
FI	.	.	.	.	.	.	.	.	.	.	.	.
CA	.	.	.	.	.	.	.	.	0.46	.	.	.
MA	.	.	.	.	.	.	.	.	0.39	.	0.37	.
DS	.	.	.	.	.	.	.	.	.	0.44	.	.
GM	.	.	.	.	.	.	.	.	.	.	.	.
EM	.	.	.	.	.	.	.	.	.	.	.	.
MF	.	.	.	.	.	.	.	.	.	.	.	.

The value of the parameter χ is only reported if the corresponding parameter $\bar{\chi}$ was not statistically smaller than one. In that case there is evidence for asymptotic dependence in the negative returns and the parameter χ measures the degree of this dependence. *Stocks (St)* = MSCI World Total Return, *Bonds (Bn)* = Citigroup Global Gov. Bond (all maturities), *LS* = HFRI Equity Hedge, *EMN* = HFRI Equity Market Neutral, *SS* = HFRI Short Selling, *FI* = HFRI Fixed Income Arbitrage, *CA* = HFRI Convertible Arbitrage, *MA* = HFRI Merger Arbitrage, *DS* = HFRI Distressed Securities, *GM* = HFRI Macro, *EM* = HFRI Emerging Markets, *MF* = Stark 300 Trader. Sample window (monthly data): Jan 1990–Sep 2004.

By far the most asymptotically dependent strategy is long/short equities (7 times), followed by distressed (5) and merger arbitrage (4). This means that observing large jointly extreme losses with these strategies is more likely. A somewhat lower tendency for asymptotic dependence in the tails is observed for emerging markets (3), macro (2), and convertible arbitrage (2). Thus, besides equity market neutral (1), fund of funds providers should consider managed futures, short sellers and fixed income strategies in their attempts to construct diversified products as these strategies do not exhibit any asymptotic dependence either with traditional assets or with the other hedge fund strategies. Due to its nature, the short seller strategy is usually negatively associated with the majority of hedge funds. The managed futures strategy is an especially good diversifier when blended with relative value and event driven strategies. The estimated $\bar{\chi}$ values for these combinations are nearly independent. Additionally, managed futures are even negatively associated with stocks and long/short strategies.

In closing this chapter one may conclude that despite the less attractive fat tail properties of some hedge funds, the probability of observing large negative values together with the traditional assets is rather limited. There is however a significant dependence in the tails but not to such a degree that extreme negative returns occur together. This means that hedge fund strategies as well as the fund of fund indices are generally able to provide tail diversification with traditional assets. This result is somewhat in contrast to the Fung and Hsieh (1997) study in which the authors recognise some downside protection from blending hedge funds in traditional portfolios but also that the tail events in asset markets are not diversifiable. This contrasting result could be explained by the difference in methodology and the strategies investigated by Fung and Hsieh (1997), as well as the time period considered.[8]

In this analysis, the tail diversification gains are especially apparent with bonds. Neither funds of funds nor individual hedge fund strategies exhibit asymptotic dependence with bonds. Stocks and hedge funds seem to be asymptotically dependent in the case of equity based strategies only. Apart from the long/short strategy and the event driven strategies, the majority of hedge funds seem not to be asymptotically dependent with other hedge funds. The maximum gains are obtained when managed futures, short sellers, fixed income arbitrage, and equity market neutral are considered. These findings have an additional implication for investors. Given the low volatility of hedge funds, it is often advised to replace bonds in portfolios with hedge funds (see e.g. Lamm 1999). However, as bonds are asymptotically independent of stocks and to all hedge funds, investors are better off replacing stocks by equity based hedge funds that additionally offer lower risks and higher mean return than stocks. Thus, an ideal portfolio blended with bonds aiming to provide the largest diversification benefits could consist of a mixture of relative value strategies together with managed futures, global macro, and merger arbitrage.

[8]The authors applied correlation in their analysis on strategies that according to the definition in this thesis are most similar to global macro, relative value, event driven and managed futures strategies. The investigated time period is January 1991 to December 1995.

Chapter 8

Conclusions

The vast bulk of research emphasised the advantages of hedge funds as they improve the risk return profile of investors' portfolio. These advantages have usually been examined under implicit or explicit assumption of normally distributed returns. However, recent evidence has questioned the normality behaviour of hedge funds. Due to the employment of dynamic trading strategies in combination with the possibility to sell securities short and to buy on leverage, hedge funds exhibit an asymmetric return distribution with an option-like payoff. Hence, the usefulness of standard risk measurement techniques such as volatility and correlation is limited in the context of hedge funds.

In this thesis, the use of Extreme Value Theory is advocated. This methodology focuses on the tails only, regardless of the underlying distribution or returns. The results have shown that even when taking into account the distributional properties of hedge funds such as fat tails and autocorrelation, the stand alone investment in hedge funds offers a lower risk of large losses than traditional investments. Moreover, when blended with traditional assets, hedge funds are generally able to provide a reduction in downside risk and thus diversification benefits to traditional portfolios.

Risk as measured by Value-at-Risk and Expected Shortfall at 95% and 99% level is smaller for hedge funds than for stocks and in many cases also smaller than bonds. The main reason for this is that large losses in hedge fund indices are rather small in absolute values when compared to traditional assets. These low risk numbers are mainly a result of active risk management by implementing dynamic long/short trading strategies that reduce volatility. It also means that the low volatility of hedge funds outweighs the fat tail effect.

When adding hedge funds to traditional portfolios a significant reduction in downside risk has been observed. In most cases, this is achieved regardless of the initial composition of the traditional portfolios. The highest reduction is obtained for an inclusion of FOF Conservative and FOF Market Defensive. The addition of the latter one produces an optimal allocation in all traditional portfolios. This is largely due to the different risk profile that this index provides. Stock dominated portfolios benefit most from hedge fund allocation whereas an optimal composition is found for bond dominated portfolios. Moreover, since hedge funds have usually higher mean returns, the improvement of downside risk is not achieved at a cost of lower expected returns.

Additionally, hedge funds in general appear to provide tail diversification benefits with traditional assets as measured by extremal dependence. The gains are substantial, especially with bonds. In no cases, neither funds of funds nor single strategies exhibit asymptotic dependence with bond markets. This means that observing large extreme returns simultaneously in bond markets and hedge funds is rather improbable. However, hedge funds appear to have a more heterogenic relationship with stocks. Especially the equity based strategies show an asymptotic dependence in the tails indicating that the potential for joint extreme losses is high. For investors, these findings imply that the greatest benefits of adding hedge funds in traditional portfolios are achieved by replacing stocks by equity based hedge fund strategies. Among hedge funds, the largest diversification benefits are found for the FOF Market Defensive and its constituents; managed futures and short sellers. None of these indices show evidence of extremal dependence to any other hedge fund strategy or traditional assets.

Further research may extend the tail dependence estimations by applying multivariate distributions such as the copula methods. Another application of tail dependence is in the context of style analysis. Traditional style analysis relies on linear relationship between returns of hedge funds and returns of factors that aim to track the exposure of hedge funds. Other non linear or time varying techniques may bring more insights into the risk characteristics of hedge funds. Examples are the Kalman/Particle filtering methods or quantile regressions. Consequently, this knowledge would also add value to the growing efforts on hedge funds' replication. Additionally, portfolio optimisations with hedge funds could be improved by replacing the variance with Expected Shortfall derived from Extreme Value Theory. The growing markets of insurance linked securities and credit derivatives, both having fat tail properties, are another areas where Extreme Value Theory may be of a useful financial application.

