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Time-variation in hedge fund risk exposures

A behavioural finance approach

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Abstract

Time-variation in hedge fund risk exposures is assessed in a behavioural setup with a methodology based on the heterogeneous agents literature. The sample consists of six hedge fund style index returns. The results indicate that global/macro and short bias hedge funds display significant time-varying behaviour. Some indication of time-varying behaviour is also found for equity market neutral and event driven managers.

Keywords: hedge funds, style analysis, risk profile, dynamic models, time-variation.

JEL-classification: G23

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1 Introduction

The hedge fund industry has received a lot of attention both inside and outside the academic world. The attack of George Soros' Quantum Fund on the pound sterling in 1992 and the collapse of Long-Term Capital Management as a consequence of the Russian debt crisis in 1998 heightened the public and academic interest in hedge funds. During the past decade, hedge funds also have attracted more attention because they ever more attempt to influence the organisational, financial and operational activities of corporations by means of shareholder activism. Just one example of this is hedge fund TCI Fund Management demanding a breakup of Dutch bank ABN AMRO in 2007.

Hedge funds are largely unregulated. They are able to create leverage, use derivatives and short positions. Their investment strategies are therefore typically very dynamic in nature. This circumstance makes it very likely that the risk exposures of hedge funds are not stable over time. For purposes of portfolio construction, risk management and performance evaluation it is very important to have a good understanding of hedge fund risk profiles. Previous studies have indicated that models assuming a linear relationship between risks factors and hedge fund returns indeed do not perform very well. This study is aimed at finding time-variation in hedge fund risk exposures. There has not been a lot of research explicitly concerned with such time-variation. The results of these few studies indeed suggest that the risk exposures of hedge funds depend on the investigated time frame. This is the first study that finds results using a dynamic model in which risk exposures are allowed to change on a month-to-month basis. This involves a maximum likelihood estimation in a behavioural framework.

The model finds significant and robust time-variation in the risk exposures of the global/macro and short bias hedge fund styles. This study provides evidence that hedge fund managers of these styles change their strategies on the basis of their performance relative to the performance of alternative strategies. The changes are both statistically and economically significant. These results are robust since similar results are found in two datasets from two different data vendors.

This thesis is as organised follows. Chapter 2 gives a general introduction by treating the characteristics of hedge funds. Previous literature closely related to this study is described in Chapter 3. In Chapter 4 the data and methodology of this study are developed. Chapter 5 elaborates on the estimation results. Chapter 6 provides a summary and conclusions.

2 Introduction to hedge funds

The literature on hedge funds is quite young. The hedge fund industry boomed at the beginning of the 1990s and the first literature on this topic arrived by the end of that decade. Before going into the details of this study, or even treating previous literature on that subject, it is necessary to have some understanding of what hedge funds are and what they do. This chapter aims to give a general introduction into the nature of hedge funds and hedge fund research.

Section 2.1 discusses the characteristics of hedge funds in order to understand the differences between hedge funds and other investment vehicles. After this general introduction, Section 2.2 discusses the data issues that are typical in hedge fund research. It is crucial to have some understanding of these problems when conducting any kind of study in this field. Section 2.3 highlights the most important statistical properties of hedge fund returns. Section 2.4 is concerned with the performance of hedge funds. To conclude, Section 2.5 treats the influence of management performance incentives on hedge fund behaviour.

2.1 What characterizes a hedge fund?

A hedge fund can be defined as a pooled investment vehicle that is privately organized, administered by professional investment managers, and not widely available to the general investing public. This definition can be found in Amin and Kat (2003) and Brooks and Kat (2002). More traditional and commonly known investment vehicles are mutual funds and pension funds. There are some typical aspects of hedge funds, however, which make them significantly different.

The first and foremost difference between hedge funds and other investment vehicles, is that hedge funds are largely unregulated.[1] Mutual funds are the most common type of public investment company. In the U.S., all public investment companies are required to register with the Securities and Exchange Commission (SEC). All registered companies have to disclose their holdings to the SEC in accordance with the Securities Act 1933. In order to be exempt from the registration requirement, a hedge fund has to make sure not to cross the maximum of 35 “non-accredited” investors. Accredited investors are mostly banks, other institutional investors and wealthy individuals. Additionally, hedge funds have to place their shares privately and so cannot make public offerings. Moreover, most U.S. investment companies are limited in their use of derivatives, borrowing and short selling by the Investment Company Act 1940. This Act enables the SEC to regulate the mutual fund industry. In order to bypass this regulation, hedge funds may only accept a maximum of 99 investors (or 499

[1] For more detailed information on the regulatory environment of hedge funds: see Stulz (2007) and Fung and Hsieh (1999b).

provided that each investor has over US$ 5 million in investment assets). Again, public offerings are not allowed. By avoiding the strict SEC regulations, hedge funds enable themselves to apply leverage, trade in derivatives and short sell securities with very few legal limitations. Hedge funds are therefore characterized by flexible investment strategies, instead of the more traditional non-leveraged, long-only strategies that mutual funds generally follow.

