BMI PAPER

Hedge funds

On their dynamics and the consequences for risk & portfolio management

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ABSTRACT

In this paper a linear change point model is used to identify changes in the risk exposures of hedge funds. For this the return history of 11 hedge fund indices over the period January 1994 to March 2010 is used. The method succeeds in identifying significant change points in this period and reveals that a change in risk exposures is very likely. The paper contributes to existing literature because the model that is used allows not only factor coefficients but also the factors themselves to change. There is also no restriction on the number of change points allowed within the period. The proposed method provides additional value in the performance and risk appraisal of hedge funds and the results suggest that the standard equity orientated factors are becoming less relevant in the explanation of returns while non-linear factors are becoming increasingly relevant. The most important consequence of this is the underestimation of risk within the widely used mean-variance framework.

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PREFACE

This paper is written as a compulsory part of the Business Mathematics & Informatics master program at the Free University of Amsterdam. The purpose of the paper is for the student to do research on a subject of his choice in which he needs to use the techniques and knowledge that he acquired over the years. The paper should display elements of at least two out of the three main pillars of the study: The problem should be business related and a computer science and/or mathematical method should be used to find answers.

During the project the student is supervised by a staff member who is specialized in the subject. Special thanks go out to Denitsa Stefanova, who supervised this paper.

Table of Contents

1. Introduction

1.1 What are hedge funds?

Many people have heard about the term "hedge fund", but only few know what is meant by it. A survey found that by 2006 no country had even adopted a formal legal definition of the term although in that year their existence was important, influential and undeniable. The reason was probably that it was (and still is) very hard to define one as the industry is very rapidly growing and constantly changing. Until the 1990's only a very few people had heard of the term, but after a couple of hedge funds, especially George Soros Quantum fund, forced the sterling out of Europe's exchange rate system in September 1992 and Long Term Capital Management, a fund advised by Nobel prize winners, crashed in 1998 and the Federal reserve had to step in to prevent a market meltdown, that changed quickly. Nevertheless, still few people know what they are, what they do, what risks they bring and what benefits they have. Philip Coggan's answer to the question; "What is a hedge fund?" was[i]:

"It is a bit like describing a monster: no single characteristic is sufficient but you know one when you see one."

Most agree on the fact that the first hedge fund was the hedge**d** fund of Alfred Winslow Jones, which he started in March 1949. He was the first to systematically invest in promising stocks while minimizing market risk by shorting (borrowing) the least promising stock. Not long after the launch he noticed that some stocks move with more frequent and wider up and down jumps than the market. This he called the velocity of a stock and was used in his hedging strategy. In 1952 the well known paper "Portfolio Selection" of Markowitz was published but, due to the lack of computer power back then, its ideas could not really be used until the paper of Sharpe in 1963. At that time Jones had been using Sharpe's ideas for more than a decade and made enormous profits with it. Of course this was noticed and soon many copied his long-short strategy, resulting in much lower returns.

This anecdote both explains why so little is known about hedge funds and why high returns are still being realized. Most hedge fund managers rather don't reveal any information to keep their strategies, clients and probably their salary a secret. That is why they're mostly not registered under any acts, especially those that restrict them in using their strategies. They have been lightly regulated because most hedge funds are private pools of capital, not quoted on any stock exchange, in which only the very wealthy or professional investors can invest. Also for tax reasons they are often registered offshore. Because of the few regulations they are very flexible in their investment choices. Other frequently seen characteristics are the illiquidity of the investment, due to the often used lockup periods and the obligation to give an advance notice of money withdrawals, and the fees paid, typically between 0.5-5% of the money managed and between 10%-44% of the profits.

Many of the above described characteristics should give them an edge over, for example, mutual funds. However for the investor this edge often vanishes because of the high fee structure. These enormous fees are also frequently mentioned in the negative press that the hedge fund industry receives from the media. In 2006 the top three hedge fund managers were said to have earned over a billion US$ each.

The high fees attract the best and the brightest who come up with new and increasingly complex trading strategies (figure 1). Though the precise strategies often remain a secret, a broad definition of some of the most popular strategies can be found in appendix 1[1]. While not all strategies are implemented successfully the ones that are can achieve high risk-adjusted returns and can have beneficial diversification properties for large portfolios. This makes them increasingly popular under institutional investors.

[1] A more detailed description of all categories displayed in figure 1 can be found at: https://www.hedgefundresearch.com/index.php?fuse=indices-str&1295885758#2561

Both the fees and performances caused the rapid growth the industry showed over the last decades. According to Hedge Fund Research, the industry managed around US$39 billion in 1990 (±600 funds), by the end of 2007 this number was US$ 1900 billion (±10.000 funds) before it dropped back to US$1300 billion (±9.000 funds) during the credit crunch period. However, now that the invest banks become increasingly more regulated the hedge fund industry seems to be an attractive alternative for investors, which (together with the performance) would explain the rapid rebound in its size as it is almost back to the pre-crises level.

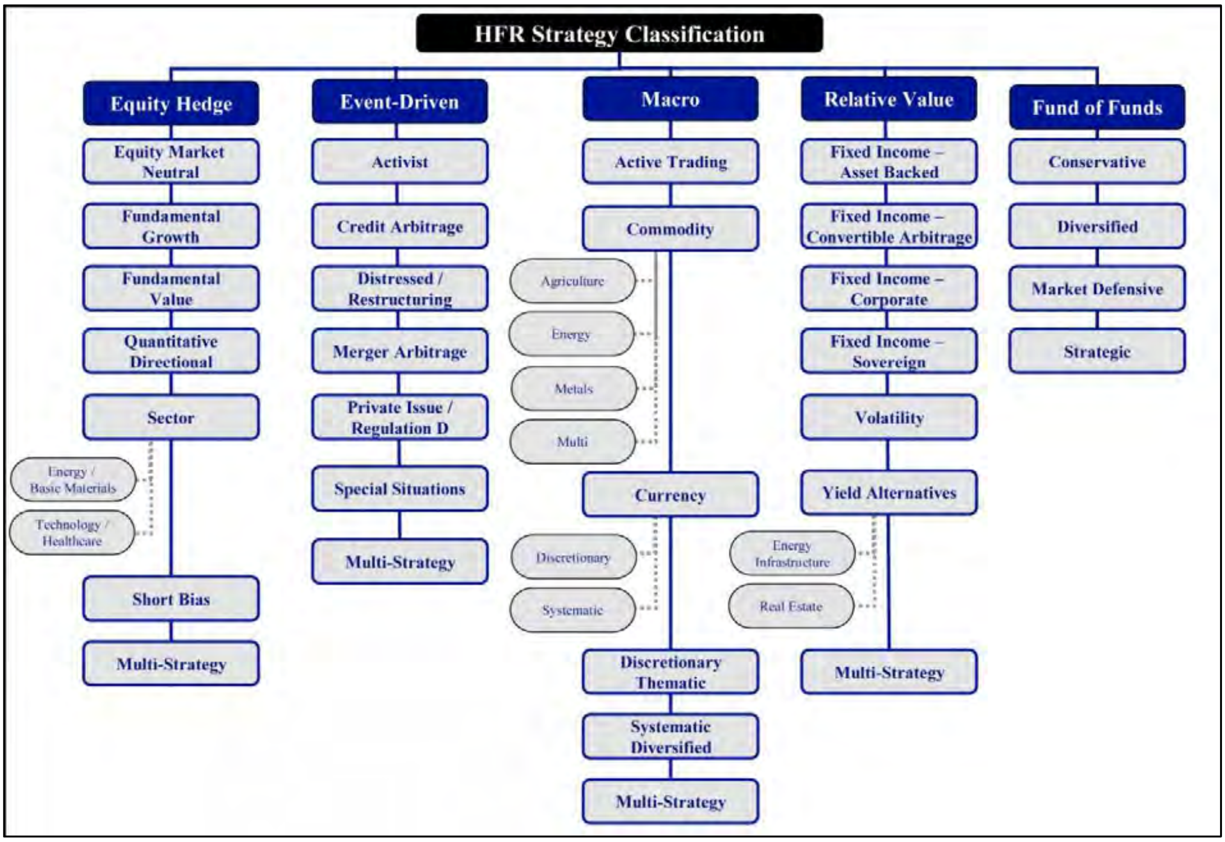

Figure 1: Strategy overview, source: Hedge Fund Research

In May 2010 the industry was again in negative publicity when some wrongly programmed computer trading algorithms caused a freefall in stock prices. The industry was lightly regulated because it was supposed to be of very limited influence on the financial stability and would not cause any systemic risk while only the financial independent or professionals were involved as investors. However, the knowledge that the highly leveraged funds can have considerable effect on the stability of financial markets when they are not fully hedged or follow dangerous/complex strategies, the rapid growth, the fees and the increased involvement of pension plans within the industry, have given reason to readdress the methods that are used for performance and risk appraisal in the industry. This is exactly what will be done in this paper. In the next paragraph an outline will be given about previous research done in the field of hedge fund performance and risk exposures. In section 2 the empirical method used to analyze the risk exposures and the dynamics of hedge funds will be described. Section 3 describes the data that is used for the research. In section 4 the performance and results of the model are analyzed and discussed. Section 5 describes in short several implications of the findings for risk and portfolio management. Section 6 concludes.

1.2 Related literature

The first assessments of portfolio risk and performance used the ideas in the previously mentioned paper of Sharpe (1964)[ii] in which he describes a model, the widely known Capital Asset Pricing Model, that splits asset returns up in a risky excess over market return part, a risk-free part and an error term. Jensen(1968)[iii] applied these ideas to analyze the performance of mutual funds using a linear factor model. Currently the performance of mutual funds is still done in a similar way using the Fama-French(1996)[iv] "Small minus Big, High minus Low"-factors in addition to the excess market return. Sometimes also the momentum factor Carhart(1997)[v] suggested is used.

The factor model used for the performance appraisal does very well on mutual funds, often explaining around 90% of the variance in returns. However, when used for hedge fund returns it performs considerably less well. An explanation for this is that mutual fund managers have relative return targets and are often only allowed to have assets in a limited number of asset classes using little leverage whereas hedge funds have absolute return targets, follow complex strategies in unlimited asset classes and are often highly levered.

Hedge funds follow many different strategies and only few use the buy and hold strategy that is often seen in the mutual fund industry. Fung & Hsieh (1997)[vi] point out this problem and address it by adding factors representing not only the traditional location but also the strategy to explain returns. They find that the returns of different strategies are better explained by a different set of factors. They also mention that this can have consequences for risk and portfolio management as some factor returns are not normally distributed. Agarwal and Naik (2004)[vii] use the returns on in and out of the money put and call options as factors to explain non-linear return characteristics. They find that a large number of equity orientated fund returns can be explained by an exposure to selling out of the money put options on the market index which implies significant left-tail risk. This risk is ignored when applying the traditional mean-variance method for portfolio optimization and they use a mean-conditional variance method to show the underestimation of risk applying the traditional method.

However, using such a linear factor model still suggest an average risk exposure to a limited set of factors over a long return history. Jensen(1968) already mentioned that this supposedly stationary risk level does not have to be true, as managers can change their exposures easily, but that the timing or skill factor "alpha" explains the remainder of the return. While research of Ferson and Schadt (1996)[viii] found that the risk exposures of mutual funds are not stationary, they do not vary too much. As mentioned it is known that hedge funds often follow strategies that can diverge substantially from the buy and hold strategies of mutual funds. Bollen & Whaley (2009)[ix] use an optimal change point regression and a vector autoregressive model to test for non-stationary exposures. They find that the optimal change point model performs best in identifying changes in factor exposures and that the majority of hedge funds risk exposures are indeed dynamic, varying a lot more than was seen in the case of mutual funds. They also find that these dynamics can have substantial consequences for the performance assessment of individual funds. However, in their optimal change point model they do allow the exposures to change over time, but do not allow the factors to which the funds are exposed to change. Patton & Ramadorai (2010)[x] suggest an alternative method to model the dynamic risk exposure of hedge funds. They try to capture the variation in risk exposure within months by using daily conditioning variables to explain monthly returns. They use this in a model for time varying exposures based on observable conditioning variables following Ferson, Henry and Kisgen (2006)[xi]. They find that their method outperforms the change point regression method for most strategies.