Appendix A

Descriptive graphs

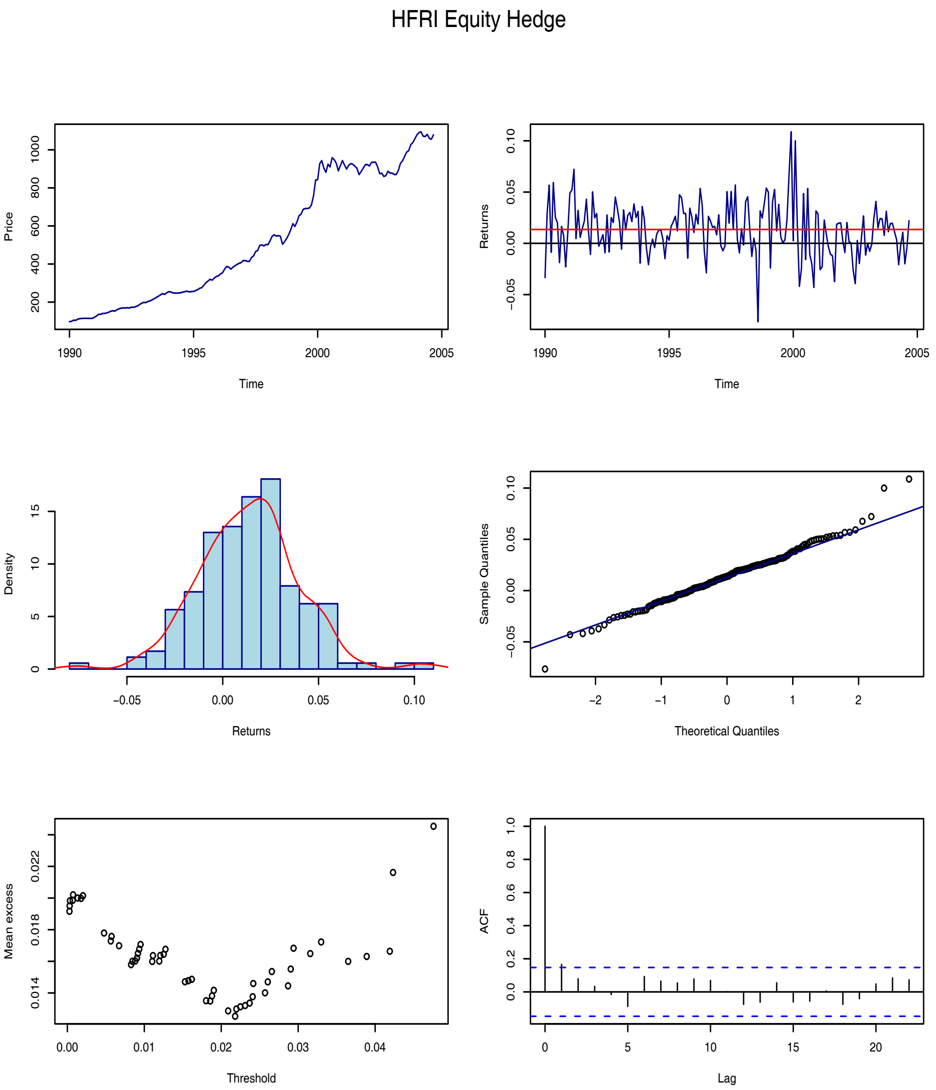

Figure A.1: *HFRI Equity Hedge index.*

Top: Price and return index. Geometric return indicated in red. Middle: Histogram and QQ-plot. Bottom: Mean excess plot and autocorrelation function. Sample window (monthly data): Jan 1990-Sep 2004.

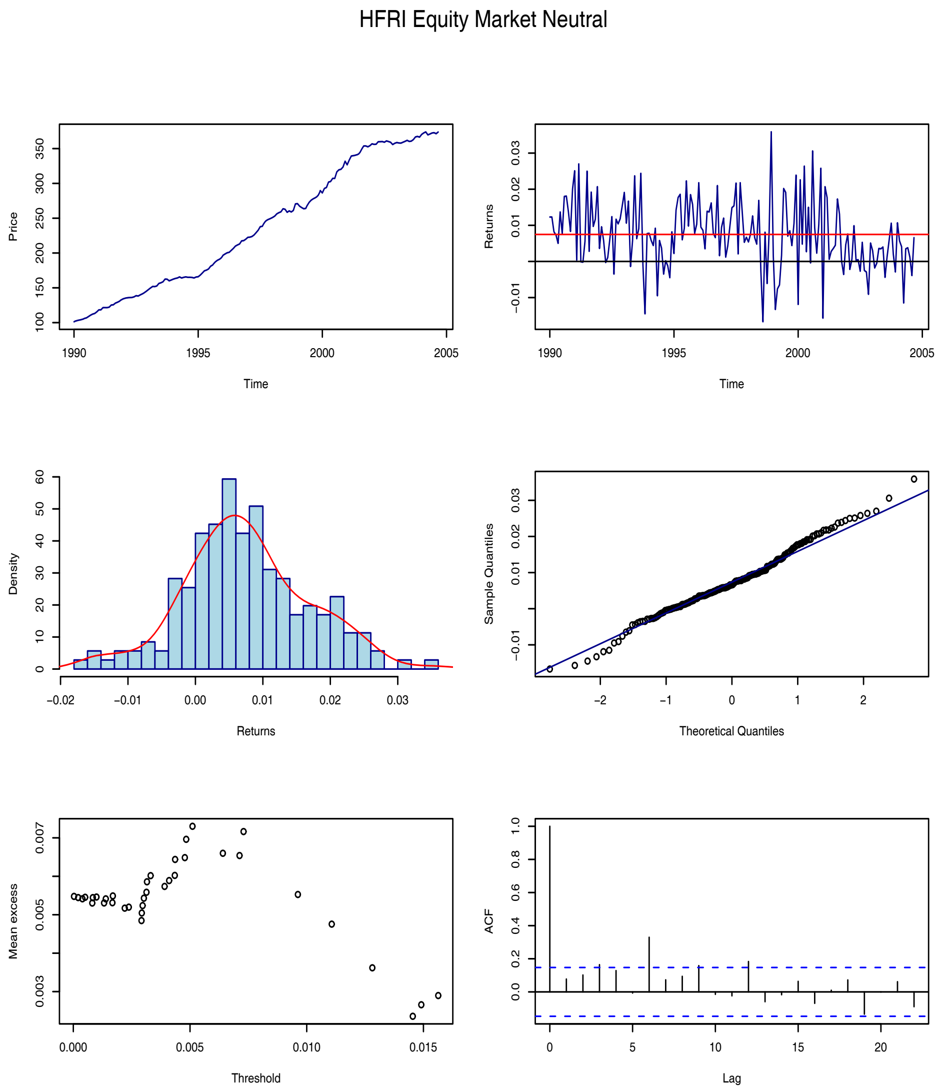

Figure A.2: *HFRI Equity Market Neutral index.*

Top: Price and return index. Geometric return indicated in red. Middle: Histogram and QQ-plot. Bottom: Mean excess plot and autocorrelation function. Sample window (monthly data): Jan 1990-Sep 2004.

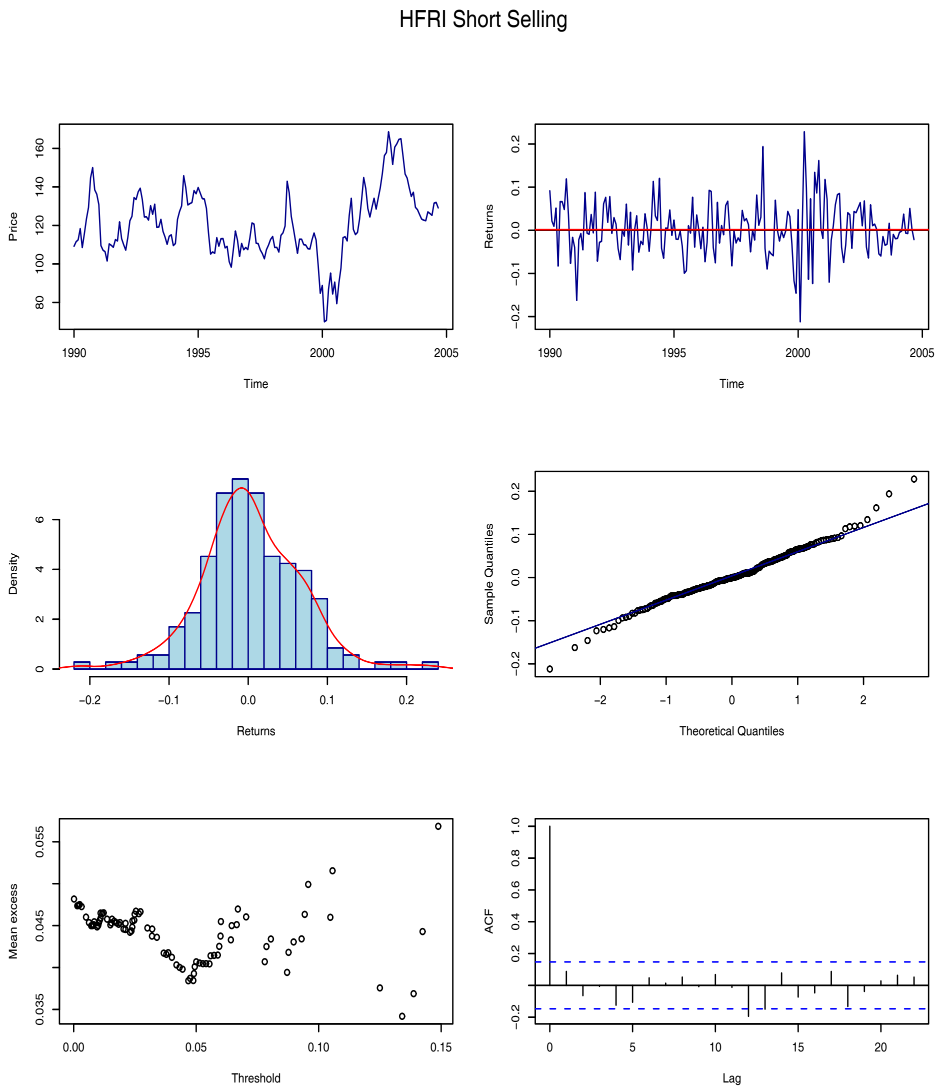

Figure A.3: *HFRI Short Selling index.*

Top: Price and return index. Geometric return indicated in red. Middle: Histogram and QQ-plot. Bottom: Mean excess plot and autocorrelation function. Sample window (monthly data): Jan 1990-Sep 2004.