Secondly, hedge funds are characterized by strong performance incentives. This is shown by Kouwenberg and Ziemba (2007). In general, mutual funds remunerate their managers by rewarding a management fee as a percentage of assets under management. Hedge fund managers earn performance based ("incentive") fees in addition to a fixed one. These incentive fees are usually asymmetric in nature, which means that the managers will receive rewards when performing well, but they do not have to rebate the fees once they perform badly. Incentive fees are usually paid only for returns beyond a "hurdle rate", however. This hurdle rate is mostly the LIBOR rate. Moreover, the incentive fees are not paid until accumulated profits pass a "high-water mark", which means that no incentive fee will be paid until past losses are recovered. The incentive fees of hedge fund managers was estimated at an average 20 percent of the annual profits by Kouwenberg and Ziemba (2007). Ackermann, McEnally and Ravenscraft (1999) have estimated it at 14 percent. The fixed component amounts to approximately 1 percent of assets under management.

The ability to employ flexible investment strategies enables hedge funds to take advantage of market inefficiencies that mutual funds cannot. For instance, having the possibility of short-selling, hedge funds have the ability to buy undervalued assets and sell overvalued assets short. Hedged strategies like this one are said to be market neutral, which means its success is largely independent of overall market conditions. As a consequence, hedge funds claim to offer *absolute returns*. They advertise to earn high returns regardless of market conditions. The term "hedge funds" indeed originated from these kind of strategies. Many authors, such as Stulz (2007) and Fung and Hsieh (2004a), refer to Alfred W. Jones, who is believed to have started the first ever hedge fund in 1949. His hedge fund pursued a strategy which involved hedging market risks by buying and shorting stocks simultaneously.

By contrast, mutual funds measure their performance relative to certain benchmarks, such as the S&P 500 index. This makes sense, since an index is some weighted average of the market that is relevant to the manager. Therefore, as Sharpe (1992) already noted, comparing a manager's performance to a benchmark index is a means of comparison between one manager and all the other managers in the market. Mutual fund managers either try to track or outperform these benchmarks, which is referred to as passive management and active management, respectively. Mutual fund managers cannot exploit market inefficiencies as well as hedge fund managers can, since mutual funds are limited in their use of derivatives and short selling.

Hedge funds employ various kinds of trading styles to obtain their "absolute return" target. Trading style refers to the exposures that hedge funds create to certain asset classes. It is about their asset allocation decision, their "location choice". Trading styles are also characterized by the trading strategy that hedge funds employ. Usually, this involves short selling, derivative trading and leverage. The classification of hedge funds into trading styles is done in a kind of arbitrary way, since hedge fund classify themselves or are classified by data vendors on the basis of their prospectus. Nor is there a fixed number of trading styles. Because of its use in the hedge fund industry and research, the classifications will also be used in this study.[2]

The observation that hedge funds engage in hedged, market neutral strategies, may give the impression that an investment in hedge funds has a relatively low risk compared to other investment possibilities. It needs to be stressed, however, that even with hedged positions to the equity or bond market, hedge funds are yet exposed to other kinds of risks. For instance, in event driven trading styles, hedge funds run the risk that no event will take place after all. In fixed income arbitrage trading styles, credit risk and duration risk are the major exposures.

Moreover, Chan, Getmansky, Haas en Lo (2005) have established that nowadays, many hedge funds have engaged in taking speculative positions by employing directional strategies. When a hedge fund manager adopts a directional strategy as opposed to a non-directional strategy, he is exposed to broad market movements. This means that hedge funds can no longer be identified by their "long/short" arbitrage positions, but rather by their exemptions from regulations and manager compensation structures.

Since hedge funds are unregulated and therefore not obliged to disclose information on achieved returns and assets under management, it is quite hard to correctly estimate the total size of the hedge fund industry. However, all estimates point in the direction of an immense growth in assets under management since the beginning of the 1990s. According to various studies, such as Malkiel and Saha (2005), the estimated total value of assets under management amounted to $50 billion around 1990. Comparing various estimates, a recent AIMA report[3] concludes that the total value of assets under management in the global hedge fund industry has risen from $400 billion in 2000 to $2.5 trillion by November 2008. This is still much less than the assets managed by pension funds and mutual funds, each accounting for a share of just over $20 trillion. The largest 100 hedge funds accounted for more than three-quarters of the total assets under management in 2007.