This paper will have a similar structure as the one of Agarwal & Naik but in this paper the dynamics of the risk exposures will be accounted for. Also non-equity orientated hedge fund returns will be analyzed. The change point regression model as suggested by Bollen & Whaley (2009) will be used but it will be implemented in a slightly different, more representative, way. The factors chosen in the regression will be discussed and tried to be explained in an intuitive manner.

Having analyzed the dynamics of the risk exposures the implications for risk and portfolio management will be addressed in short.

2. DATA

2.1 HEDGE FUND DATA

The returns of all hedge fund indices are retrieved from the Hedge Fund Research (HFR) Database. The data consists of monthly returns on all indices from January 1990 to December 2010. The sample used in this paper consists of 11 indices, 5 equity orientated, 3 event driven, 1 macro, 1 relative value and 1 fund of funds index. All indices are equally weighted and only funds with more than US$ 50 million in assets under management are admitted. All reported returns are in net of fees. A summary of the data is presented in table 1.

Equity orientated indices:

- Equity Hedge Market Neutral [EHMNeutral]
- Equity Hedge Quantitative Directional [EHQDir]
- Equity Hedge Short Bias [EHShortB]
- Equity Hedge Emerging Markets [EHEmerg]
- Equity Hedge Total [EHTotal]

Event driven indices:

- Event Driven Distressed/Restructuring [EDDisRes]
- Event Driven Merger Arbitrage [EDMerArb]
- Event Driven Total [EDTotal]

Macro index:

- Marco Total [MacroTotal]

Relative value index:

- Relative Value Total [RVTotal]

Fund of Funds index:

- Fund of Funds Total [FoFTotal]

As discussed earlier, due to the low regulatory requirements the reporting by hedge funds is voluntary. This can bias the data in a number of ways:

Survivorship bias. Dead funds will stop reporting. If only the alive funds are used this will positively bias returns. Fung & Hsieh(2000)[xii] estimated that the difference in performance between a portfolio of alive funds and a portfolio of all funds is around 3% annually. Before 1994 data vendors often just discarded funds that stopped reporting, therefore the sample used will start in 1994.

Self selection bias. Other reasons for funds to stop or start reporting are that a fund does not want any more assets under management. It does not have to “advertise” with its, probably good, performance. But also funds that perform bad have an incentive not to report. Fung & Hsieh (1997) find that these events will offset each other and will therefore not bias the data significantly.

	Index	# observations	μ	σ	skewness	kurtosis	min	max
1	EHMNeutral	195	0,0052	0,0128	-0,11	4,49	-0,036	0,051
2	EHQntDir	195	0,0095	0,0477	-0,38	3,46	-0,162	0,122
3	EHShortB	195	0,0017	0,0628	0,26	5,49	-0,244	0,255
4	EHEmerg	195	0,0081	0,0538	-2,25	17,76	-0,393	0,138
5	EHTotal	195	0,0095	0,0375	-0,14	4,16	-0,110	0,134
6	EDDisRes	195	0,0083	0,0300	-1,27	9,27	-0,161	0,088
7	EDMerArb	195	0,0071	0,0162	-1,55	9,27	-0,088	0,048
8	EDTotal	195	0,0091	0,0302	-1,09	6,88	-0,144	0,078
9	RVTotal	195	0,0071	0,0209	-2,57	16,62	-0,117	0,053
10	FoFTotal	195	0,0051	0,0257	-0,67	6,08	-0,115	0,086
11	MacroTotal	195	0,0076	0,0245	0,11	3,62	-0,072	0,079

Table 1: Index statistics

This table shows some statistics for the indices, described on the previous page, that are used in this paper. The data is monthly, obtained from Hedge Fund Research and covers the period January 1994 – March 2010.

Backfilling bias. Funds are free to backfill performance data when they start reporting. Of course a fund has an incentive only to do this when past returns were good. This bias could be overcome by discarding a significant number of the first months of returns for all funds. As fund specific data was not available and because this bias is probably most significant for small funds (i.e. fewer than 25 million under management) this bias is not accounted for.

Return smoothing. Hedge funds have an incentive to smooth returns over a couple of periods. This way they can i.e. lower their observed volatility and artificially increase some performance measures like the Sharpe ratio. Sometimes it's just a result of the illiquid assets they often hold. Asness, Krail and Liew (2001)[xiii] present evidence for this. It is important to account for this problem because the revealing of the real variance in returns will be beneficial for its explanation. Several studies have been done on how to overcome this problem and unsmooth the "smoothed" returns. I will use the moving average (MA) method proposed by Getmansky, Lo & Makarov (2004)[xiv]. They suggest to model that the observed return $[R_t^o]$ is a weighted average of the previous n "clean" returns $[R_t^c]$:

$$R_t^o = \theta_0 R_t^c + \theta_1 R_{t-1}^c + \cdots + \theta_n R_{t-n}^c$$

$$with \qquad \theta_j \in [0,1] \; j = 0, 1, .., n$$

$$\sum_{j=0}^{n} \theta_j = 1$$

The Herfindahl index can be used to measure the extent of smoothing observed in the returns of an index:

$\zeta = \sum_{j=0}^{n} \theta_j^2$, by construction $0 < \zeta \leq 1$, 1 meaning "no smoothing".

First the new return series are created by centering the returns. De process is then described by:

$$X_t = R_t^o - \mu = \theta_0(R_t^c - \mu) + \theta_1(R_{t-1}^c - \mu) + \cdots + \theta_n(R_{t-n}^c - \mu) + (\theta_0 + \theta_1 + \cdots + \theta_n)\mu - \mu$$

$$write \;\; R_t^c - \mu = \eta_t, \; R_{t-1}^c - \mu = \eta_{t-1} \; \dots \; R_{t-n}^c - \mu = \eta_{t-n}$$

$$X_t = \theta_0 \eta_t + \theta_1 \eta_{t-1} + .. + \theta_n \eta_{t-n}$$

To estimate the MA(n) process the demeaned returns are assumed to be normally distributed $\eta_t \approx N(0, \sigma_\eta^2)$, this is of course a disadvantage given that returns are generally not normally distributed. S.P. Amvella, I. Meier, N. Papageorgiou (2009) suggest a method that not assumes a distribution but has other downsides. For the purpose of this paper this disadvantage is discarded.

Getmansky's assumption of 2 lags is used and with a maximum likelihood technique the $\theta's$ are estimated. The real return $[R_t^c]$ can be estimated by inverting the equation.

The Herfindahl index found for the return indices are given in table 2.

	Index	θ_0	θ_1	θ_2
EHMNeutral	0,530	0,7	0,15	0,15
EHQntDir	0,660	0,79	0,2	0,01
EHShortB	0,810	0,89	0,11	0
EHEmerg	0,540	0,69	0,22	0,09
EHTotal	0,530	0,69	0,21	0,1
EDDisRes	0,400	0,52	0,32	0,16
EDMerArb	0,480	0,64	0,22	0,14
EDTotal	0,460	0,61	0,27	0,12
RVTotal	0,400	0,53	0,31	0,16
FoFTotal	0,480	0,640	0,24	0,13
MacroTotal	0,650	0,79	0,16	0,05

Table 2: Return smoothing summary

In this table the Index shows to what extent the returns of 11 hedge fund indices are smoothed; 0 meaning a lot of smoothing, 1 meaning no smoothing. The thetas show how the return information is scattered among the lags. The data spans the period January 1994 to March 2010.

2.2 RISK FACTOR DATA

Earlier papers have used very different amounts of risk factors. Fung and Hsieh (2004)[xv] found a sample of 7 different factors that can explain the excess returns pretty well. Though it is unlikely that these factors really represent all different strategy exposures it is often possible to explain their excess returns due to the high correlations seen among factors. These seven factors will also be used in this paper, however other factors will be added to the sample as well. The factors can be categorized into 6 broad groups: equity, commodity, fixed income, liquidity, volatility and non-linear factors. Other papers often differentiate between traded and non-traded factors. The goal of this paper is however not trying to create a replicating portfolio that can be used in practice, it is only to identify changes in risk exposures and evaluate the implications for portfolio decisions.

Equity. The factors used to capture exposure to equity are focused mainly on U.S. equity. This is because it can be expected to be more important, but also because the data is better available. The factors include returns on: S&P 500, NASDAQ, Fama and French (1993) size (SMB) and value (HML) factor. For non-US equity the returns on the MSCI Europe index and the returns on the Dow Jones Total Market: World Emerging Market have been added. To capture a change in for example a previously U.S. equity diversified fund to a more globally focused fund also the Russel3000 returns are used as a factor.

Commodity. Commodities are represented by the returns on the S&P GSCI Gold Spot index and the S&P GSCI Commodity Total Return index.

Fixed income. Hedge funds are generally significantly leveraged. The amount of leverage they have can be of big influence on the portfolio they hold. To capture the exposure to risk in leverage, interest rate changes and foreign exchange rates several factors have been added: 3 month Treasury-bill yield, 10 year constant maturity US government bond yield, Moody's Baa yield, spread between 3 month T-Bill and 10 year bond and the spread between Moody's Baa and the 10 year bond.

Liquidity. Liquidity can have a similar effect as leverage on hedge fund exposures. When markets are highly liquid hedge funds can increase exposure and vice versa. Or they could invest more in illiquid times. This way they can profit from the previously described lock-up periods by earning the liquidity premium. As liquidity factor the S&P turnover by volume is added.

Volatility. If hedge funds want to keep their volatility constant the risk exposures of funds will change when the volatility in the market changes. Volatility can therefore be a good factor to capture changes in risk exposure. For volatility in equity the VIX index is added and to capture volatility in the bond market the Merrill Lynch 1 month MOVE index has been added. The first captures the volatility of the S&P 500 by extracting the implied volatility in options on the index. The second is a yield curve weighted index of the normalized implied volatility on 1-month Treasury options.

Non-linear factors. It is known that hedge funds often display non-linear payoffs, see for example Agarwal & Naik (2004). Following this paper the returns on out of the money put and call options on the S&P 500 are added as a factor to capture these effects[2]. The option values are estimated using the Black & Scholes option pricing formula[3]. Also the primitive trend following strategies of Fung & Hiesh (2001) are added. These represent payoffs on lookback straddles on bonds, stocks, currencies and commodities[4]. A lookback straddle is a combination of a lookback put and a lookback call that pays the holder the difference between the maximum and minimum value of the underlying over a certain time period. The idea is that the holder profits from trends in a volatile period, being neutral in its direction. The no arbitrage price of this security can be derived in closed form relatively easy using a Black & Scholes framework.

Combined the factor data is summarized below and in table 3.

Fung & Hsieh seven factors:

- Fama-French excess market return factor [MKTRF]
- Fama-French size factor: small - big[5] [SMB]
- Change in 10 year constant maturity government bond yield [10YGBond]
- Change in spread between this 10 year bond and Moody's Baa yield [Spr10YBaa]
- Return on bond lookback straddle [PTFSBD]
- Return on currency lookback straddle [PFTSFX]
- Return on commodity lookback straddle [PTFSCOM]

Additional factors:

- Return on short term interest rate lookback straddle[6] [PTFSIR]
- Return on stock index lookback straddle[6] [PTFSSTK]

[2] In the money option are not added separately because they can be replicated by already available factors.
[3] Volatility is measured over past 23 trading days, as risk-free rate the fama-french reported factor is used.
[4] This can be found on Hsieh's website : http://faculty.fuqua.duke.edu/~dah7/DataLibrary/TF-Fac.xls
[5] All Fama-French factors can be at found here: http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html
[6] Also proposed by Fung & Hsieh later.