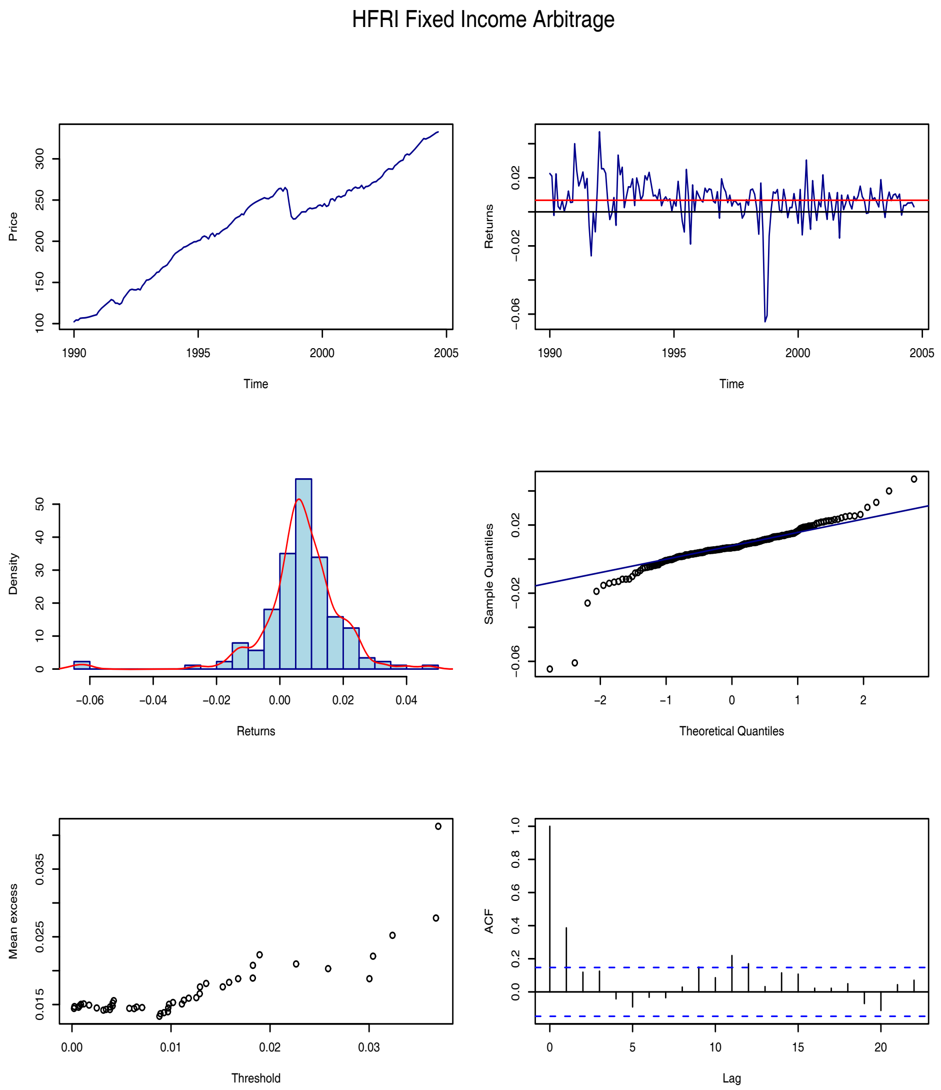

Figure A.4: *HFRI Fixed Income Arbitrage index.*

Top: Price and return index. Geometric return indicated in red. Middle: Histogram and QQ-plot. Bottom: Mean excess plot and autocorrelation function. Sample window (monthly data): Jan 1990-Sep 2004.

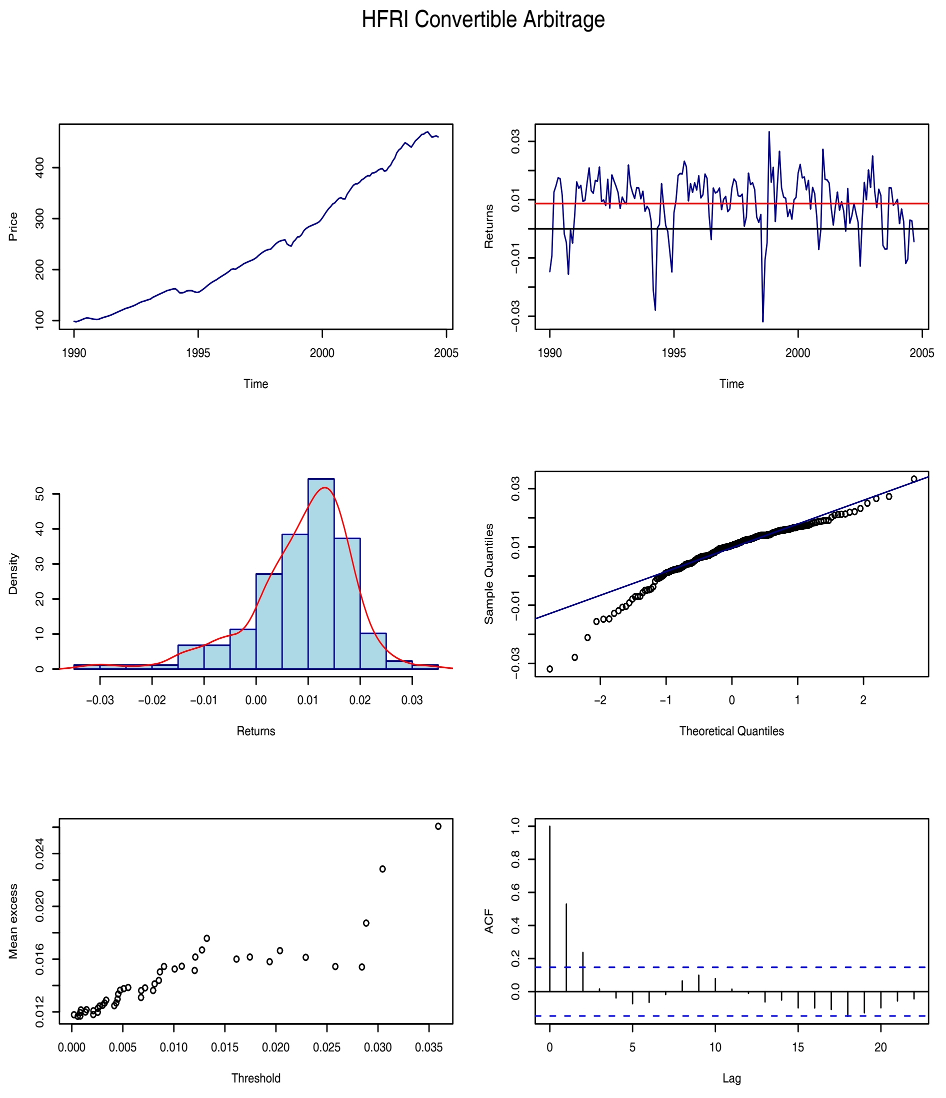

Figure A.5: *HFRI Convertible Arbitrage index.*

Top: Price and return index. Geometric return indicated in red. Middle: Histogram and QQ-plot. Bottom: Mean excess plot and autocorrelation function. Sample window (monthly data): Jan 1990-Sep 2004.