[2] See Appendix A for the definitions of the various trading styles that are mentioned in this study.
[3] AIMA's Roadmap to hedge funds, November 2008.

2.2 Data issues in hedge fund research

Mutual funds are required to report their net asset value on a daily basis to the Investment Company Institute. Therefore, vast amounts of historical data about securities and mutual funds are available to the investment community. This is especially true for the case of the United States. In contrast, hedge funds are privately organized entities and are therefore not obliged to disclose information to the public.[4] All information we have on hedge fund returns and trading styles is voluntarily provided by hedge funds to data vendors. This gives rise to some problems regarding the reliability of data used in academic studies such as this one.

In order to draw valid conclusions on hedge fund performance, risk exposures, portfolio value and so on, it is necessary to obtain reliable data. It is therefore important to recognize and deal with the irregularities in hedge fund data samples. This Section will discuss the literature that is concerned with potential measurement biases that occur in hedge funds data.

2.2.1 Survivorship bias

Survivorship bias refers to the distortion that occurs because a sample of hedge fund returns does not contain the results of funds that have terminated operations at the end of the sampling period. Survivorship bias is not only inherent to hedge fund data series, but is also present in mutual fund data. The issue is of more importance to hedge funds, however, because of the higher degree of termination in the hedge fund industry compared to the mutual fund industry. Amin and Kat (2002) report that 40.5 percent of hedge funds in 1998 are not around anymore by the year 2003. In 2000, only 87.7 percent of hedge funds made it through their first year. Since survivorship bias presumably stems from the exclusion of funds with a bad performance, returns in hedge fund return data are biased upward and risk is biased downward.

Earlier studies have tried to measure the survivorship bias that is present in mutual fund data. This is done by comparing the returns of the sample in question with a sample containing the returns of all mutual funds that operated during that period. Brown et al. (1992) and Malkiel (1995) have estimated the yearly bias to be in the range of 0.5 to 1.4 percentage points. In other words, the average mutual fund return is about 0.5 to 1.4 percentage points lower when considering the entire universe of mutual funds instead of only the surviving ones.

[4] See Section 2.1.

It needs to be pointed out that it is much harder to estimate survivorship bias correctly in hedge fund data, because we do not know the universe of hedge funds. This, of course, is due to the fact that hedge funds are privately organized. Survivorship bias has to be estimated by using the databases at hand, which gives rise to a couple of new issues. In the first place, data vendors do not have information on defunct funds that terminated their operations before 1994. This means that survivorship bias before 1994 cannot be assessed with any degree of certainty. Secondly, funds that are defunct from a hedge fund dataset are not necessarily dead (in the sense that they terminated operations). It can also be the case that a defunct funds has chosen to stop reporting or that is delisted by the data vendor. An estimation of the survivorship bias by calculating the difference between the returns of the "surviving portfolio" and "observed portfolio" as Fung and Hsieh (2002) call it, may therefore be somewhat inaccurate. It includes a portion of self-selection bias as well.[5]

Brown, Goetzmann and Ibbotson (1999) and Fung and Hsieh (2000) report a 3 percentage points bias in the Tass database. Liang (2000) reports a 2 percentage points bias in the Tass database and 0.6 percentage points bias in the HFR database. Amin and Kat (2002) report a 2 percentage points bias in the Tass database.

2.2.2 Self-selection and backfill bias

Self-selection bias occurs because of the voluntary reporting by hedge funds. For different reasons, funds may choose to stop reporting or not to report at all. Underperforming funds may want to hide their bad results as this could lead to investors withdrawing their money or stop the inflow of capital. Outperforming funds may want to showcase their performance instead. On the other hand, outperforming funds may want to keep their strategies hidden when they are not looking to attract new capital. Therefore it cannot be said whether self-selection leads to an upward or downward bias in a sample.

Again, the issue in estimating the bias is that we do not know the universe of hedge funds. The estimation of self-selection bias is even more complicated than the estimation of survivorship bias. In estimating the survivorship bias, it was still possible to include returns of funds that were defunct, even though defunct funds may have been funds that survived after all. It is impossible to add returns of hedge funds that never reported to a data sample, however. Nor is it possible to add the returns of hedge funds they realised after they were delisted or had stopped reporting.