- Return on NASDAQ [NASDAQ]
- Return on S&P 500 [SP500]
- Return on Russel3000 [Rus3000]
- Return on emerging market index [DJEmMark]
- Return on European equity [MSEUR]
- Fama-French high minus low factor [HML]
- Return on gold [SPGold]
- Return on commodities [SPComm]
- Change in 3 month T-Bill yield [3mTBill]
- Change in Moody's Baa yield [MoodyBaa]
- Change in spread between the 10 year bond and 3month T-Bill [spr10Y3M]
- S&P 500 turnover by volume [Spturn]
- Change in VIX [VIX]
- Change in Merril lynch 1- month Move index [1mMove]
- Return of 5% OTM call option on the S&P 500 [SPOTMC]
- Return of 5% OTM put option on the S&P 500 [SPOTMP]

	Factor	**# observations**	**μ**	**σ**	**skewness**	**kurtosis**	**min**	**max**
1	S&P500	195	0,0059	0,0470	-0,56	4,74	-0,168	0,157
2	NASDAQ	195	0,0113	0,0709	-0,20	4,12	-0,215	0,232
3	Rus3000	195	0,0060	0,0478	-0,63	5,03	-0,176	0,159
4	MSEUR	195	0,0058	0,0541	-0,55	4,68	-0,207	0,146
5	DJEmMark	195	0,0057	0,0751	-0,28	4,95	-0,293	0,243
6	SMB	195	0,0021	0,0371	0,82	10,55	-0,169	0,220
7	HML	195	0,0033	0,0351	0,01	5,39	-0,124	0,139
8	MKTRF	195	0,0047	0,0465	-0,85	4,40	-0,185	0,110
9	SPComm	195	0,0062	0,0667	-0,44	4,63	-0,295	0,195
10	SPGold	195	0,0064	0,0460	0,38	5,35	-0,181	0,194
11	3MTBill	195	0,0119	0,2932	7,79	88,32	-0,842	3,333
12	10YGBond	195	-0,0006	0,0526	-0,47	9,46	-0,314	0,195
13	MoodyBaa	195	-0,0006	0,0300	1,86	15,76	-0,085	0,215
14	spr10Y3M	195	-0,0199	1,8299	-8,37	110,30	-22,000	7,750
15	spr10YBaa	195	0,0035	0,0693	1,44	9,02	-0,208	0,401
16	Spturn	195	0,0323	0,1842	0,80	5,02	-0,338	0,864
17	VIX	195	0,0166	0,1808	1,07	5,98	-0,416	0,928
18	1mMove	195	0,0110	0,1641	2,36	13,45	-0,313	0,960
19	PTFSBD	195	-0,0164	0,1478	1,45	5,98	-0,254	0,689
20	PTFSFX	195	0,0002	0,1972	1,39	5,71	-0,301	0,903
21	PTFSCOM	195	-0,0047	0,1389	1,28	5,58	-0,230	0,648
22	PTFSIR	195	0,0280	0,2879	4,10	25,73	-0,306	2,219
23	PTFSSTK	195	-0,0473	0,1277	0,98	4,90	-0,302	0,461
24	SPOTMC	195	0,1431	0,7696	6,16	59,52	-0,845	8,038
25	SPOTMP	195	0,1559	0,8652	7,13	74,25	-0,866	9,569

Table 3: Index statistics

This table shows some statistics for the factors that are used in this paper. The data is obtained from the Hedge Fund Research Database and covers the period January 1994 – March 2010.

3. MODEL

As mentioned mutual fund risk exposures are often modeled by:

$R_t = \beta^T F_t + \varepsilon_t$,

with R_t the index excess return at t, F a vector of k factors (incl. constant) $\begin{bmatrix} 1 \\ F_{2,t} \\ \vdots \\ F_{k,t} \end{bmatrix}$, β the weights on the factors $\begin{bmatrix} \beta_1{}^{7} \\ \vdots \\ \beta_k \end{bmatrix}$ and an error term $\varepsilon_t \sim N(0, \sigma^2)$.

In this model the vector β is constant. However, if the risk exposures change significantly over time the weight vector should be $\begin{bmatrix} \beta_{1,t} \\ \vdots \\ \beta_{k,t} \end{bmatrix}$, as the coefficients can change over time.

A significant number of methods have been proposed in previous literature to capture the dynamics of risk exposures. In this paper an optimal change point model is used to identify structural changes. In contrast to the stochastic beta model, that models a change as an event that occurs in a continuous smooth way during a period, the optimal change point model assumes a discrete change in risk exposure. Of course a manager will need some time to unwind positions and take new ones. However, as only monthly returns are available, it's assumed that if a manager wants to change risk exposures he will have managed to do this during the course of one month, implying that the model should be able to notice a change. This model can be represented, in case of a single change point, by:

$R_t = (\beta_C^T + \beta_\Delta^T 1_{t \geq \pi T})\, F_t + \varepsilon_t$, with πT the change point, β_C the fitted coefficients in the constant model and β_Δ a possible change in coefficients after the change point.

Bollen & Whaley (2009) allow only one structural change because of their limited return history. Also the number of factors k is constant (at 2) and the explaining factors do not change during the whole period in their model, only the weights are allowed to change. This paper will not use these restrictions; both the factors as their coefficients are free to change at a change point. Also the number of factors allowed is not restricted beforehand.

In this model the hypotheses tested are:

$$H_0: \beta_\Delta = \begin{bmatrix} 0 \\ \vdots \\ 0 \end{bmatrix}$$

$$H_1: \beta_\Delta \neq \begin{bmatrix} 0 \\ \vdots \\ 0 \end{bmatrix}$$

The moments that these discrete changes take place are not known beforehand and must be inferred from the data. Brown, Durbin and Evans (1975)[xvi], developed a generalized fluctuation test method that tries to capture significant changes in regression residuals that imply a change in regression coefficients. They compute the

[7] This would be the α used in most finance literature.

cumulative sum (CUSUM) of recursive residuals and the cumulative sum of squared recursive residuals and estimate bounds for these sums under the assumption of constant parameter values. Another way of capturing structural changes in parameters is the use of F-test statistics. The difference is that the alternative is specified whereas the generalized fluctuation tests are suitable for various patterns of structural changes. These tests are designed to test for a single shift. Chow(1966)[xvii] first proposed this method and the major drawback of his method was that the change point had to be known beforehand. A way to solve this problem is to calculate F-test statistics for all possible change points. Andrews & Ploberger (1994)[xviii] do this and use the F-statistics to compute three suggested test statistics. According to Bollen & Whaley (2009) this method is preferred to the CUSUM method in this case so it will also be used in this paper.

Concretely for all time intervals $t \in (\underline{t} = 0 + x\ , T - x = \bar{t})$, the F-statistic, defined by

$$F(\pi) = \frac{(\mathrm{Q}^{*} - \mathrm{Q}(\pi)) * (\mathrm{T} - 2 * \#\mathrm{factors})}{Q(\pi) * \#factors} \qquad , \pi = \frac{t}{T}\ so\ \frac{\underline{t}}{T} < \pi < \frac{\bar{t}}{T}\ , x = 12$$

is computed. Here Q^* represents the sum of squared residuals under the null hypothesis and $\mathrm{Q}(\pi)$ represents the sum of squared residuals in case of a change point at time interval $t = \pi T$.

The boundaries can be computed under the null hypothesis of no structural change from the empirical distribution such that the probability that a test statistic of the F-statistics F(π) exceeds this boundary is α. In this paper the test statistics are

$$aveF = \frac{1}{\bar{t} - \underline{t} + 1} \sum_{t=\underline{t}}^{\bar{t}} F(\frac{t}{T})$$

$$expF = \ln\left(\frac{1}{\bar{t} - \underline{t} + 1} \sum_{t=\underline{t}}^{\bar{t}} \exp\left(0.5 * F\left(\frac{t}{T}\right)\right)\right)$$

To compute the empirical distribution a bootstrap method is used. For each index the model is fitted under the null hypothesis of constant parameter values. The residuals under this model are than randomly added to the fitted returns to simulate 500[8] sets of returns. Then on all sets the change point regression is fitted $\bar{t} - \underline{t}$ times and the weights and test statistics are saved. By ordering the empirical distribution is found and the critical values are known.

The only problem left now is the method used for factor selection. Both the fact that only a limited number of index returns is available and that many of the factors are probably correlated imply that degrees of freedom and multi-collinearity pose a threat to the reliability of results. Because of this a stepwise regression method is used. This method selects factors sequentially based on their power to explain variation in returns. It is a greedy algorithm so it will not necessarily give the optimal result.

[8] The limit of 500 return samples is used because the time to estimate the model can take up to 6 hours and it can be assumed that robust results are achieved this way.

Testing for multiple change points will be done in an iterative way. When one change point has been detected at $\pi_1 = \frac{t}{T}$, the sample will be divided into 2 subsamples: the first from 0 to $\pi_1 T$ and the second from $\pi_1 T$ to T. Than the method will be applied recursively until the sample size gets smaller than $2x$.

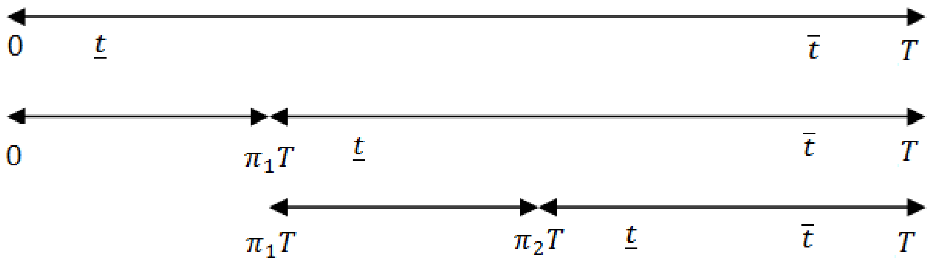

Figure 2: Algorthm explanation

This figure shows how the algorithm is implemented: When a single change point is identified the sample period will be split up in a prior- and post change point period. On the post change point period a new change point will searched for, and so on.

4. Model Performance & Results

In this section the performance of the model will be assessed and the results will be evaluated. A first summary of results is given in table 4 below.

	EHMNeutral		EHQntDir		EHShortB		EHEmerg		EHTotal		EDDisRes	
	CP. Mod.	C. Mod.	CP. Mod.	C. Mod.	CP. Mod.	C. Mod.	CP. Mod.	C. Mod.	CP. Mod.	C. Mod.	CP. Mod.	C. Mod.
#changepoints	3	0	2	0	2	0	3	0	2	0	1	0
#distinct factors	17 [10]	5	11 [8]	9	10 [7]	4	15 [6]	5	17 [8]	9	15 [10]	9
factors/month	6,4	5	8,3	9	5,0	4	6,2	5	9,5	9	9,0	9
R-squared	0,507	0,147	0,942	0,913	0,869	0,828	0,880	0,762	0,905	0,856	0,751	0,682
adj R-Squared	0,460	0,124	0,938	0,909	0,862	0,824	0,870	0,755	0,896	0,848	0,730	0,667
SSresid	0,015	0,026	0,026	0,038	0,100	0,131	0,068	0,134	0,026	0,039	0,044	0,056
SStotal	0,030	0,030	0,440	0,440	0,763	0,763	0,564	0,564	0,271	0,271	0,176	0,176
alpha(weighted)	0,001	0,002	0,001	0,003	0,003	0,002	0,006	0,003	0,003	0,006	0,005	0,004

	EDMerArb		EDTotal		RVTotal		FoFTotal		MacroTotal		TOTAL	
	CP. Mod.	C. Mod.	CP. Mod.	C. Mod.	CP. Mod.	C. Mod.	CP. Mod.	C. Mod.	CP. Mod.	C. Mod.	CP. Mod.	C. Mod.
#changepoints	3	0	1	0	1	0	4	0	2	0	**2,18**	**0,00**
#distinct factors	15 [14]	5	12 [9]	7	15 [9]	9	23 [12]	12	18 [8]	10	**15,27**	**7,64**
#factors/month	5,3	5	6,2	7	0,0	9	11,8	12	10,0	10	**7,1**	**7,64**
R-squared	0,649	0,463	0,825	0,777	0,731	0,631	0,875	0,734	0,630	0,475	**0,779**	**0,661**
adj R-Squared	0,620	0,449	0,814	0,769	0,709	0,613	0,858	0,717	0,592	0,447	**0,759**	**0,647**
SSresid	0,017	0,027	0,031	0,039	0,023	0,031	0,016	0,034	0,043	0,061	**0,037**	**0,056**
SStotal	0,049	0,049	0,177	0,177	0,085	0,085	0,128	0,128	0,116	0,116	**0,254**	**0,254**
alpha(weighted)	0,003	0,004	0,003	0,004	0,004	0,004	0,001	0,003	0,005	0,007	**0,003**	**0,004**

Table 4: Results with HFR equally weighted indices

This table shows results of the change point regression model and the constant model on the returns from January 1994 to March 2010 of several indices obtained from the HFR database. It shows the number of change points identified (significant at 5% level), number of different risk exposures identified -[significant at 5% level] during the period, the intercept alpha weighted by the number of months, the time weighted average number of factors that are in the model per month and some general statistics on model performance.