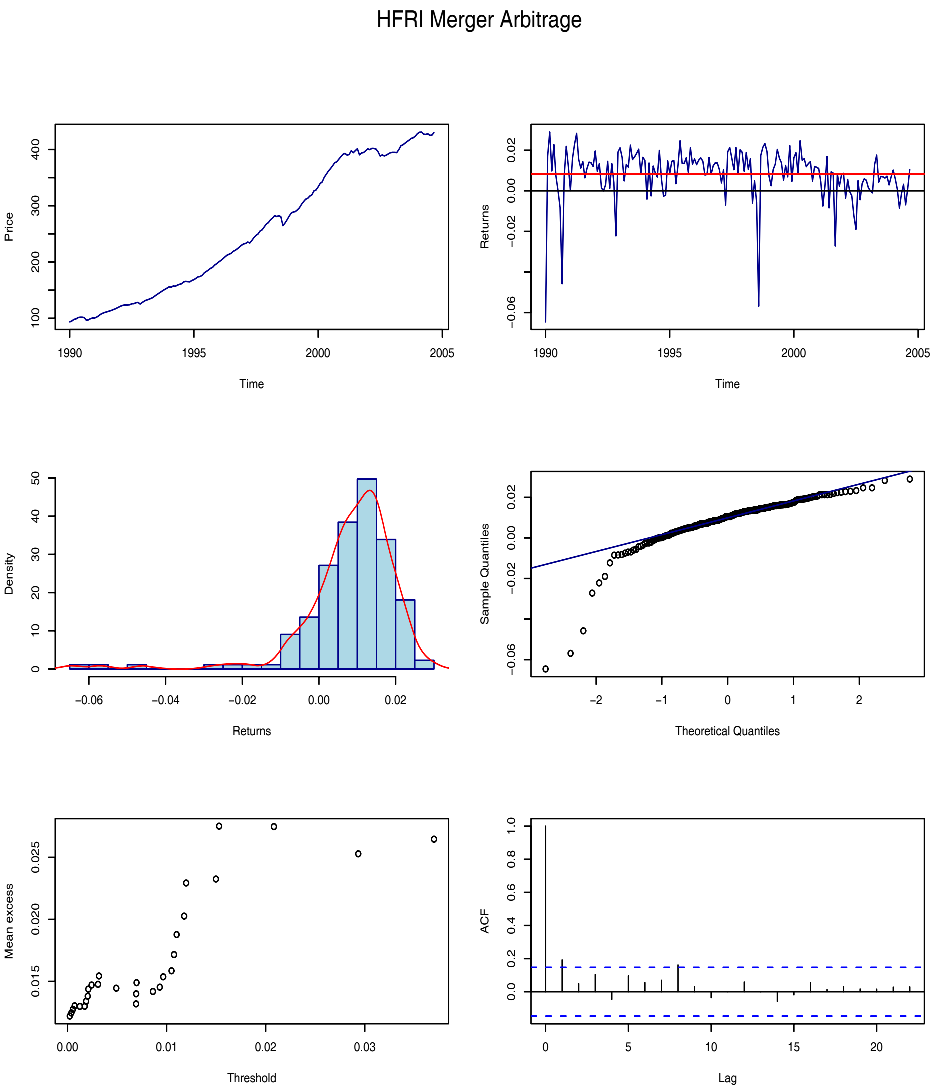

Figure A.6: *HFRI Merger Arbitrage index.*

Top: Price and return index. Geometric return indicated in red. Middle: Histogram and QQ-plot. Bottom: Mean excess plot and autocorrelation function. Sample window (monthly data): Jan 1990-Sep 2004.

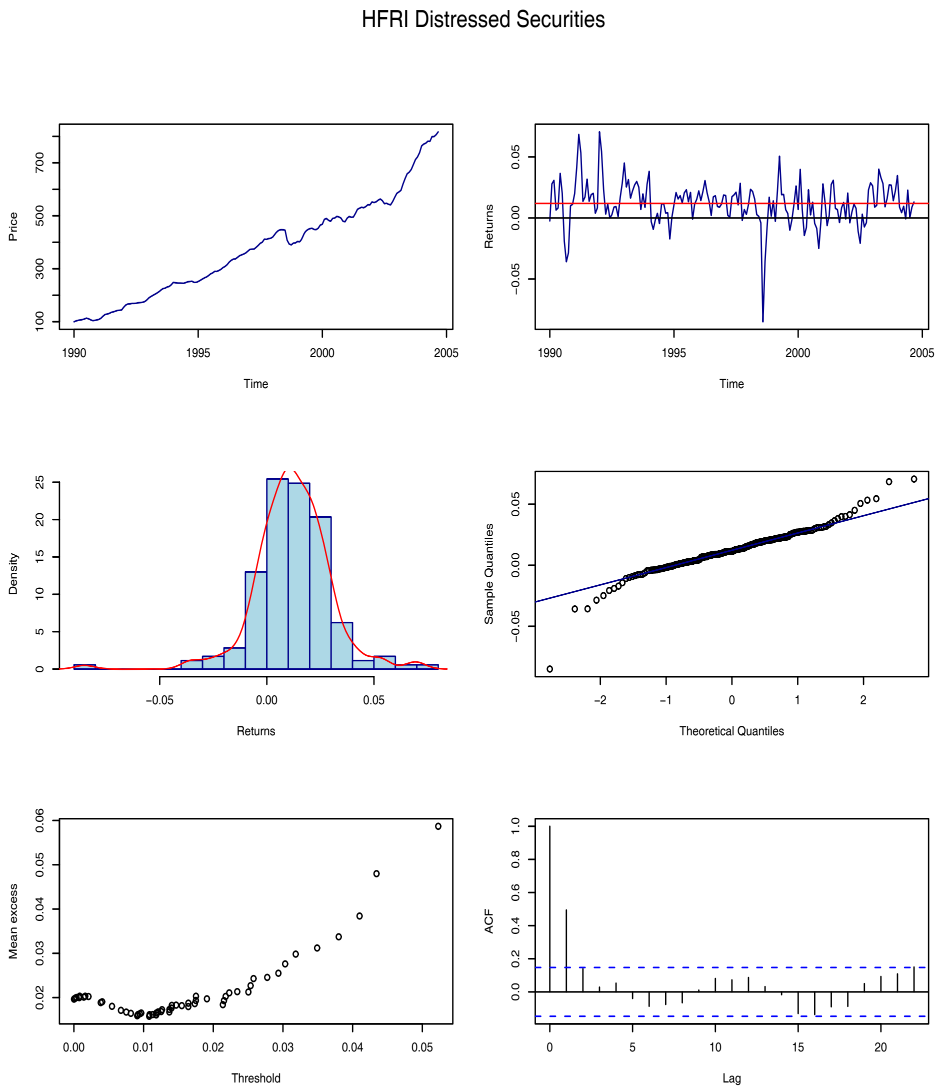

Figure A.7: *HFRI Distressed Securities index.*

Top: Price and return index. Geometric return indicated in red. Middle: Histogram and QQ-plot. Bottom: Mean excess plot and autocorrelation function. Sample window (monthly data): Jan 1990-Sep 2004.

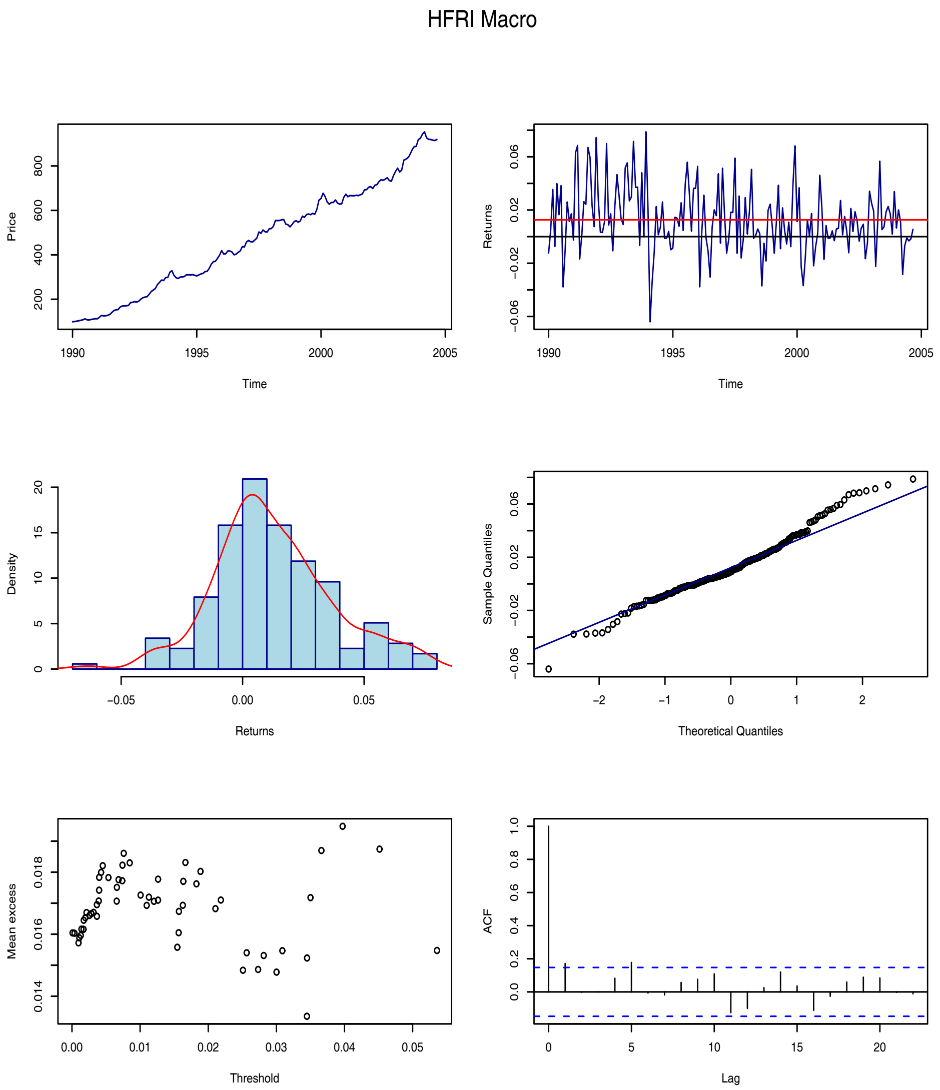

Figure A.8: *HFRI Macro index.*

Top: Price and return index. Geometric return indicated in red. Middle: Histogram and QQ-plot. Bottom: Mean excess plot and autocorrelation function. Sample window (monthly data): Jan 1990-Sep 2004.