[5] See Section 2.2.2.

Hedge funds have the ability to start and stop reporting whenever they wish. Moreover, data vendors allow hedge funds to backfill their data to show their track record. It is natural to assume that especially hedge funds with a good track record will backfill their return data in order to showcase it to investors. Funds with a bad track record will not backfill since it might reduce capital inflow or cause reputation damage. This phenomenon of backfilling is therefore likely to bias the returns in hedge fund data samples upward, which can lead to overestimation of hedge fund performance. Since backfill bias is a consequence of voluntary choice by hedge funds, it can be classified as a subcategory of self-selection biases.

Backfill bias is estimated by many authors. One way to eliminate backfill bias is by assuming that all funds have a certain amount of backfilled returns. The first two years of reported data from a hedge fund are removed from the sample. The backfill bias is then estimated by comparing the average return of the original sample with the adjusted sample. In doing so, Ackermann, McEnally and Ravenscraft (1999), Fung and Hsieh (2000) and Edwards and Caglayan (2001) estimate the backfill bias to be around 0.5 to 1.5 percentage points. Later studies explicitly accounted for the entry dates of individual hedge funds which makes the estimates much more accurate. Malkiel and Saha (2005) estimate it at 5 percentage points. Posthuma and Van der Sluis (2003) estimate the backfill bias to be about 4 percentage points.

2.2.3 Return smoothing

There is one more issue with hedge fund data that needs to be put forward. It has been mentioned that biases occur due to the voluntary reporting of hedge funds. This leads to omission of information on, on balance, bad performing funds. In addition to this, the quality of return data can be questioned. Mutual funds usually trade securities that are listed on the stock exchange. They can value their portfolios by using closing prices. As we know, hedge funds engage in derivative trading for which the over-the-counter market is much larger than the exchange-traded market.[6] They usually have to resort to theoretical models to value their holdings. Since the inputs to the model are often not directly observable in the market, hedge fund managers have some flexibility in valuating their portfolios and, hence, their returns. The hypothesis is that hedge fund managers will use this flexibility to smooth returns which means they try to avoid large jumps in the return series. The reason for this is to present low volatility and consistent performance. Getmansky, Lo and Makarov (2004) come to the conclusion that return smoothing is one of the reasons why hedge fund return series show serial correlation.

[6] J.C. Hull (2006), p.3.

2.3 Statistical properties of hedge fund returns

2.3.1 Individual hedge fund returns

Since hedge funds claim to offer low correlation with the market and obtain absolute returns, investors may find it attractive to invest at least a portion of their wealth in hedge funds. The most widely used model by investors for portfolio construction is the Markowitz (1952) mean-variance framework. One type of research on hedge funds is concerned with the question whether hedge funds can deliver additional value to a portfolio as a separate asset class, especially with regard to the mean-variance framework. Reviewing this research gives an indication of hedge fund risk/return characteristics.

In order to determine the value hedge funds can have in portfolio construction, several authors have investigated the risk/return profile of hedge fund investments. Ackermann, McEnally and Ravenscraft (1999) start by simply comparing the returns of hedge fund indices with common equity indices and find nothing spectacular: hedge funds sometimes outperform, sometimes they do not. This result also holds when taking into account the risk profile by means of the Sharpe ratio. However, Fung and Hsieh (1997) and Agarwal and Naik (2000c) have shown that hedge funds exhibit much better risk-adjusted returns in comparison with the market with variance as risk measure. Fung and Hsieh (1999b) show that even though the mean hedge fund return is only slightly lower than the S&P 500 return over the 1990-1997 period (15.1 as opposed to 16.2 percent), the standard deviation of hedge fund returns is much lower (5.7 as opposed to 12.3 percent). Other authors in these earlier stages of hedge fund research, such as Liang (1999) and Brown, Goetzmann and Ibbotson (1999), also mention the favourable risk/return characteristics and conclude that hedge funds add value to investors because of the positive risk-adjusted returns.