First of all the performance of the constant model is in line with the Agarwal&Naik(2004) paper. The performance of their model is slightly outperformed but this is probably explained by the larger factor sample and increased return history. What can be seen immediately is that often a much wider range of distinct factors is recognized when the set is not constrained to be constant over the whole period. A result is that the amount of explained variation in returns significantly increases the bigger the difference in identified factors. This is, as expected, in line with the increase of change points identified because only then a change in factors is possible. Because n change points allow n+1 different factor sets of size q equal to the original constant model factor set, it makes sense to look at the ratio of the number of identified distinct factors divided by (n +1)*q. The closer this ratio is to one, the more the model profits from the increased freedom. The most dramatic increase is found with the Equity Market Neutral index, but it seems that the performance of the model is not explained that easy; i.e. the model performance on the Equity Short Biased index is little better while the just mentioned ratio is high.

On average the skill factor alpha seems to be lower than a constant model suggests. So a part of the return explained by manager skill factor in the constant model seems unrightfully allocated because it can just be explained by exposure to risk bearing factors.

From the results it follows that the Fund of Funds index displays the most significant changes in risk exposures. This can be explained by the fact that for managers of these funds it's probably easier to switch between funds with different exposures than it is for a manager of a "not Fund of Funds" to switch exposures. The indices that do not change exposures very often, for example the Distressed & Restructuring index, are probably very focused on a specific sector where their expertise lies. However, with the entering and exiting of funds with different expertise and the change points identified in the Merger Arbitrage index, this does not seem to be a very strong argument.

The results show very clearly that a significant change in risk exposure weights is very likely and a change in the exposure to the factors themselves as well. Therefore a closer look at the variation in weights for the different indices is needed to explain risks. Also, as the exposure to different factors changes significantly over time it is useful to know if the exposure remains within the in section 2.2 described groups, in other words: does the exposure continue to relate to factors with somewhat the same risk return characteristics or does this change. The latter would imply that there might be a change in style or strategy; this would not be preferred by investors, who like a more constant risk return profile for their portfolio.

	EHMNeutral		**EHQntDir**		**EHShortB**		**EHEmerg**		**EHTotal**		**EDDisRes**	
	CP. Mod.	C. Mod.	CP. Mod.	C. Mod.	CP. Mod.	C. Mod.	CP. Mod.	C. Mod.	CP. Mod.	C. Mod.	CP. Mod.	C. Mod.
Equity	48%	0%	56%	56%	69%	75%	51%	60%	38%	44%	48%	44%
Commodity	3%	20%	21%	11%	9%	0%	6%	0%	13%	22%	7%	11%
Fixed income	18%	20%	13%	33%	2%	25%	3%	0%	25%	0%	7%	22%
Vol. & Liq.	9%	0%	0%	0%	8%	0%	19%	40%	7%	11%	8%	11%
Non-linear	21%	60%	10%	0%	11%	0%	21%	0%	17%	22%	30%	11%
	EDMerArb		**EDTotal**		**RVTotal**		**FoFTotal**		**MacroTotal**		**TOTAL**	
	CP. Mod.	C. Mod.	CP. Mod.	C. Mod.	CP. Mod.	C. Mod.	CP. Mod.	C. Mod.	CP. Mod.	C. Mod.	CP. Mod.	C. Mod.
Equity	49%	40%	49%	57%	52%	22%	42%	42%	30%	30%	47%	42%
Commodity	1%	20%	13%	14%	20%	22%	5%	8%	13%	10%	11%	13%
Fixed income	22%	0%	16%	14%	13%	33%	15%	8%	13%	10%	14%	15%
Vol. & Liq.	9%	40%	13%	14%	9%	11%	10%	8%	10%	10%	9%	12%
Non-linear	18%	0%	8%	0%	5%	11%	28%	33%	33%	40%	19%	18%

Table 5: Percentage of exposure to different groups

This table shows the average of the amount of factors identified by the change point model and the constant model for the period January 1994 to March 2010 belonging to groups with a somewhat similar risk profile as a percentage of the total amount of identified factors.

The percentage of exposure to factors in different groups in the change point model compared to the constant model for the different indices seems to be significantly different for some indices. These figures take into account the length of the period in which there was exposure to these groups so the large differences suggest that using the constant model can have dramatic consequences for performance evaluation. If one looks at the Equity Market Neutral index this neutrality seems to be true under the constant model but not at all true under the change point model with average exposure over the 195 month period of 48% to equity orientated risk factors![9]

[9] The percentage does not tell everything: a fund could be long half the stocks in a market index and short the other half, resulting in a, to a large extent, market neutral portfolio.

Figure 3 shows how the exposure to different risk factor groups change over time. From this graph it is clear that these allocations do not display very large changes but that there are "trends" in popularity. Basic equity factor exposure seems to be in a downward trend and non-linear factors, especially over the last 5 years, seem to enjoy increasingly more explanatory power. When it is taken into account that for example volatility and liquidity might be seen as additional non-linear factors[10] (over the last year increasingly more products with payoffs related to these factors were introduced), the factors can explain up to 43% of the variation in returns.

Figure 3 also shows implicitly that during the first years of the return history little change points are detected compared to more recent periods (keep in mind also that change points during the first and last 12 months are not possible because of the algorithm properties). Figure 4 shows the distribution of detected change points more clearly.

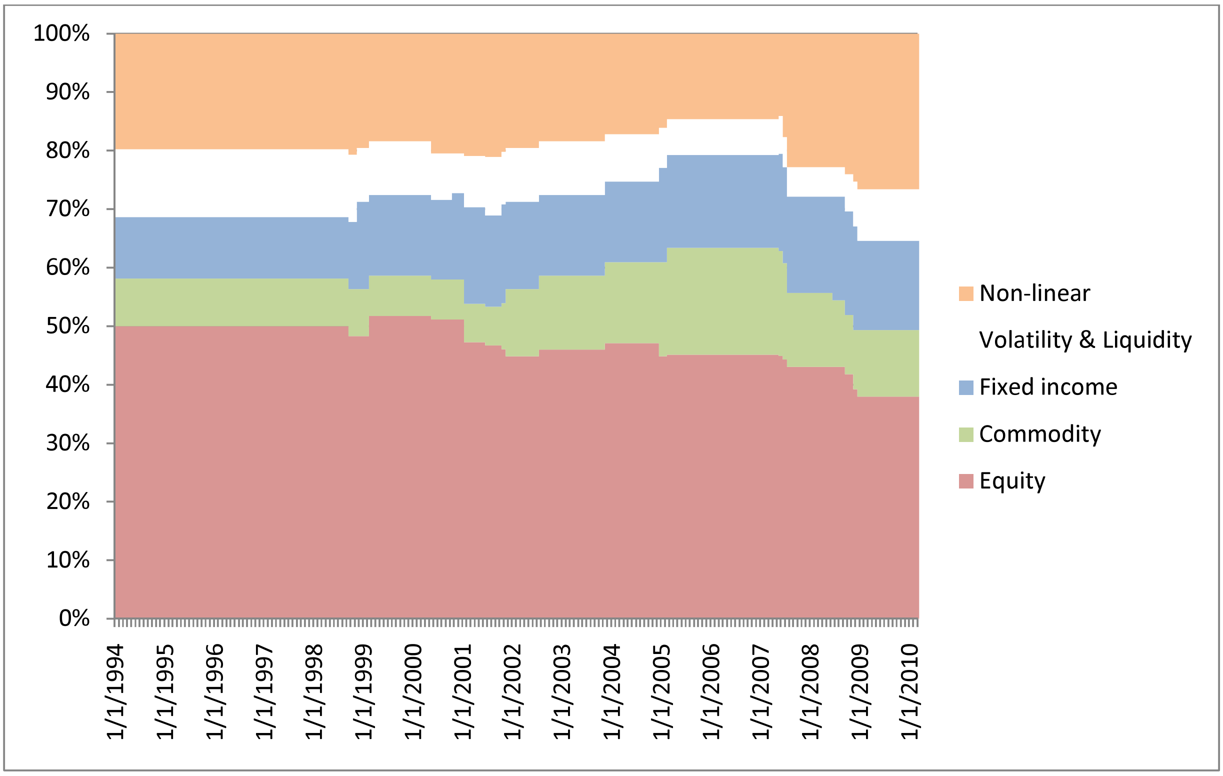

Figure 3: Time variation in hedge fund risk exposures

This figure shows how the risk exposures of found in the returns of 11 different hedge fund indices change over time. On the X-axis the time-line, on the Y-axis the explanatory power in percentages. The return data is obtained from the Hedge Fund Research Database and covers the period January 1994 – March 2010.

[10] A straddle on a market index can for example be seen as a volatility product, so these groups do show some overlap.

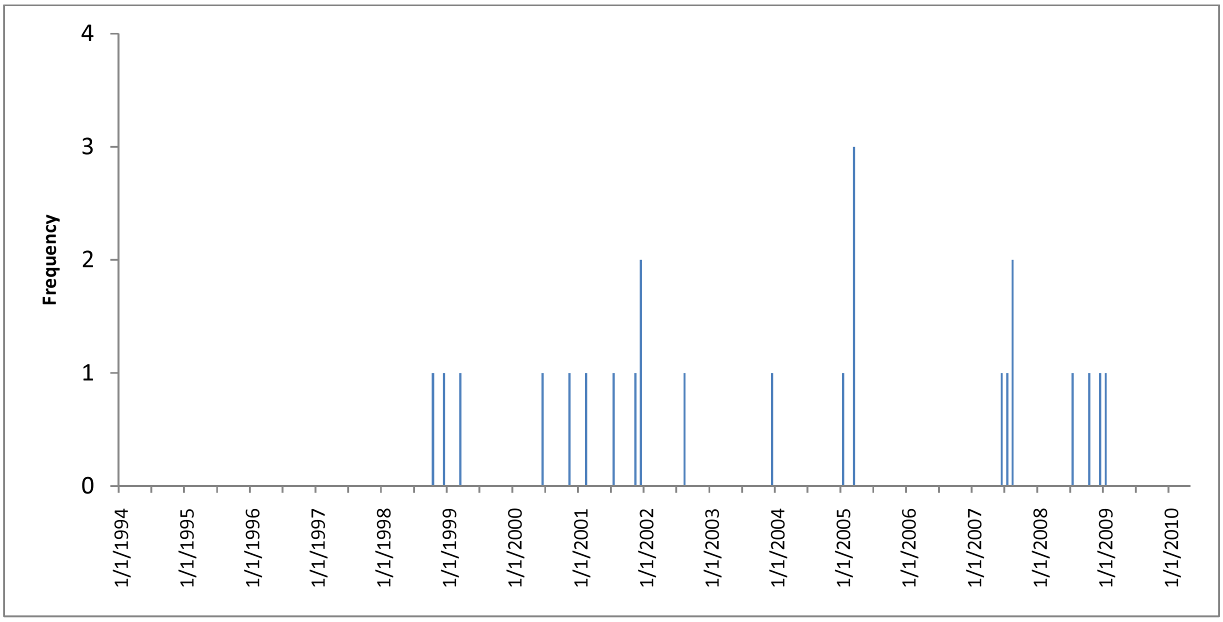

Figure 4: Histogram of detected change points

This figure shows the frequency of change point occurrences detected in 11 hedge fund return histories, obtained from the Hedge Fund Research Database, per month.