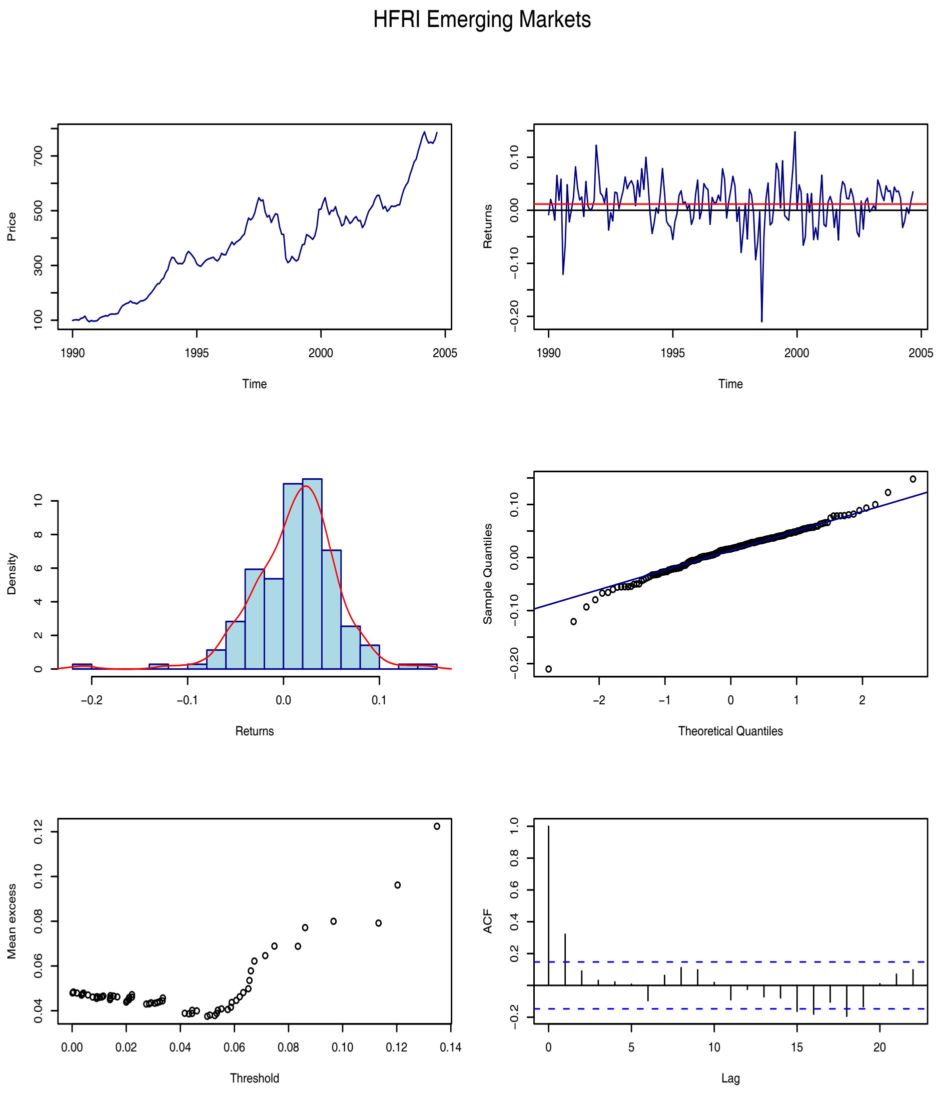

Figure A.9: *HFRI Emerging Markets index.*

Top: Price and return index. Geometric return indicated in red. Middle: Histogram and QQ-plot. Bottom: Mean excess plot and autocorrelation function. Sample window (monthly data): Jan 1990-Sep 2004.

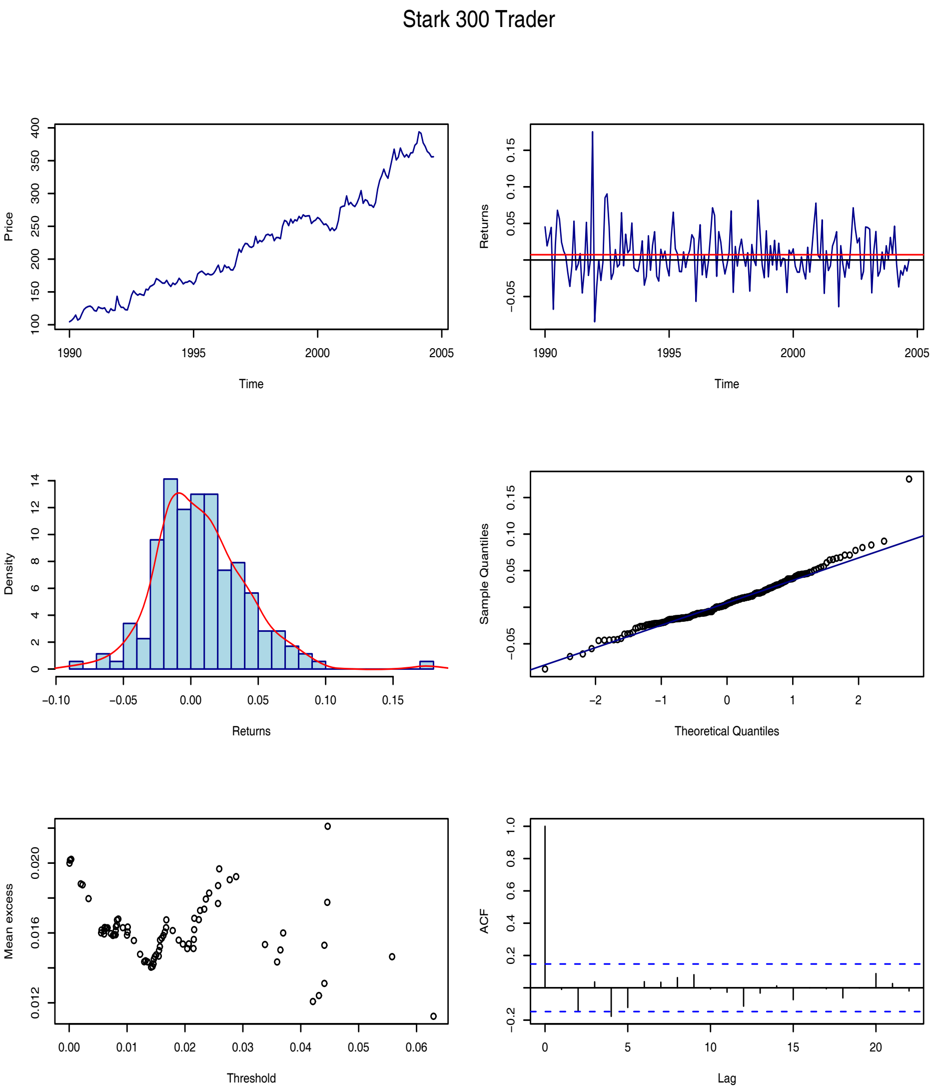

Figure A.10: *Stark 300 Trader index.*

Top: Price and return index. Geometric return indicated in red. Middle: Histogram and QQ-plot. Bottom: Mean excess plot and autocorrelation function. Sample window (monthly data): Jan 1990-Sep 2004.

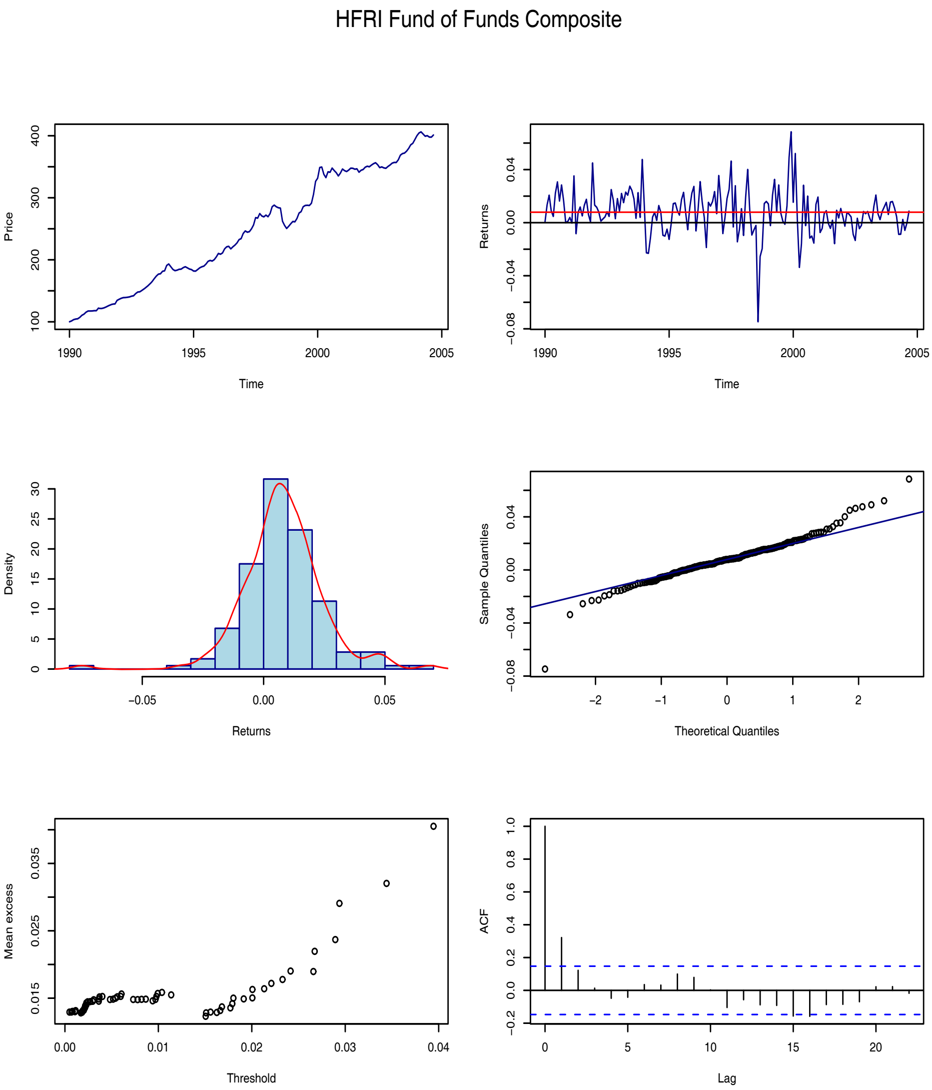

Figure A.11: *HFRI Fund of Funds Composite index.*

Top: Price and return index. Geometric return indicated in red. Middle: Histogram and QQ-plot. Bottom: Mean excess plot and autocorrelation function. Sample window (monthly data): Jan 1990-Sep 2004.