It needs to be recognized however, that mean and variance do not tell the entire story. Mean-variance analysis assumes that assets have normally distributed returns. However, hedge fund returns exhibit significant negative skewness and positive kurtosis. This is shown by Agarwal and Naik (2001), Brooks and Kat (2002), Malkiel and Saha (2005) and Eling (2009). These distributional characteristics imply a much higher downside risk than the variance would make us believe. The non-normality of the hedge fund return distribution is due to the dynamic trading strategies most hedge funds employ, adding to the effect that the use of derivatives has on the return distribution. From this, Amin and Kat (2003) draw the conclusion that performance measures rooted in the mean-variance framework, such as the Sharpe ratio and Jensen's alpha, overstate hedge fund performance and are therefore incapable of evaluating it correctly. Agarwal and Naik (2000a, 2000c) recognize the non-normality of hedge funds returns and evaluate the variability of hedge funds not only by the standard deviation of returns, but also by the downside deviation (which is the variance of returns below a target rate) and by counting the number of positive and negative returns. In all three analyses, it appears that hedge funds with directional styles are outperformed by non-directional styles.

It needs to be pointed out that when the return distribution is non-normal, mean-variance analysis is still a justified method to rank funds in case investors' preferences are quadratic. This is shown by Levy and Markowitz (1979) for the case of mutual funds. Fung and Hsieh (1999a) conclude that the mean-variance criterion measured as the second order Taylor approximation of the utility function can be used to rank hedge funds as well. They also conclude, however, that mean-variance should not be used for risk assessment, since the mean-variance criterion does not take the probability of large negative losses into account. Since hedge fund return distributions are negatively skewed with high positive kurtosis (i.e. have significant negative tail risk), the mean-variance framework is unreliable to work with in evaluating the probability and magnitude of large negative returns. This is also pointed out by Agarwal and Naik (2004). For purposes of risk management, they apply the Conditional Value-at-Risk (CVaR) framework. This framework explicitly considers the probability and size of losses that occur in extreme cases (usually the 10, 5 or 1 percent worst-case scenario's). By comparing the mean-variance efficient frontier with the mean-CVaR efficient frontier, they indeed find that mean-variance analysis understates the downside tail risk by approximately 12 to 54 percent for 90 to 99 percent CVaR confidence intervals. The understatement is higher for portfolios with low standard deviation and for higher CVaR confidence levels.

Using leverage, short selling, derivatives and dynamic trading strategies creates a non-linear relationship of hedge fund returns to market returns. This is also found by many authors, among whom Agarwal and Naik (2004) and Mitchell and Pulvino (2001). Usually, Fung and Hsieh (1997) are cited as the first to find this phenomenon. They find that the explanatory power of linear regressions of hedge fund returns on market returns is much lower than that of regressions performed on mutual fund returns.[7] Nor do they find any dominant asset class to be a significant explanatory variable when it comes to hedge funds, whereas U.S. equities and U.S. government bonds are significant variables for eighty-seven percent of mutual funds. They find low and sometimes even negative correlation coefficients. The latter can be explained by the short selling possibilities that hedge funds have, as opposed to mutual funds, for which indeed only positive correlations are found.

[7] More than half the mutual funds have R^2s above 75 percent, whereas nearly half of the hedge funds have R^2s below 25 percent.

The low correlation of hedge funds with market factors can quickly lead to the conclusion that hedge funds do well in a portfolio context. Agarwal and Naik (2000c) indeed argue that hedge funds' low correlation with market indices offer diversification benefits for investors since it improves the mean/variance efficient frontier. Brown, Goetzmann and Ibbotson (1999) and Amin and Kat (2003) also argue that hedge funds can be of added value to a portfolio because of diversification benefits. The latter find very low correlation coefficients between hedge fund returns and the S&P 500 index (about 0.29 on average, using a sample of 77 hedge funds). Fung and Hsieh (1999b) also find a low correlation coefficient between hedge funds and the market (0.37). In combination with the favourable return and volatility characteristics, hedge funds appear to be a very attractive asset class to invest in.

2.3.2 Index returns

Data providers not only keep information on individual hedge funds. They also create hedge fund style indices and composite indices (the former also called "sub-indices" and the latter also called "overall" or "aggregate" indices). In Appendix A descriptions can be found of the various hedge fund styles that are mentioned throughout this thesis. Several authors have investigated both the virtues of these indices and the difficulties that may arise when using them. Brooks and Kat (2002) observe that many investors who consider investing in hedge funds will use a mean-variance portfolio construction approach. This usually entails comparing the mean-variance characteristics of portfolios including hedge funds with portfolios excluding hedge funds. As is common in this kind of procedure, the asset classes are represented by an index, such as the MSCI World Index as a proxy for global equities. Hedge funds are usually proxied by a hedge fund index. Although it is argued that hedge fund indices are non-investible because most are equally weighted, Amin and Kat (2002) have shown that the indices reasonably proxy an actual portfolio of individual hedge funds, provided a sufficient number of hedge funds is invested in. It is important to analyse the characteristics of hedge fund indices because of their frequent use by investors.