Although this paper only evaluates return histories of 11 indices and only a total of 24 change points are available some interesting remarks can be made from figure 3. The first change points are detected during the interval July – Dec 1998, more precisely October and November 1998, which is just after the implosion of LTCM in August that year. During that time hedge fund managers became more aware of the dangers of a high concentration of "big" funds in a limited pool of assets which might have lead them to diversify more and use more dynamic strategies, explaining the larger number of detected change points in later periods. The second peak, during the last six months of 2001, in which 4 change points are detected, is probably the result of the Dotcom bubble deflating at full speed. During the first months of 2005 also 4 change points are detected. This is very interesting because all earlier papers do not detect this period and the period cannot be explained by some market crash. The detection might be a consequence of the freedom of the model used in this paper to allow a switch in factors instead of only a switch in weights. A closer look at what happens within the model confirms this (see table 6). The Equity Market Neutral, Distressed & Restructuring, Merger Arbitrage and Fund of Funds indices change a large percentage of their significant factor exposures within these months. The change points are all significant at 5% level except the one of the Equity Market Neutral index, which is significant even at 1% level. Though it is interesting that the Fama French factors SMB and HML become less important and emerging markets become much more important in three of them, a very clear cause cannot be deduced. It might have to do with the act that was adopted in late 2004 by the SEC that caused more regulation[11]. Another explanation could be that the economy was entering a new bull market and for example the amount of mergers and acquisitions started to grow very rapidly. The change points detected in June, July and August 2007 can of course be explained by the deflation of the mortgage bubble that lighted the last financial crises. The last four change points are at the height of the credit crisis, in which Lehman fell and many banks were rescued. Another 7 change points were detected during this last period but were not identified as significant.

[11] www.sec.gov/rules/final/ia-2333.pdf

Figure 4 also shows something about the manager skills. For example, no index as a whole saw the LTCM implosion(or Russian default), Dotcom crash or the fall in house prices coming. However, some indices were out early and some were out late. The 4 Indices that changed exposures in June, July and August 2007 were probably better off in the last crises. To be sure the weights and signs of the exposures of the earlier and later indices need to be checked. This does however not lead to some easy conclusion and no specific index is mostly early in changing exposures the right way, which is in line with the average weighted alpha values seen earlier. It should be stressed however that on fund specific basis this form of evaluation could be useful.

Month - Index	March 2005 - EHMNeutral				January 2005 - EDDisRes				March 2005 - EDMerArb				March 2005 - FoFTotal			
# significantly different factors	7	100%			4	80%			3	60%			5	71%		
	Before		After		Before		After		Before		After		Before		After	
S&P500							0,70	***			-0,03	***			-0,49	***
NASDAQ													0,09			
Rus3000			-0,08	*							-0,95					
MSEUR			-0,01	*	0,28								0,03	***		
DJEmMark			0,05	***	0,31	***					0,25	***	0,11	***	0,53	***
SMB	0,19	*			-0,04	***			0,20	***			0,08			
HML	0,02	***			0,09	*	-0,46		0,16	***			0,09	***	0,18	***
MKTRF					-0,04	***	0,22	***	0,11	***	0,11	***			-0,01	***
SPComm			0,10	***			-0,28									
SPGold							0,04						0,03		-0,19	
3MTBill			-0,01	***												
10YGBond	0,11						-0,01	***	0,02	**			-0,08			
MoodyBaa	-0,02						-0,01	***					0,01			
spr10Y3M													0,03			
spr10YBaa			-0,10	***											0,02	**
Spturn	-0,01	***														
VIX																
1mMove	-0,01				0,13	***					0,02	***			-0,06	
PTFSBD	0,01				0,01	***			-0,05	***						
PTFSFX			-0,10												0,02	
PTFSCOM									-0,03	*	0,71	*			0,06	***
PTFSIR	-0,01		0,01	**	0,01		-0,12								-0,02	***
PTFSSTK					-0,05								-0,02	***		
SPOTMC							0,05	*								
SPOTMP																

Table 6: Explanatory table changepoints in early 2005

This table shows the change in the factor and weight selection in a change point model before and after the change points that are identified in early 2005 in the return histories of 4 indices. The return data of the indices is obtained from the Hedge Fund Research database an covers the period January 1994 to March 2010.

Up till now the results discussed were mostly about the aggregate of factors or indices and not really on the importance of specific risk factors and the role they play on average within the indices. Table 7 shows how often individual factors are in the model for both models.

	TOTAL	
	CP. Mod.	C. Mod.
factor	0.003	0.004
S&P500	73%	73%
NASDAQ	27%	0%
Rus3000	27%	9%
MSEUR	73%	0%
DJEmMark	91%	55%
SMB	100%	64%
HML	82%	45%
MKTRF	100%	73%
SPComm	64%	36%
SPGold	82%	64%
3MTBill	82%	18%
10YGBond	55%	36%

	TOTAL	
	CP. Mod.	C. Mod.
Factor	0.003	0.004
spr10Y3M	45%	0%
spr10YBaa	64%	18%
Spturn	45%	18%
VIX	36%	18%
1mMove	73%	55%
PTFSBD	36%	18%
PTFSFX	55%	27%
PTFSCOM	64%	18%
PTFSIR	73%	45%
PTFSSTK	55%	27%
SPOTMC	36%	0%
SPOTMP	36%	0%

Table 7: Explanatory power of factors

This table shows for what percentage of 11 different hedge fund indices returns obtained from HFR a specific factor plays, at any time, a role in the explanation of returns.

From this table it can be seen that some factors that are never important in the constant model are important in at least one period of the change point model. However, because neither the lengths of the periods in which these factors are important or the weights are taken into account, one should be careful in reading this table. A time weighted importance can better be read from figure 5.

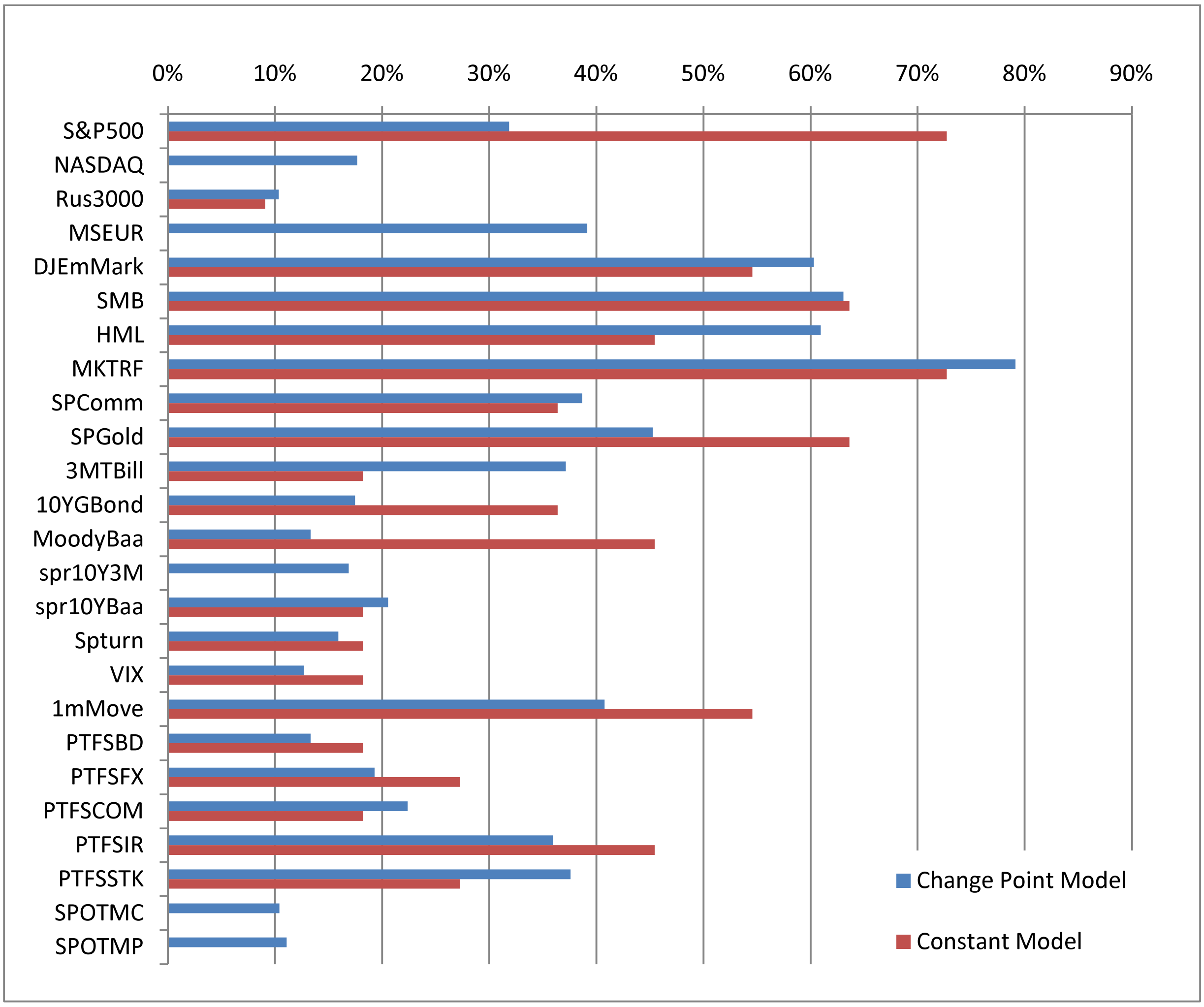

Figure 5: Time weighted importance of factors

This figure shows the average percentage of times a factor is part a change point an constant linear model. The model is fitted on the return history of 11 hedge fund indices over the period January 1994 to March 2010. The data is obtained from the HFR database.

Figure 5 shows that the S&P500 and the market excess return are the most important factors for the constant models, but the S&P500 is significantly less important for the change point models. Also interesting is that MSEUR is never used in a constant model, but is on average in 40% of the change point models. This can be said as well for the spread between 10 government bonds and the T-Bill, and the out of the money put and call option factors. It is clear that the Fama French factors Small-minus-Big, High-minus-Low and market excess return enjoy a lot of explanatory power in both models. These are however averages over the whole period. Figure 6 shows the evolution of the explanatory power of individual factors over time. From this figure it is very interesting to see that the explanatory power of the Fama French factors SMB and HML seems to decrease. Because a lot of fund evaluations are based on these factors this is an interesting finding. Also the return on an interest rate lookback straddle (PTFSIR) is gaining a lot of explanatory power over the last years. In this graph the percentages should be seen as a weight of importance not as the percentage of models it is in at a specific month.

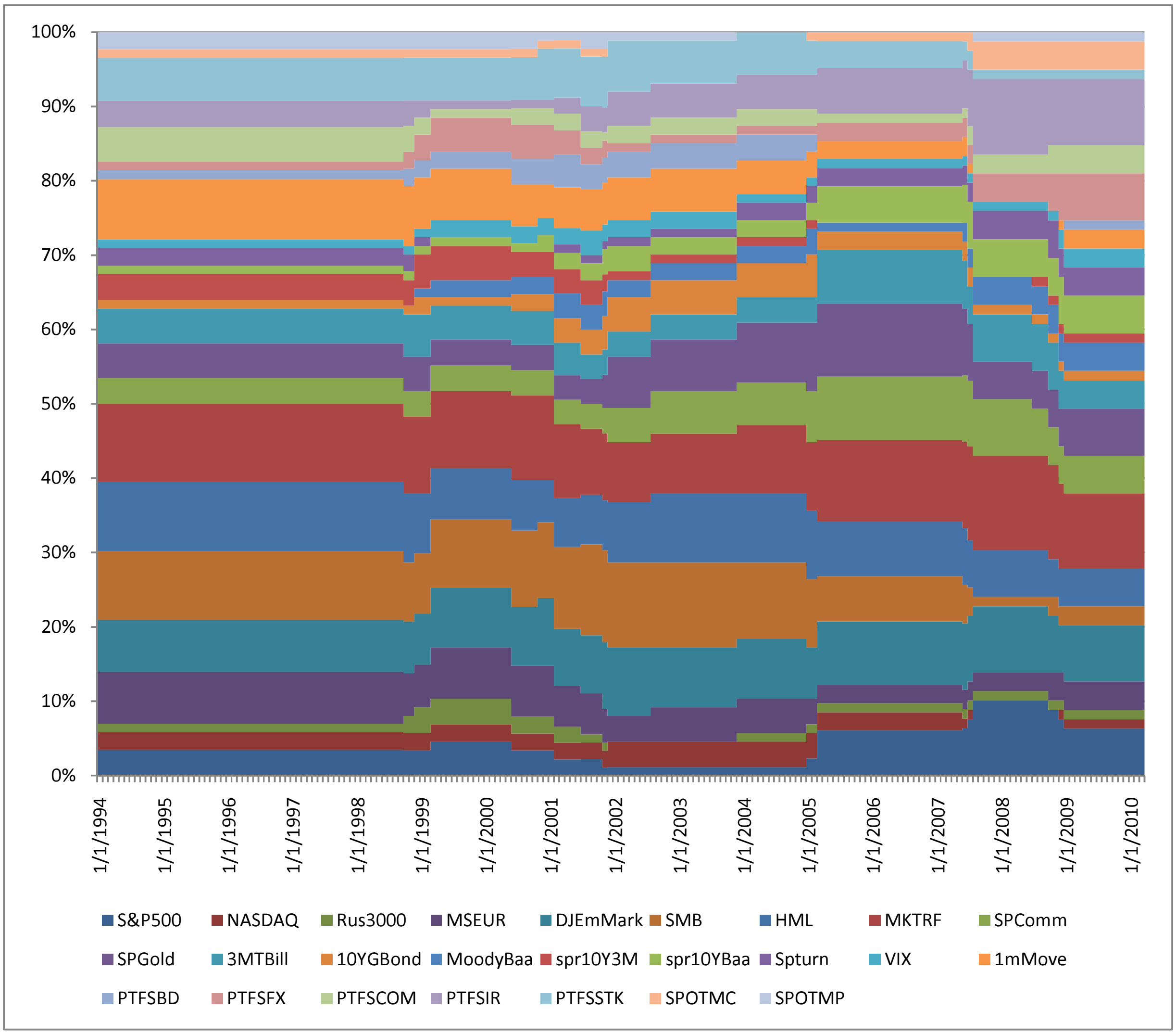

Figure 6: Evolution of the explanatory power of factors

This figure gives an indication of how much explanatory power 25 factors have relative to each other in the explanation of the returns of 11 indices from HFR over the period January 1994to March 2010. The legend respectively shows from left to right what is displayed in the graph from bottom o top.