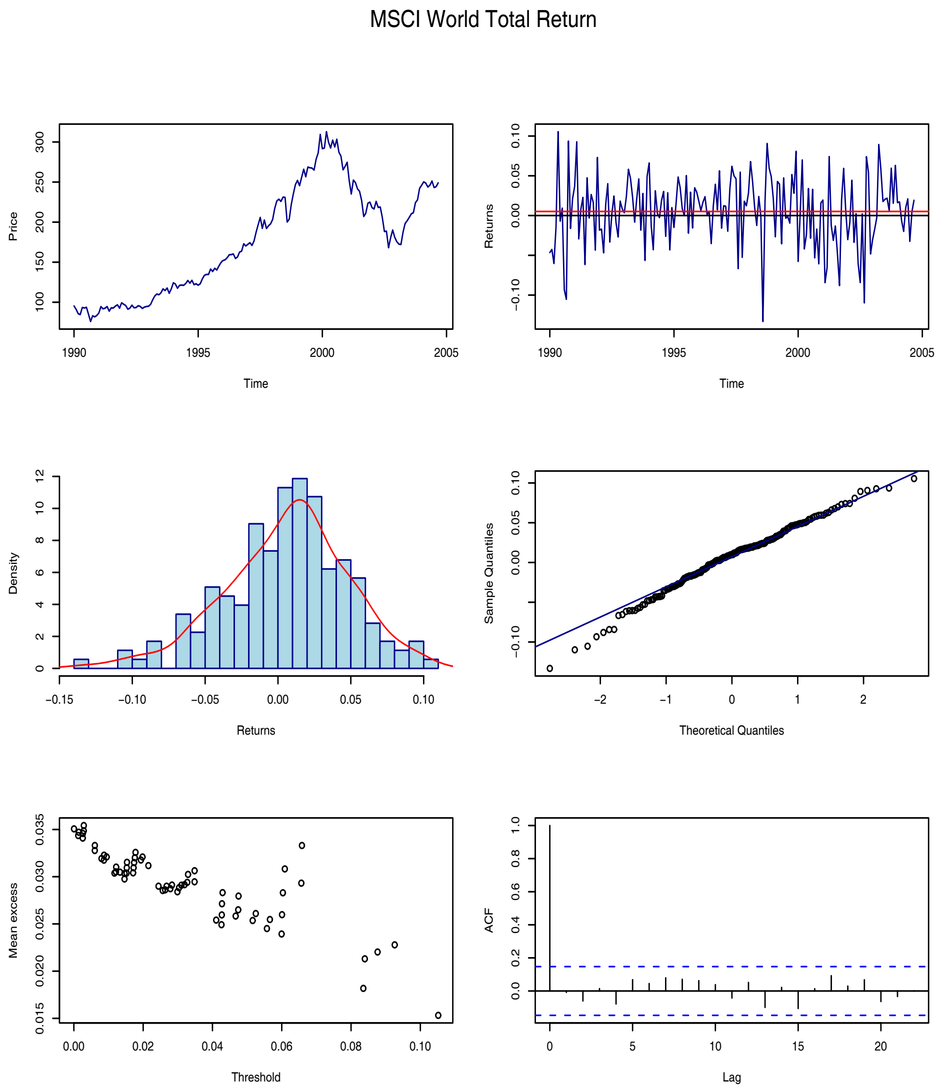

Figure A.12: *MSCI World Total Return index.*

Top: Price and return index. Geometric return indicated in red. Middle: Histogram and QQ-plot. Bottom: Mean excess plot and autocorrelation function. Sample window (monthly data): Jan 1990-Sep 2004.

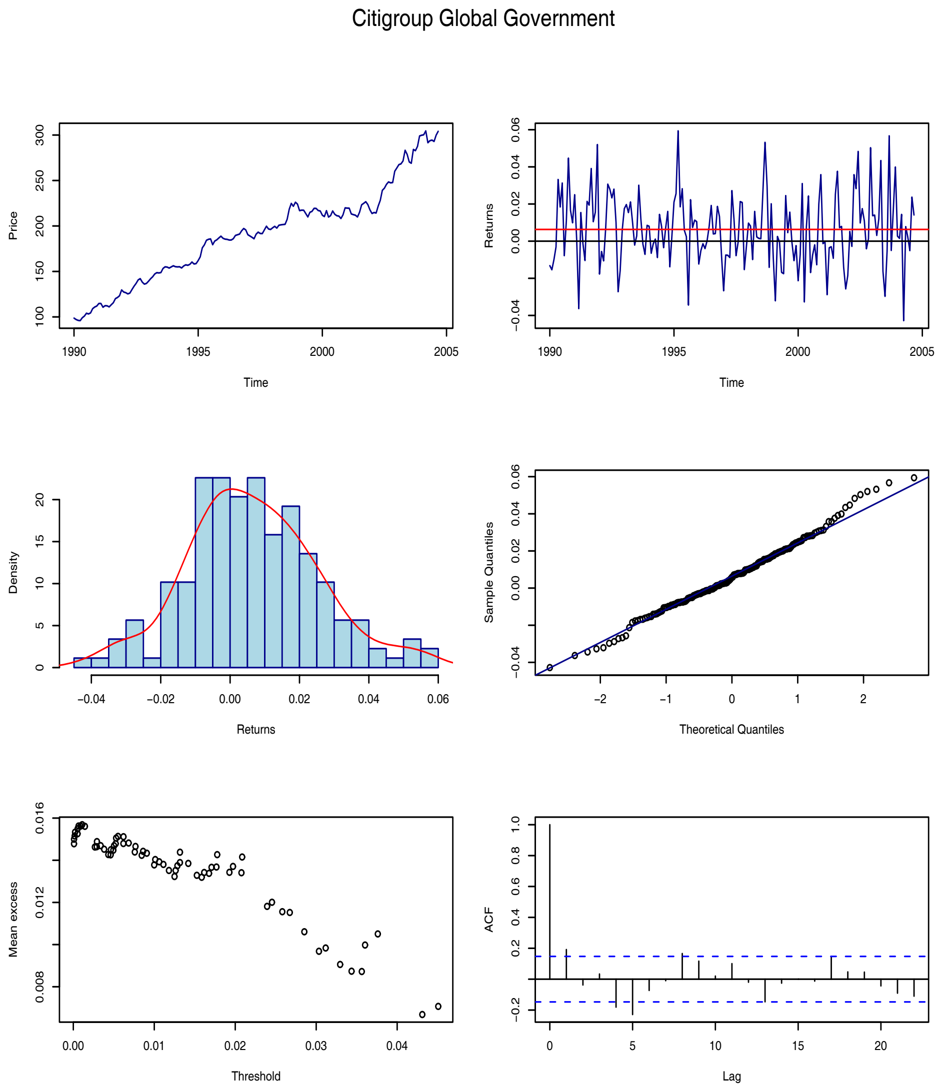

Figure A.13: *Citigroup Global Government index (all maturities).*

Top: Price and return index. Geometric return indicated in red. Middle: Histogram and QQ-plot. Bottom: Mean excess plot and autocorrelation function. Sample window (monthly data): Jan 1990-Sep 2004.