There are several data vendors. The indices they provide have different calculation methods. For example, Hedge Fund Research (HFR)[8] provides equally weighted indices whereas CreditSuisse/Tremont (CS/Tremont)[9] provides asset weighted indices. Moreover, the data vendors all capture a different part of the hedge fund universe. Their composite indices include around 2,000 and 900 individual hedge funds, respectively. The differences between hedge fund indices should warn the investor who uses these indices for portfolio construction. It is likely that the indices exhibit

[8] www.hfr.com
[9] www.hedgeindex.com

substantial differences which will have its effects on the conclusions of the mean-variance analysis. This is also concluded by Fung and Hsieh (2002) who add that the impact of various construction methods and hedge fund universes is magnified by the diversity in trading styles and performance of underlying hedge funds in composite indices.

Brooks and Kat (2002) investigate and compare the various indices that are provided by a number of data vendors. They find that hedge fund indices (both composite and style indices) have much better returns compared to their volatility than stock and bond market indices have. However, hedge fund indices also exhibit low or negative skewness and high excess kurtosis. This type of return distribution is actually quite similar to the ones found for individual hedge funds, as stated in Section 2.3.1. The return distributions are non-normal, with only a few exceptions. Correlations between hedge fund index and equity market index returns are usually around 0.6, but the average correlation with the Russell 2000 is even higher. The exceptions are the convertible arbitrage style and the equity market neutral style, although it quite depends on which data provider is used. The CS/Tremont database shows much lower correlations for these arbitrage styles (0.08 and 0.35 with the S&P 500, respectively) than the HFR database does (0.36 and 0.52). Agarwal and Naik (2000c) find correlations between hedge funds style indices and market indices to be below 0.5, except for correlations with the S&P 500, emerging markets and high-yield bond index. Correlations with these asset classes are around 0.60 for most hedge fund style indices.

Considering the similar level of non-normality in index returns, the conclusions drawn by Brooks and Kat (2002) are about the same as the authors who investigated individual hedge fund return distributions. They conclude that the mean-variance framework and its performance measures are unsuitable for analysis when using hedge fund indices because it will overestimate performance. The correlations found between hedge fund indices and the stock market are higher than the ones found between individual hedge funds and market indices. This suggests that investors, who usually invest in a basket of hedge funds, as they do with other asset classes, in fact pick up quite some equity risk. This result does not hold for the convertible arbitrage and equity market neutral styles, however. The equity market neutral style index also has low correlation with other style indices (around 0.2 in the HFR database), whereas the other styles seem to show a lot of common systematic exposures (correlations varying between 0.5 and 0.95 in the HFR database).

To be able to fairly evaluate the returns of hedge funds, it is necessary to adjust for the risk that hedge funds run. As outlined in this section, it is not sufficient to look at volatility alone, measured as the standard deviation of returns. Performance measures rooted in the mean-variance framework are somewhat naïve when applied to hedge funds. Hedge fund returns need also be adjusted for market exposures, which is a well-known concept in performance evaluation. However, we have seen that straightforward linear relationships between hedge fund returns and market factors cannot be assumed. The next section summarizes the more detailed research into the risk exposures of hedge fund returns.

2.4 Performance and persistence

Considering the fact that many hedge funds claim to generate absolute returns, it is interesting to see whether hedge funds are indeed capable of outperforming the market. Moreover, investors would like to know whether any outperformance is due to luck or whether hedge funds persistently outperform the market. It is very common in performance evaluation literature to measure fund performance relative to a benchmark. Jensen (1968) uses a single factor model and Sharpe (1992) uses a multifactor model in the performance evaluation of mutual funds.

$$(1) \qquad R_{i,t} = \alpha_i + \sum_{k=1}^{K} \left(b_{i,k} F_{k,t}\right) + u_{i,t}$$

The degree of outperformance of a fund is then given by the difference between the actual return and the expected return according to the given model. In the model of Sharpe (1992), this is represented by $\alpha + u_t$ in Equation (1). Since u is defined as the error term and therefore equal to zero in a regression, α_i ("alpha") represents the outperformance of a hedge fund i over the regression period. R represents an individual hedge fund's return. The returns of systematic risk factors F and average factor loadings b represent the mix of static buy-and-hold exposures ("location choices") as well as dynamic trading strategies. That part of (1) is referred to as the benchmark. Of course, the benchmark needs to be accurate in order for the performance evaluation to be accurate as well. Therefore, the equation is required to have a high degree of explanatory power. In Section 2.3 it was mentioned that this can be difficult to obtain because of the dynamic trading strategies and derivative trading that hedge funds engage in. This means that these issues also need to be addressed in hedge fund performance evaluation.