The question remains whether something can be said about the coefficients of different factors. For all indices a short intuitive explanation will be given for the observed results. The tables with results can be found in Appendix 2.

The EH Equity Market Neutral index returns are explained best by (from most important to less important); equity(!), commodity, fixed income and, to a less extent, some non-linear factors. Interesting is the fact that not one equity factor is identified by the constant model, but 5 are by the change point model! Also the return of a lookback straddle on a short term interest rate is significant at 1% level in the constant model, but is not in the change point model. This index mostly displays negative coefficients for non linear and volatility factors, and positive coefficients for equity and fixed income factors. This implies that they are mostly receiving the risk premia involved with these products. That equity factors are among the most significant factors is interesting, however, the model is not very useful if one looks at the adjusted R^2 of 0.46 so the term neutral might still be appropriate.

The EH Quantitative Directional index returns are best explained by equity and commodity factors. Non linear factors or volatility do not seem important at any level in both models. With an adjusted R^2 of 0.94 this model has the best fit. Though the term quantitative suggests complex strategies this does not seem to be true and these funds seem mostly long in the risk of these factors. Interesting is the significant negative weight in market excess return, though this weight is only used from May 2007 on.

As expected, the EH Short Biased funds mostly display negative coefficients for equity orientated factors though the change in spread between the 10 year government bonds and Moody Baa yield seems also important. With an adjusted R^2 of 0.86 the observations are very representative.

The model for the explanation of the EH Emerging Markets index has a highly significant heavy weight in the DJ Emerging market factor, which is not detected in the constant model. Also some interest rate factors seem to have some explanatory value which can be explained by the need to hedge the foreign investments. Interesting is that only the equity orientated factors are most significant. This is probably because the markets for other products are often not very accessible yet. This index shows the biggest alpha of 0.006.

The EH Total index returns are best explained by equity and commodity orientated factors, so not only equity. In line with earlier papers equity orientated hedge fund returns can be explained relatively well with an adjusted R^2 of 0.90.

It is interesting to notice that in all equity orientated funds short and long positions in factors are seen over the period. This is what was expected because hedge funds try to hedge the general market risk and profit from some specific price irregularities. So the observation should show both negative and positive weights in the general equity factors and mostly positive weights in factors like SMB, HML and MKTRF. This is what is seen in general though it holds less in the change point model than in the constant model. Together with the observation that the Fama French factors show a decreasing explanatory power this suggests that it is becoming increasingly more difficult to find those irregularities.

For the ED Distressed & Restructuring index returns the S&P 500 and Dow Jones Emerging Market returns seem very significant with always positive weights. This can partly be explained by the fact that probabilities of recovering are higher in bull markets. The SMB factor is significant but has a small negative weight, what might be because small firms recover less than large firms. Agarwal & Naik(2004) also found a negative weight for an out of the money put option factor. This is not found in either the constant or the change point model. Volatility in short term interest rates does seem to be an important explanatory factor. This might be because price irregularities tend to be largest in volatile markets. Together with the fact that there is exposure to bond factors, these funds probably profit from distressed fixed income products in times of interest rate uncertainty.

The ED Merger Arbitrage fund shows a lot of highly significant factors, though only an adjusted R^2 of 0.62. Equity, commodity, fixed income and volatility orientated factors all have a at 1% significant factor. Most important though are the S&P 500, Russel 3000 and Fama French factors. Interesting is that from January 2009 the Dow Jones Emerging market factor also becomes important, suggesting that merger arbitrage hedge funds become more active in these markets. The relatively large number of positive weights might be explained by more merger deals succeeding in bull markets.

The Event Driven Total index returns can be explained in a similar way as the Merger Arbitrage index. Factors and weights do not really differ from the constant model.

The Relative Value Total index returns are explained, though only with 1 significant change point, a lot better by the change point model, the adjusted R^2 increases from 0.61 to 0.71. The Fama French factors seem more important, a relatively large negative weight on 3 month T-bill factor and a very large negative weight on the Fung & Hsieh portfolio of lookback straddles on interest rates factor are observed. These funds generally use a contrarian strategy, which is in line with the negative weights on the Fama French factors. The significance of the 1 month move index factor, the 3 month T-bill factor and the Fung & Hsieh interest rate factor imply that these funds probably operate a lot in interest rate markets. The large negative weights on the lookback straddle factor suggest that they suffer huge losses in times of very volatile interest rates but receive risk premia in more quite markets. Relative value funds often profit from small price anomalies by using leverage. So it can also imply that these funds are highly leveraged and are sensitive to short term interest rate changes.

The Fund of Funds index returns are also explained much better by the change point model, the adjusted R^2 increases from 0.72 to 0.86, and indeed 4 significant change points are identified. This increase comes more from the ability of the model to change weights and does not really seem to come from a very different set of factors chosen, what was the case for the previous index. Fund of funds can easily get exposure to a lot of risk factors and a relatively large amount of significant factors is indeed observed.

The Macro Total index returns are explained best by a set of equity factors that span North America, Europe and the Emerging markets. Interesting is that only positive weights are observed on the S&P 500 factor, the Dow Jones emerging markets factor and the commodity factors. Also the Fama French factors are important but the HML factor is not significant in the change point model anymore. Also two Fung & Hsieh non-linear factors are not important anymore in the change point model. The often positive weights suggest less hedging.

Overall all indices seem to have exposure to a relative large set of factors and never only positive weights are observed. Often non-linear and volatility factors are to some extent important in the explanation of returns. This all indeed suggests rather complex trading strategies and especially the significance of non-linear factors has consequences for the evaluation of performance and the involved risks.

5. IMPLICATIONS FOR RISK & PORTFOLIO MANAGEMENT

The results from the previous paragraph put serious question marks behind the traditional way of fund performance assessment for hedge funds. Both their dynamic strategies as the involvement of more complex products within their portfolios will probably cause the standard linear factor models to fail in capturing the involved risks appropriately, as will the widely used performance measures like the Sharpe ratio.

It has been observed already in the previous paragraph that the alpha in the constant model differs from the one in the more dynamic change point model. This will have consequence when selecting funds based on their alpha. See for example table 8: The emerging market index is ranked first in the change point model while it is ranked among the worst three in the constant model.

	Change Point Model		Constant Model	
1	EHEmerg	0,006	MacroTotal	0,007
2	MacroTotal	0,005	EHTotal	0,006
3	EDDisRes	0,005	EDTotal	0,004
4	RVTotal	0,004	EDMerArb	0,004
5	EDMerArb	0,003	RVTotal	0,004
6	EDTotal	0,003	EDDisRes	0,004
7	EHShortB	0,003	FoFTotal	0,003
8	EHTotal	0,003	EHQntDir	0,003
9	FoFTotal	0,001	EHEmerg	0,003
10	EHQntDir	0,001	EHShortB	0,002
11	EHMNeutral	0,001	EHMNeutral	0,002

Table 8: Index ranking on alpha

This table ranks index performance based on the intercept found in the fit of a constant and a change point linear regression model over the period January 1994 to March 2010. Return histories are obtained from the HFR database.

Because fund specific data is not available in this paper the above implications might not look that overwhelming. For a better assessment of the implications for fund ranking based on alpha see Bollen&Whaley(2009).

Probably the most widely used and taught portfolio optimization methods use a mean-variance optimization framework. These methods are however subject to some underlying assumptions, most importantly the normality of asset return distributions. This assumption is not very wrong for the return distribution of most asset classes, so the framework might work sufficiently well for not too complex portfolio constructions. However the results seen so far suggest not only more dynamic trading but also more complex portfolios. Often non-linear factors explain significant parts of the returns and the results show that hedge funds are long most risk premia. All this causes fat left tails in the return distribution implying larger losses in bear markets than assumed. Figure 7 shows evidence of a fat left tail for the Distressed & Restructuring return index.

What is also interesting about figure 7 is that it shows a risk of the trades that are often made by hedge funds that are in this index. These hedge funds take positions in for example stocks or bonds of nearly bankrupt companies. This is essentially a bet on recovery; if the company fails and goes bankrupt all is lost, if it recovers a profit is made. This is a bit like writing a put option on a company.

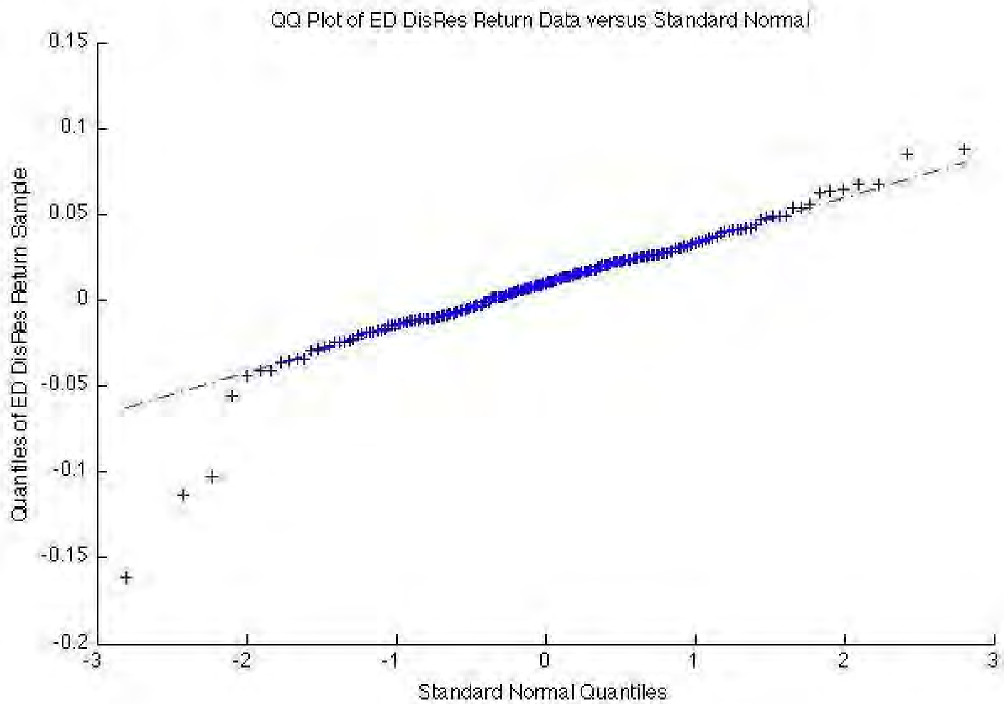

FIGURE 7: QQ-PLOT

This figure displays a quantile-quantile plot of the quantiles of the Distressed & Restructuring index returns versus theoretical quantiles from a normal distribution. If the distribution is normal, the plot will be close to linear. This plot thus gives evidence that, especially in the left tail, the distribution is not normal.