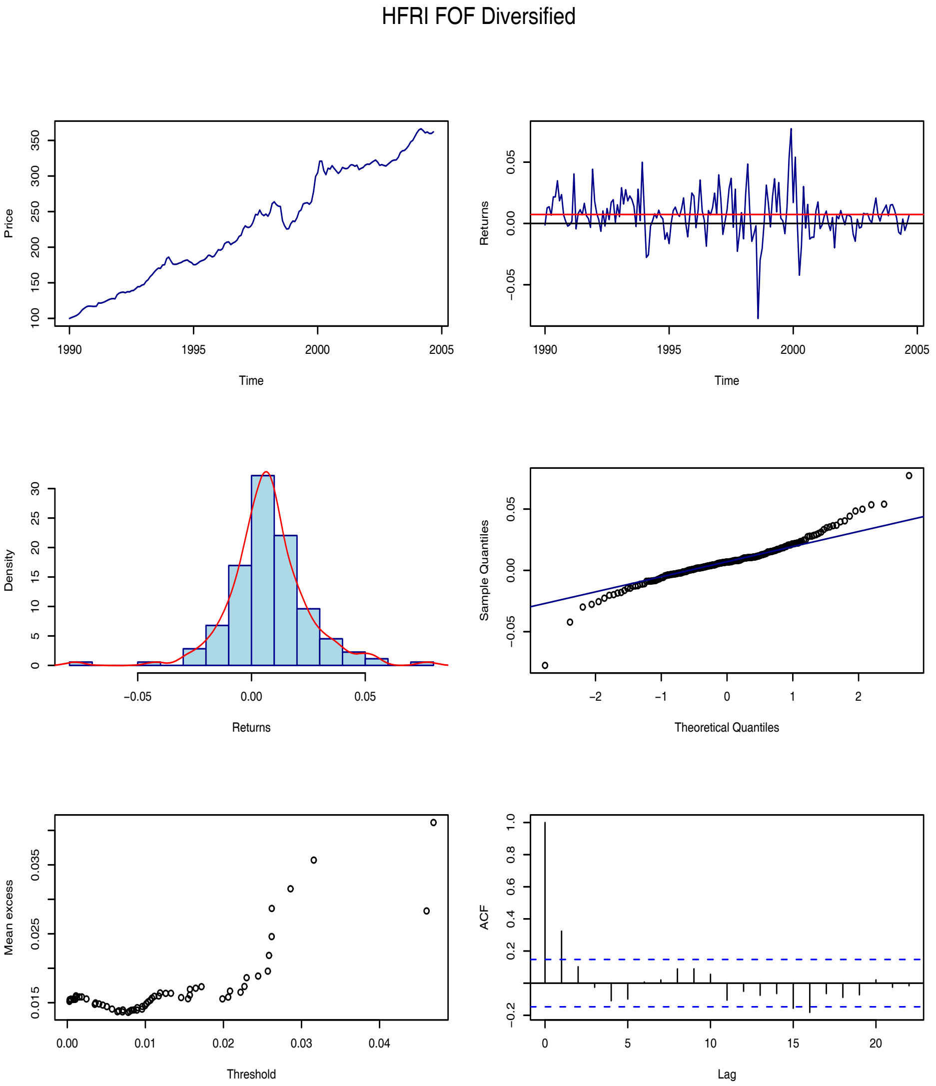

Figure A.14: *HFRI FOF Diversified index.*

Top: Price and return index. Geometric return indicated in red. Middle: Histogram and QQ-plot. Bottom: Mean excess plot and autocorrelation function. Sample window (monthly data): Jan 1990-Sep 2004.

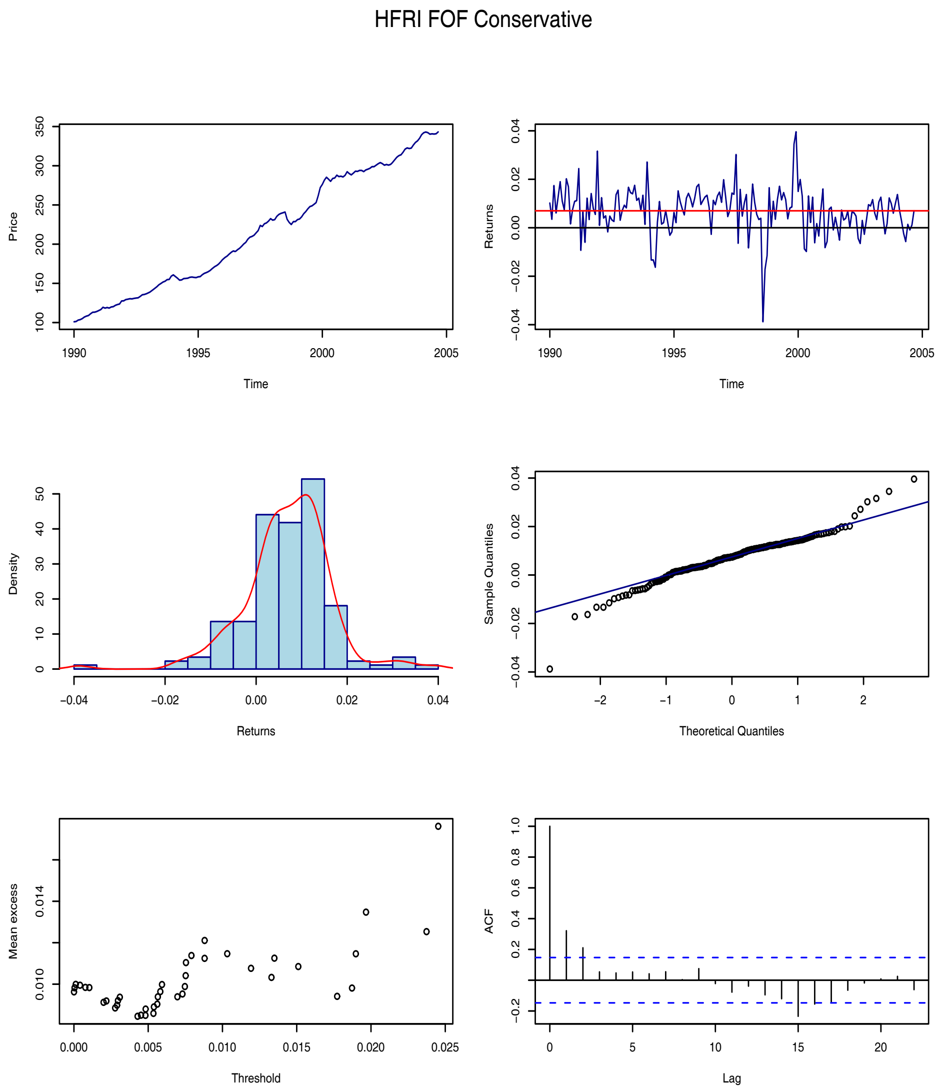

Figure A.15: *HFRI FOF Conservative index.*

Top: Price and return index. Geometric return indicated in red. Middle: Histogram and QQ-plot. Bottom: Mean excess plot and autocorrelation function. Sample window (monthly data): Jan 1990-Sep 2004.

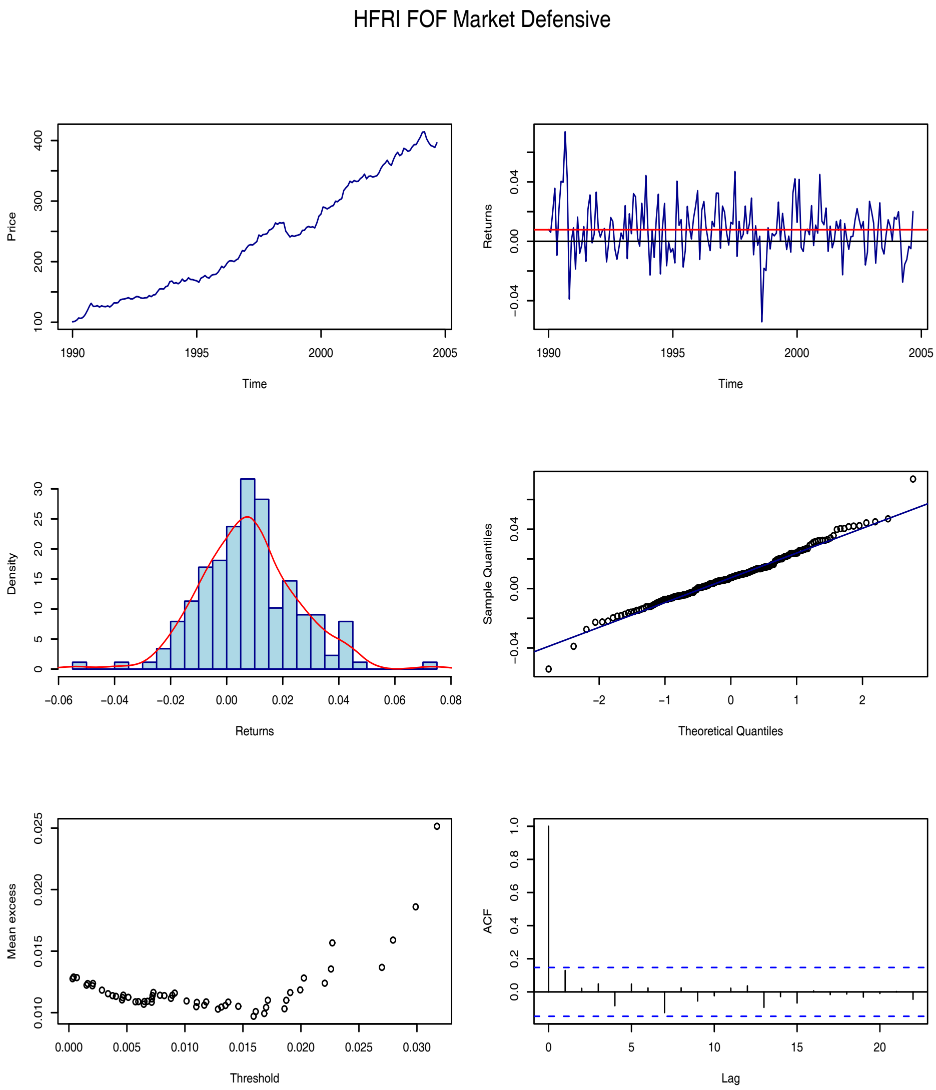

Figure A.16: *HFRI FOF Market Defensive index.*

Top: Price and return index. Geometric return indicated in red. Middle: Histogram and QQ-plot. Bottom: Mean excess plot and autocorrelation function. Sample window (monthly data): Jan 1990-Sep 2004.