The alpha is by far the most frequently used tool to analyse the performance of hedge funds, especially when considering hedge fund indices. Ackermann, McEnally and Ravenscraft (1999) use only equity market indices as a benchmark. They find low systematic risk exposures of hedge fund to these indices, combined with high alpha's (typically ranging from six to eight percent). This would imply that hedge funds add a lot of value. However, considering the non-linear relationship of hedge funds to the market, this result is likely to be distorted.

Agarwal and Naik (2000c) use a multifactor benchmark portfolio to analyse the performance of hedge funds. They find an alpha for each hedge fund style ranging between 6 and 15 percent per year. The explanatory power of the regressions varies quite a bit, the R^2s are between 0.41 to 0.83. They find that this alpha persists at a quarterly horizon. Agarwal and Naik (2000b) also find persistence at the quarterly horizon, but reject persistence over longer periods. The persistence seems to be driven by the losers rather than by winners. Jaganatthan, Malakhov and Novikov (2006) on the other hand, find persistence driven by superior funds rather than inferior funds.

Edwards and Caglayan (2001) allow for an exposure to the S&P 500 and to five passive strategies. The factors they use are similar to Fama and French (1993), for instance including a portfolio of previous year's winners minus previous year's losers, a term spread exposure and an exposure to the credit spread between long-term government and long-term corporate bonds. They, too, find a positive alpha for each hedge fund style in the same range as Agarwal and Naik (2000c). Moreover, they find persistence at one-year and two-year horizons. This persistence is consistent across both winners and losers, contrary to the Agarwal and Naik (2000b) results.

Kosowski, Naik and Teo (2007) regress hedge fund style indices on the Fung and Hsieh (2004a) benchmark and do not find significant intercepts to the regression, thereby drawing the conclusion that hedge funds do not outperform. When evaluating individual hedge funds by a bootstrapping method, however, they find that some funds outperformed others and that this performance persists at a yearly horizon. Fung and Hsieh (2004a), on the other hand, find significant alpha's when using the composite hedge fund indices.

Capocci (2009) analyses the performance of hedge funds in a multifactor setting like the one Agarwal and Naik (2004) use to measure the exposures of hedge funds. Again, significant positive alpha's are found for all hedge fund style indices. They find significant positive persistence in hedge funds that have limited volatility and/or limited exposure to the equity market.

Fung, Hsieh, Naik and Ramadorai (2008) split up their regression in three periods and find that hedge funds obtain a significant alpha only for the 1998-2000 period and not for the 1996-2000 period, nor for the 2000-2004 period.

Amin and Kat (2003) use a different method to evaluate the performance of hedge funds. The advantage of their method is that no assumptions need to be made with regard to hedge fund return distributions. In short, they consider the distribution of pay-offs of an individual hedge fund and replicate it by creating a dynamic trading strategy, combining the S&P 500 with cash. If the net present value of this replicating strategy is higher than the initial investment to the hedge fund, the hedge fund has added value. The hedge fund has underperformed if the initial investment is higher than the net present value of the pay-offs. They find that 72 out of 77 investigated hedge funds and 12 out of 13 hedge fund indices underperform, although the average so-called "efficiency loss" is less in hedge fund indices (2.76 percent) than in stand-alone hedge funds (6.42 percent). This implies that some value is gained by diversifying between hedge funds. The results are strikingly different from the multifactor model results, however.

Surveying the previous literature on performance evaluation, it appears that any conclusion should be drawn with some reservation. The value of alpha depends on the quality of the multifactor model employed. Because of the non-normalities, non-linearities and biases in hedge fund returns series, a proper model is hard to construct. However, all things considered, the preponderance of the evidence currently points towards non-negative alpha's among hedge funds. Positive alpha's are found for individual hedge funds, a variety of hedge fund indices and across various periods. Performance persistence appears also to be present in hedge fund returns. In a survey of 25 studies on performance persistence by Eling (2009), he finds that persistence is present in hedge funds returns at short horizons up to six months. There is yet no consensus as to whether top performers or inferior performers drive persistence across hedge funds return data.