Because asset allocation based on the mean variance framework assumes a symmetrical return distribution and from the summary statistics in section 2.1 it can also be seen easily that the distributions are mostly negatively skewed, it is clear that this framework underestimates tail risk. It does not take into account the large losses in bear markets implied by the fat left tails so it is dangerous to use this framework when working with hedge funds. This is especially worrying if we consider the fact that the results of the change point model presented in figure 3 show clearly that the value of non-linear factors for the explanation of returns is increasing over the last years.

To better understand and manage the risk of a fat left tail the concept of Value at Risk (VaR) was introduced some years ago, this method gives an indication of the number of losses exceeding a certain amount(the VaR). This concept is widely used within the banking sector, but has some huge downsides. Probably the biggest downside being that it does not take into account the size of the losses exceeding the VaR. The Conditional Value at Risk (CVaR) computes the expected mean of losses exceeding the VaR, so size is taken into account. Constructing optimized portfolios based on these measures does not fit in the timeline of this paper[12]. To give some intuition table 9 shows an index ranking based on sharpe ratio, VaR and CVaR.

	Index	**σ (Sharpe Ratio)**		**Index**	**VaR**		**Index**	**CVaR**
1	EHMNeutral	0,40	**1**	RVTotal	0,38	**1**	EHMNeutral	0,20
2	EHQntDir	0,20	**2**	EDMerArb	0,32	**2**	EDMerArb	0,19
3	EHShortB	0,03	**3**	EHMNeutral	0,29	**3**	MacroTotal	0,17
4	EHEmerg	0,15	**4**	EDTotal	0,26	**4**	RVTotal	0,14
5	EHTotal	0,25	**5**	EDDisRes	0,24	**5**	EDTotal	0,13
6	EDDisRes	0,28	**6**	MacroTotal	0,24	**6**	EHTotal	0,13
7	EDMerArb	0,44	**7**	EHTotal	0,19	**7**	EDDisRes	0,12
8	EDTotal	0,30	**8**	FoFTotal	0,14	**8**	EHQntDir	0,09
9	RVTotal	0,34	**9**	EHEmerg	0,14	**9**	FoFTotal	0,09
10	FoFTotal	0,20	**10**	EHQntDir	0,13	**10**	EHEmerg	0,06
11	MacroTotal	0,31	**11**	EHShortB	0,02	**11**	EHShortB	0,01

Table 9: Index rankings using different risk criteria

This Table shows a ranking of indices based on return data obtained from Hedge Fund Research over the period January 1994 – March 2010 and three different risk measures: The standard deviation, the Value at Risk (VaR) at 5% level and the Conditional Value at Risk (CVaR) at 5% level. Figures are computed by dividing the average return by the (absolute) risk measure.

Though this table does not show the differences for portfolios optimized using the described measures it is clear that very different portfolios will be constructed.

[12] To read more about this see Alexander&Baptista(2004).

6. CONCLUSION

The hedge fund industry is already very large and still growing rapidly. Now that many investment banks become more severely regulated this growth can be expected to increase even more. With also pension funds allocating increasing amounts into these funds the need for proper risk and performance assessment becomes increasingly crucial. Because hedge funds in general do not have relative return targets as mutual funds do, but use absolute return targets, traditional performance appraisal techniques can provide misleading results. In particular the linear regression model that assumes constant coefficients over an entire period does not suffice with the dynamic trading character that most hedge funds display.

This paper tries to capture and prove this dynamic trading by the use of an optimal change point model that searches for discrete months in which factor exposures or their coefficients change. The data used in this model are the return histories of 11 hedge fund indices over the period January 1994 to March 2010, obtained from the Hedge fund Research Database. The independent variables are categorized in five groups: Equity, Commodities, Fixed income, Liquidity & Volatility and Non linear. The results show clearly that the exposures change significantly over the period. Similar change point periods are observed as in earlier papers and, due to the increased freedom of the model used in this paper, an additional period at the start of 2005, is identified.

On average the model is able to explain an additional 10% of the variation in returns. Equity orientated risk factors are most important, though it is interesting to see that their explanatory power is decreasing. Non-linear factors seem to become increasingly more important. The Fama French SMB and HML factors are also becoming less valuable as explanatory factors, suggesting that it becomes harder to profit from well known price irregularities.

Several implications of these findings for risk and portfolio management are given. Firstly, the use of a regression model that assumes constant coefficients when risk factors and their coefficients are time varying will provide misleading performance measures. The expensive alpha, known as skill, will be unreliable and often lower than found with a constant model. Secondly, the importance of non-linear factors in the explanation of the returns cause the return distribution to become asymmetrical, often displaying fat left tails. This will cause the traditional mean-variance framework to fail in optimizing portfolio constructions. Also evidence for return smoothing is found, this will cause traditional performance measures as the Sharpe ratio to be positively biased.

Overall the paper proves that the used change point model can provide more reliable information and can be of value in the performance and risk appraisal of hedge funds. Understanding the risk of the hedge fund industry is important and though research is more difficult due to the light regulations and, consequently, limited information, the methods used in this paper seem useful.

REMARKS

All data, results and methods used in this paper are available for evaluation and reuse:

The factor data can be found at http://www.few.vu.nl/~jgk600/MatLab_Dataset_Factors.xls

The return data can be found at http://www.few.vu.nl/~jgk600/MatLab_Dataset_Returns.xls

The change point model MatLab code at http://www.few.vu.nl/~jgk600/fitChangePoint.m

The results can be found at http://www.few.vu.nl/~jgk600/results.xlsm

Appendices

Appendix 1 – Broad definition of strategies[13]

Equity Hedge

Equity Hedge strategies maintain positions both long and short in primarily equity and equity derivative securities. It can be subdivided into 7 sub-strategies:

Equity Market Neutral strategies employ sophisticated quantitative techniques of analyzing price data to ascertain information about future price movement and relationships between securities, select securities for purchase and sale. Equity Market Neutral Strategies typically maintain characteristic net equity market exposure no greater than 10% long or short.

Fundamental Growth or Value strategies employ analytical techniques in which the investment thesis is predicated on assessment of the valuation characteristics on the underlying companies. Growth focuses more on which are expected to have prospects for earnings growth and capital appreciation exceeding those of the broader equity market whereas Value managers determine which are inexpensive and undervalued when compared with relevant benchmarks.

Quantitative Directional strategies employ sophisticated quantitative techniques of analyzing price data to ascertain information about future price movement and relationships between securities, select securities for purchase and sale. The often heard of statistical arbitrage and high frequency trading categories often fall into this category.

Sector strategies employ investment processes designed to identify opportunities in securities in specific niche areas of the market in which the Manager maintains a level of expertise which exceeds that of a market generalist.

Short-Biased strategies employ analytical techniques in which the investment thesis is predicated on assessment of the valuation characteristics on the underlying companies with the goal of identifying overvalued companies. They are going against the trend as stock markets move up on average and therefore often underperform. However they can have diversification benefits for the investor.

Equity Hedge: Multi-Strategy uses a combination of the above to arrive at investment decisions.

Event Driven

Event Driven investment managers maintain positions in companies, currently or prospectively involved in corporate transactions of a wide variety, based on market anomalies. Investment theses are typically predicated on fundamental characteristics (as opposed to quantitative), with the realization of the thesis predicated on a specific development exogenous to the existing capital structure. Sub categories are:

Activist strategies may obtain or attempt to obtain representation of the company's board of directors to employ an investment process primarily focused on opportunities in equity and equity related instruments of companies which are currently or prospectively engaged in a corporate transaction, security issuance/repurchase, asset sales, division spin-off or other catalyst oriented situation.

[13] Source: Hedge fund research

Credit Arbitrage Strategies employ an investment process designed to isolate attractive opportunities in mostly corporate fixed income securities.

Distressed Restructuring strategies employ an investment process focused on corporate fixed income instruments, primarily on corporate credit instruments of companies trading at significant discounts to their value at issuance or obliged (par value) at maturity.

Merger Arbitrage strategies employ an investment process primarily focused on opportunities in equity and equity related instruments of companies which are currently engaged in a corporate transaction.

Private Issue/Regulation D strategies employ an investment process primarily focused on opportunities in equity and equity related instruments of companies which are primarily private and illiquid in nature.

Special Situations strategies employ an investment process primarily focused on opportunities in equity and equity related instruments of companies which are currently engaged in a corporate transaction, security issuance/repurchase, asset sales, division spin-off or other catalyst oriented situation.

Event-Driven: Multi-Strategy uses a combination of the above to arrive at investment decisions.

Macro

Macro investment managers trade a broad range of strategies in which the investment process is predicated on movements in underlying economic variables and the impact these have on equity, fixed income, hard currency and commodity markets. Sub categories are:

Active Trading strategies utilize active trading methods, typically with high frequency position turnover or leverage; these may employ components of both Discretionary and Systematic Macro strategies. Strategies may contain distinct, identifiable sub-strategies, such as equity hedge or equity market neutral, or in some cases a number of sub-strategies are blended together.

Commodity strategies are reliant on the evaluation of market data, relationships and influences as they pertain primarily to specific sectors, i.e. agriculture, energy and metals, or can adopt a macro form include both discretionary and systematic strategies in multiple sectors. Systematic commodity have investment processes typically as function of mathematical, algorithmic and technical models, with little or no influence of individuals over the portfolio positioning. Discretionary Commodity strategies are reliant on the fundamental evaluation of market data, relationships and outside influences.

Currency: Discretionary strategies are reliant on the fundamental evaluation of market data, relationships and influences as they pertain primarily to currency markets including positions in global foreign exchange markets, both listed and unlisted, and as interpreted by an individual or group of individuals who make decisions on portfolio positions. Systematic strategies have investment processes typically as function of mathematical, algorithmic and technical models, with little or no influence of individuals over the portfolio positioning.

Discretionary Thematic strategies are primarily reliant on the evaluation of market data, relationships and influences, as interpreted by an individual or group of individuals who make decisions on portfolio positions; strategies employ an investment process most heavily influenced by top down analysis of macroeconomic variables.

Systematic Diversified strategies have investment processes typically as function of mathematical, algorithmic and technical models, with little or no influence of individuals over the portfolio positioning. Strategies which employ an investment process designed to identify opportunities in markets exhibiting trending or momentum characteristics across individual instruments or asset classes.

Macro: Multi-Strategy strategies use a mix of the above.

Relative Value

Relative Value investment managers maintain positions in which the investment thesis is predicated on realization of a valuation discrepancy in the relationship between multiple securities. Managers employ a variety of fundamental and quantitative techniques to establish investment theses. It can be subdivided into 6 sub-strategies:

Fixed Income - Asset Backed includes strategies in which the investment thesis is predicated on realization of a spread between related instruments in which one or multiple components of the spread is a fixed income instrument backed physical collateral or other financial obligations (loans, credit cards) other than those of a specific corporation.

Fixed Income - Convertible Arbitrage includes strategies employ an investment process designed to isolate attractive opportunities between the price of a convertible security and the price of a non-convertible security, typically of the same issuer.

Fixed Income - Corporate includes strategies in which the investment thesis is predicated on realization of a spread between related instruments in which one or multiple components of the spread is a corporate fixed income instrument.

Fixed Income - Sovereign includes strategies in which the investment thesis is predicated on realization of a spread between related instruments in which one or multiple components of the spread is a sovereign fixed income instrument.

Volatility strategies trade volatility as an asset class, employing arbitrage, directional, market neutral or a mix of types of strategies, and include exposures which can be long, short, neutral or variable to the direction of implied volatility, and can include both listed and unlisted instruments.

Yield Alternatives Energy infrastructure or Real Estate strategies employ an investment thesis which is predicated on realization of a valuation differential between related instruments in which one or multiple components of the spread contains exposure to energy Infrastructure or real estate.

Relative Value: Multi-Strategies employ a combination of the above.

Fund of Funds

Fund of Funds invest with multiple managers through funds or managed accounts. The strategy designs a diversified portfolio of managers with the objective of significantly lowering the risk (volatility) of investing with an individual manager.

Conservative strategies seek consistent returns by primarily investing in funds that generally engage in more "conservative" strategies.

Diversified strategies invest in a variety of strategies among multiple managers.