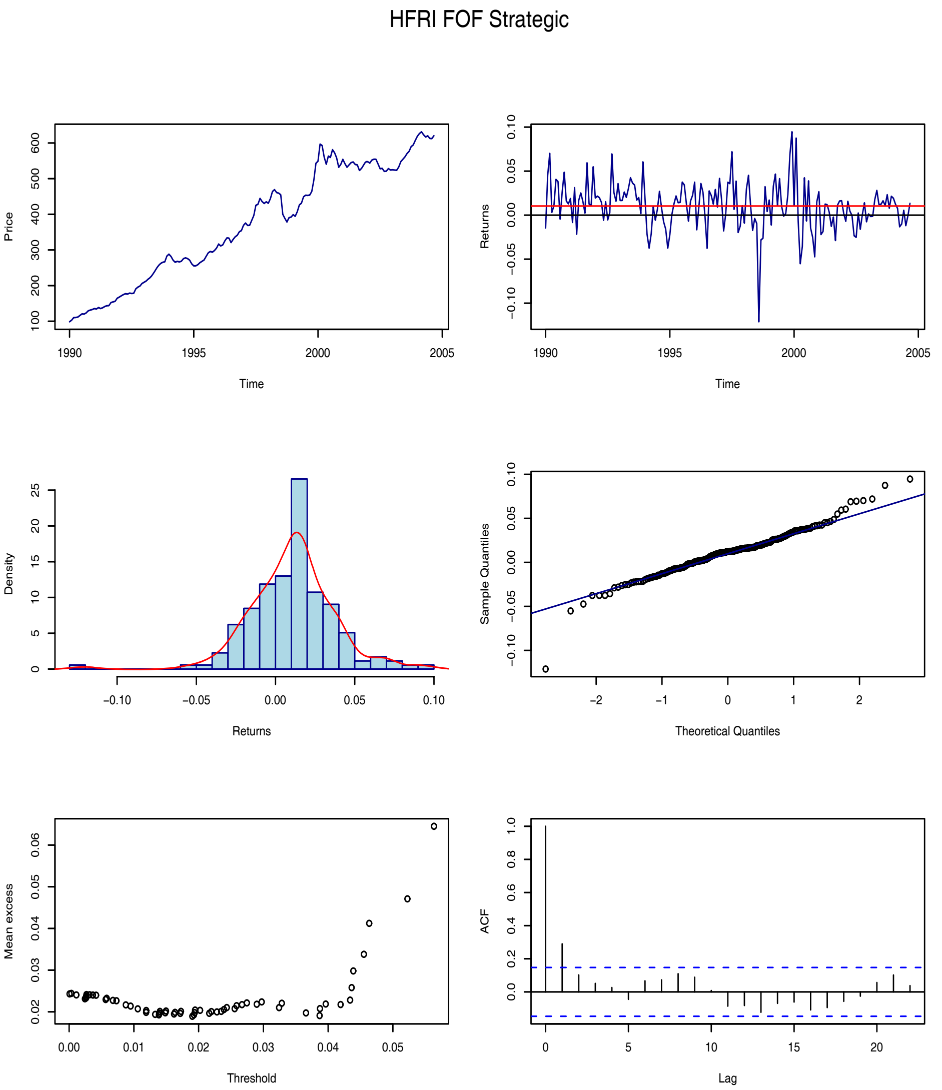

Figure A.17: *HFRI FOF Strategic index.*

Top: Price and return index. Geometric return indicated in red. Middle: Histogram and QQ-plot. Bottom: Mean excess plot and autocorrelation function. Sample window (monthly data): Jan 1990-Sep 2004.

Appendix B

Descriptive statistics of extended data

Table B.1: *Descriptive statistics of raw data extended to Dec 2006.*

Index	Mean	Std.Dev	Skew	Kurt	Min	Max	ACF1	S-W test
LS	16.03%	8.64%	0.19	1.49	-7.65%	10.88%	0.16	0.984**
EMN	8.73%	3.05%	0.21	0.51	-1.67%	3.59%	0.07	0.987*
SS	3.44%	20.33%	0.16	1.90	-21.21%	22.84%	0.09	0.976***
FI	8.01%	4.08%	-1.76	11.58	-6.45%	4.70%	0.39	0.843***
CA	9.71%	3.47%	-1.12	2.15	-3.19%	3.33%	0.56	0.932***
MA	10.09%	4.21%	-2.52	11.23	-6.46%	3.12%	0.21	0.815***
DS	14.38%	5.86%	-0.65	6.03	-8.50%	7.06%	0.49	0.930***
GM	14.57%	8.09%	0.39	0.71	-6.40%	7.88%	0.17	0.975***
EMG	16.15%	14.33%	-0.86	4.28	-21.02%	14.80%	0.31	0.950***
MF	8.92%	11.05%	0.84	3.36	-8.45%	17.53%	0.00	0.959***
Stocks	8.71%	13.99%	-0.49	0.63	-13.32%	10.55%	-0.01	0.984**
Bonds	7.18%	6.47%	0.25	0.15	-4.28%	5.94%	0.19	0.993
Comp	9.65%	5.49%	-0.27	4.20	-7.47%	6.85%	0.31	0.953***
Cons	8.34%	3.20%	-0.47	3.39	-3.88%	3.96%	0.31	0.955***
Diver	9.07%	5.86%	-0.12	4.28	-7.75%	7.73%	0.31	0.948***
Defen	9.39%	5.84%	0.19	1.28	-5.42%	7.38%	0.13	0.985**
Strat	12.76%	8.77%	-0.38	3.79	-12.11%	9.47%	0.28	0.958***

Mean and standard deviation annualised. *Kurt* = excess kurtosis, *Skew* = skewness. *Min* and *Max* represent the lowest and highest monthly return, respectively. *ACF1* = first order autocorrelation coefficient, *S-W test* = Shapiro-Wilk normality test. Significant evidence against the null hypothesis that the distribution is normal at 10%/5%/1% level is found for values labelled by */**/***, respectively. *Stocks* = MSCI World Total Return, *Bonds* = Citigroup Global Gov. Bond (all maturities), *LS* = HFRI Equity Hedge, *EMN* = HFRI Equity Market Neutral, *SS* = HFRI Short Selling, *FI* = HFRI Fixed Income Arbitrage, *CA* = HFRI Convertible Arbitrage, *MA* = HFRI Merger Arbitrage, *DS* = HFRI Distressed Securities, *GM* = HFRI Macro, *EM* = HFRI Emerging Markets, *MF* = Stark 300 Trader. *Comp* = HFRI FOF Composite, *Cons* = HFRI FOF Conservative, *Diver* = HFRI FOF Diversified, *Defen* = HFRI FOF Market Defensive, *Strat* = HFRI FOF Strategic. Sample window (monthly data): Jan 1990–Dec 2006.

Appendix C

Historical Value-at-Risk and Expected Shortfall

Table C.1: *Historical VaR and ES of hedge fund indices.*

Name	95%		99%	
	VaR	*ES*	*VaR*	*ES*
Equity long/short	**2.99**	**4.62**	**4.91**	**7.21**
Equity market neutral	**0.72**	**1.37**	**1.62**	**1.85**
Short selling	**9.80**	**14.56**	**15.52**	**20.57**
Fixed income arbitrage	**1.99**	**4.13**	**4.24**	**7.83**
Convertible arbitrage	**1.96**	**3.52**	**3.91**	**6.20**
Merger arbitrage	**1.12**	**2.98**	**4.17**	**6.34**
Distressed securities	**2.96**	**5.49**	**5.36**	**11.10**
Macro	**3.18**	**4.63**	**5.43**	**6.90**
Emerging markets	**7.22**	**13.60**	**15.26**	**25.73**
Managed futures	**4.24**	**5.42**	**6.38**	**7.42**
Stocks	**6.21**	**9.17**	**10.61**	**12.05**
Bonds	**3.16**	**4.10**	**4.58**	**5.21**
FOF Composite	**2.35**	**4.11**	**4.23**	**8.00**
FOF Conservative	**1.39**	**2.48**	**2.47**	**4.21**
FOF Diversified	**2.57**	**4.53**	**5.08**	**8.81**
FOF Defensive	**2.07**	**3.31**	**3.65**	**5.69**
FOF Strategic	**4.23**	**6.37**	**6.10**	**12.08**

Historical estimates of Value-at-Risk and Expected Shortfall for hedge fund indices and traditional assets. Hedge fund indices represented by HFRI indices and managed futures by Stark 300 Trader index. *Stocks* = MSCI World Total Return, *Bonds* = Citigroup Global Gov. Bond (all maturities). Sample window (monthly data): Jan 1990–Sep 2004.

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Curriculum Vitae

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