Market Defensive strategies invest in funds that generally engage in short-biased strategies such as short selling and managed futures.

Strategic strategies seek superior returns by primarily investing in funds that generally engage in more opportunistic strategies such as Emerging Markets, Sector specific, and Equity Hedge.

APPENDIX 2 – MODEL RESULTS

	index 9	RVTotal						index 10	FoFTotal						index 11	MacroTotal					
#changepoints	1	Changepoint M.			Constant M.			4	Changepoint M.			Constant M.			2	Changepoint M.			Constant M.		
adj R-Squared	0,709				0,613			0,858				0,717			0,592				0,447		
alpha(weighted)	0,004				0,004			0,001				0,003			0,005				0,007		
		Weight				Weight			Weight				Weight			Weight				Weight	
		MIN	MAX						MIN	MAX						MIN	MAX				
S&P500	1		0,617	***	1	0,372	***	1		0,613	***	1	0,424	***	1		0,380	**	1	0,372	***
NASDAQ	1		0,284		0			1	-0,235	0,093		0			0				0		
Rus3000	0				0			1		0,200	***	0			0				0		
MSEUR	1		0,105	***	0			1		0,703	*	0			1		0,121	***	0		
DJEmMark	0				0			1	-0,061	0,146	**	1	0,124	***	1	-0,339	0,190	***	1	0,055	***
SMB	1	-0,027		***	0			1	-0,651	0,291	*	1	-0,312	**	1		0,093	***	0		
HML	1	-0,222	0,109	***	0			1		0,085	**	1	-0,028	***	1		0,562		0		
MKTRF	1	-0,350		***	1	-0,230	***	1		0,176	***	1	-0,016	***	1	-0,049	0,115		1	-0,308	***
SPComm	1	-0,036	0,017		1	-0,241	*	0				1	-0,105	**	1		0,044	**	0		
SPGold	1		0,042		1	0,103	***	1	-0,376	0,034		0			1		0,031		1	0,036	***
3MTBill	1	-0,233		***	1	-0,023	***	1	-0,019		***	0			1		0,028		0		
10YGBond	0				1	0,063	***	1	-0,084	0,043		0			1		0,031	***	1	0,025	***
MoodyBaa	1	-0,005		*	1	0,010	***	1		0,182		1	0,025	*	1	-0,465			0		
spr10Y3M	0				0			1	-0,354	0,033		0			1		0,253		0		
spr10YBaa	1		0,021		0			1	-0,154		***	0			0				0		
Spturn	0				0			1		0,337		0			1	-0,035			0		
VIX	0				0			1		0,052	***	0			1	-0,169	0,100		1	0,095	**
1mMove	1	-0,010		***	1	-0,008	***	1		0,065		1	0,026	***	0				0		
PTFSBD	0				0			0				0			0				0		
PTFSFX	0				0			1		0,004		1	0,039	*	1		0,225	**	1	-0,071	***
PTFSCOM	0				0			1	-0,174		***	1	0,071	***	1	-0,027			1	0,082	***
PTFSIR	1	-1,663		*	1	0,032	*	1	-0,032	0,031		1	-0,081	***	1		0,188		1	-0,027	*
PTFSSTK	0				0			1	-0,019	1,211	***	1	0,012	***	1	-0,152		**	1	-0,011	***
SPOTMC	1		1,666		0			1	-1,180	0,032		0			0				0		
SPOTMP	1		0,058		0			1	-0,026	0,060		0			0				0		

This table shows the importance of the factors used to explain the return history of 11 hedge fund return indices. The return histories are obtained from the Hedge Fund Research database and span the period January 1994 – March 2010. The results are shown both for a change point and for a constant linear model. Behind the minimum and maximum weight observed over the period the average significance of the factor is displayed; *, **, *** meaning significant at respectively 5%, 2.% and 1% level.

	index 5	EHTotal						index 6	EDDisRes					
#changepoints	2	Changepoint M.			Constant M.			1	Changepoint M.			Constant M.		
adj R-Squared	0,896				0,848			0,730				0,667		
alpha(weighted)	0,003				0,006			0,005				0,004		
		Weight				Weight			Weight				Weight	
		MIN	MAX						MIN	MAX				
S&P500	1		1,041	***	1	0,686	***	1		0,698	***	0		
NASDAQ	0				0			0				0		
Rus3000	0				0			0				1	0,452	***
MSEUR	1	-0,029	0,267	**	0			1		0,279		0		
DJEmMark	1		0,492	***	1	0,207	*	1		0,306	***	1	-0,277	***
SMB	1	-0,470	0,269	***	1	-0,177	***	1	-0,037		***	1	0,168	***
HML	0				1	0,063	***	1	-0,461	0,092		0		
MKTRF	1	-0,385	0,093	***	0			1	-0,038	0,221	***	1	0,144	***
SPComm	1		0,146	*	1	0,032	***	1	-0,284		**	0		
SPGold	1		0,031	***	1	-0,207		1		0,041		1	-0,285	*
3MTBill	1	-0,217	0,020		0			0				0		
10YGBond	1	-0,018			0			1	-0,008		***	1	0,086	***
MoodyBaa	0				0			1	-0,010		***	1	-0,028	***
spr10Y3M	1	-0,079			0			0				0		
spr10YBaa	1	-0,051	0,015		0			0				0		
Spturn	1	-0,009		***	1	-0,011	**	0				0		
VIX	1		0,016		0			0				0		
1mMove	0				0			1		0,128	***	1	-0,022	**
PTFSBD	0				0			1		0,010	***	1	0,058	***
PTFSFX	1		0,005		0			0				0		
PTFSCOM	1		0,012		0			0				0		
PTFSIR	1		0,026		1	-0,015	***	1	-0,117	0,012		0		
PTFSSTK	1	-0,002	0,026		1	0,047	***	1	-0,052			0		
SPOTMC	0				0			1		0,048	*	0		
SPOTMP	0				0			0				0		

	index 7	EDMerArb						index 8	EDTotal					
#changepoints	3	Changepoint M.			Constant M.			1	Changepoint M.			Constant M.		
adj R-Squared	0,620				0,449			0,814				0,769		
alpha(weighted)	0,003				0,004			0,003				0,004		
		Weight				Weight			Weight				Weight	
		MIN	MAX						MIN	MAX				
S&P500	1		1,291	***	0			1		0,515	***	1	0,530	***
NASDAQ	0				0			0				0		
Rus3000	1	-1,114		***	0			0				0		
MSEUR	0				0			0				0		
DJEmMark	1		0,056	***	0			1	-0,408	0,451	***	1	0,178	***
SMB	1		0,198	***	1	0,158	***	1		0,286	***	1	0,081	***
HML	1		0,158	***	0			1		0,151	***	0		
MKTRF	1	-0,449	0,113	***	1	-0,024	***	1	-0,101		***	1	-0,201	***
SPComm	0				0			0				0		
SPGold	1		0,037	***	1	0,066	**	1	-0,023			1	-0,023	**
3MTBill	1	-0,042		***	0			1		0,058	*	0		
10YGBond	1		0,019	**	0			0				0		
MoodyBaa	0				0			0				1	0,060	*
spr10Y3M	1	-0,040		***	0			0				0		
spr10YBaa	1	-0,094		***	0			1		0,169	***	0		
Spturn	0				1	0,045	**	0				0		
VIX	0				0			0				0		
1mMove	1	-0,087	0,116	***	1	-0,011	***	1	-0,036		***	1	-0,083	***
PTFSBD	1	-0,046		***	0			0				0		
PTFSFX	1		0,018		0			0				0		
PTFSCOM	1	-0,029		*	0			1	-0,014			0		
PTFSIR	0				0			1		0,027	**	0		
PTFSSTK	0				0			0				0		
SPOTMC	0				0			1	-0,009			0		
SPOTMP	0				0			0				0		

This table shows the importance of the factors used to explain the return history of 11 hedge fund return indices. The return histories are obtained from the Hedge Fund Research database and span the period January 1994 – March 2010. The results are shown both for a change point and for a constant linear model. Behind the minimum and maximum weight observed over the period the average significance of the factor is displayed; *, **, *** meaning significant at respectively 5%, 2.% and 1% level.

	index 1	EHMNeutral						index 2	EHQntDir					
#changepoints	3	Changepoint M.			Constant M.			2	Changepoint M.			Constant M.		
adj R-Squared	0,460				0,124			0,938				0,909		
alpha(weighted)	0,001				0,002			0,001				0,003		
		Weight				Weight			Weight				Weight	
		MIN	MAX						MIN	MAX				
S&P500	1	-0,119	0,172	**	0			0				1	0,870	*
NASDAQ	0				0			1		0,882		0		
Rus3000	0				0			0				0		
MSEUR	1	-0,096	0,247	***	0			0				0		
DJEmMark	1	-0,073	0,059	***	0			1		0,451		1	0,300	***
SMB	1	-0,007	0,188		0			1		0,058	***	1	-0,252	***
HML	1	-0,010	0,017	*	0			1	-0,108	0,309	**	1	-0,218	***
MKTRF	1		0,016	***	0			1	-0,514	0,040	***	1	0,286	***
SPComm	1	-0,035		***	1	-0,009	**	1	-0,037	0,210	**	0		
SPGold	0				0			1		0,038	***	1	-0,086	**
3MTBill	1	-0,049	0,076	***	1	-0,007	**	1		0,012	*	0		
10YGBond	1		0,112		0			0				1	0,061	***
MoodyBaa	1	-0,019			0			1	-0,086	0,276	*	1	0,056	***
spr10Y3M	0				0			1		0,054	*	0		
spr10YBaa	1	-0,159		***	0			0				1	-0,131	***
Spturn	1	-0,014	0,019		0			0				0		
VIX	0				0			0				0		
1mMove	1	-0,010			0			0				0		
PTFSBD	1		0,014		1	0,012	*	0				0		
PTFSFX	1	-0,181		*	1	0,033	**	0				0		
PTFSCOM	1		0,006	*	0			0				0		
PTFSIR	1	-0,100			1	-0,013	***	0				0		
PTFSSTK	0				0			1	-0,010			0		
SPOTMC	0				0			0				0		
SPOTMP	0				0			0				0		

	index 3	EHShortB						index 4	EHEmerg					
#changepoints	2	Changepoint M.			Constant M.			3	Changepoint M.			Constant M.		
adj R-Squared	0,862				0,824			0,870				0,755		
alpha(weighted)	0,003				0,002			0,006				0,003		
		Weight				Weight			Weight				Weight	
		MIN	MAX						MIN	MAX				
S&P500	0				1	-1,111	*	0				1	0,519	***
NASDAQ	0				0			0				0		
Rus3000	0				0			1		0,521	***	0		
MSEUR	1	-0,886		***	0			1		0,681		0		
DJEmMark	1	-1,303		**	0			1	-0,459	1,745	***	0		
SMB	1	-1,143		***	1	0,487	***	1		0,362	*	0		
HML	1	-0,502	0,067		1	-0,455	***	0				1	0,628	**
MKTRF	1		0,613	***	0			1	-1,601	0,065	*	1	-0,071	***
SPComm	1		0,084	***	0			0				0		
SPGold	0				0			1		0,354		0		
3MTBill	0				0			1	-0,098			0		
10YGBond	0				0			0				0		
MoodyBaa	0				0			0				0		
spr10Y3M	0				0			0				0		
spr10YBaa	1		0,225	***	1	0,209	*	0				0		
Spturn	0				0			1		0,064		0		
VIX	0				0			1		0,238		1	-0,537	**
1mMove	1	-0,035			0			1	-0,392	0,059	*	1	0,034	***
PTFSBD	0				0			1	-0,123			0		
PTFSFX	0				0			1		0,044		0		
PTFSCOM	0				0			1		0,382		0		
PTFSIR	0				0			1	-0,035			0		
PTFSSTK	1	-0,081		**	0			0				0		
SPOTMC	0				0			0				0		
SPOTMP	1		0,004		0			1		0,037	**	0		

This table shows the importance of the factors used to explain the return history of 11 hedge fund return indices. The return histories are obtained from the Hedge Fund Research database and span the period January 1994 – March 2010. The results are shown both for a change point and for a constant linear model. Behind the minimum and maximum weight observed over the period the average significance of the factor is displayed; *, **, *** meaning significant at respectively 5%, 2.% and 1% level.

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