2.5 Management performance incentives

One way in which hedge funds differ from other investment vehicles is the performance structure of their managers. Hedge fund manager performance incentives have therefore also been of interest to academics. Usually, hedge fund managers earn about 20 percent of profits above the hurdle rate.[10] Goetzmann, Ingersoll and Ross (2003) calculate that the combined value of performance fees (including both incentive fees and fixed fees) of hedge fund managers claims between 30 and 40 percent of investor wealth, which a rational investor would only except if the hedge fund's alpha is expected to be between 2 and 5 percent. Surveying the evidence on the performance of hedge funds, it appears that the incentive contracts are priced about right.

Because of the high-water marks, manager performance schemes in hedge funds create call option-like features to the incentive contract. This suggests that hedge fund managers will try to increase the risk of the fund in order to maximize the value of their incentive contracts. Kouwenberg and

[10] See Section 2.1.

Ziemba (2007) find that loss aversion is greatly reduced by the incentive fees, which leads to increased risk taking. But when the hedge funds manager’s own stake in the fund is at least 30 percent, risk taking is substantially reduced. In a cross-section analysis, they find no significant relation between volatility and incentive fees. The first finding is in accordance with Carpenter (2000) who finds that incentive fees of hedge fund manager leads to increased risk taking when the fund returns are below the hurdle rate. However, when a fund’s return is above this hurdle rate, managers tend to reduce volatility. All things considered, it is believed that risk taking by hedge funds is not determined by the nature of incentive contracts. Brown, Goetzmann and Park (2001) find that peer-to-peer comparison is a better explanatory variable for risk taking than the level of a high-water mark. Ackermann, McEnally and Ravenscraft (1999) find no relationship between the magnitude of the incentive fee and total risk taking.

Does a relation exist between the type of incentive contract and the performance of hedge funds? Kouwenberg and Ziemba (2007) conclude that hedge funds with 20 percent incentive fees obtain 2.93 percent lower net-of-fee returns compared to funds without incentive fees, all other things equal. Taking into consideration that incentive fees do not influence the level of risk taking, this would mean that the asymmetric incentive schemes of hedge funds lead to a lower risk-adjusted performance. This is not in accordance with Ackermann, McEnally and Ravenscraft (1999), who find that an increase in the incentive fee from zero to 20 percent leads to an increase in the Sharpe ratio of 66 percent. Management fees (which are fixed reward components) raise total risk and reduce Sharpe ratios.

Agarwal, Daniel and Naik (2004) and Liang (1999) find that greater managerial incentives lead to greater money inflows, suggesting that investors prefer funds with managers’ interests aligned with theirs. Moreover, they find that hedge funds with higher managerial incentives outperform other hedge funds.

3 Literature review

In the previous chapter, some important insights from the hedge fund literature were reviewed. This chapter will treat the literature that is closely related to this study more profoundly. First of all, Section 3.1 discusses the research on the risk exposures of hedge funds. What drives hedge fund returns? Most studies are aimed at finding the exposures in a linear model by means of a style analysis. This study distinguishes itself by aiming to find time-variation in risk exposures of hedge funds. Therefore, previous studies on time-variation of returns should also be treated. This is done separately in Section 3.2.

3.1 Style analysis

One strand of literature focuses on determining the risk exposures of hedge funds. This involves so-called style analysis, in which researchers not only try to establish the markets in which hedge funds trade, but also the kind of dynamic trading strategies hedge funds tend to employ. Since the research of this thesis contains a style analysis, this section will treat the most important results of previous research in this field somewhat more elaborately. In Section 2.3, it was noted that hedge funds exhibit low correlations with the market, which gives low explanatory power to (linear) multifactor models. The goal of style analysis is to establish the systematic risk exposures of hedge funds. Do the low correlations between hedge fund returns and market returns indeed reflect the fact that hedge funds are hedged and earn absolute returns? Or, alternatively, are hedge funds in some other way related to market factors which is not captured by correlation coefficients?

Once the risk exposures of hedge funds are known, it becomes a natural follow-up question whether the returns of hedge funds are in conformity with their risk profile. Or, to put it differently, how hedge funds perform on a risk-adjusted basis. Style equations are therefore often used in performance evaluation. Section 2.4 can be consulted for the results of performance evaluation studies.

The pioneering work of Sharpe (1992) with regard to style analysis of mutual funds was followed-up by Fung and Hsieh (1997) with regard to hedge funds. In order to find the asset classes that hedge fund managers invest in, Fung and Hsieh (1997) use a multifactor regression model. Each hedge fund holds a portfolio of assets. The return on individual assets is determined as in Equation (2).

$$(2) \qquad r_{j,t} = \sum_{k=1}^{K} (\beta_{j,k} F_{k,t}) + \varepsilon_{j,t}$$

The return F on each of the K systematic risk factors independently impacts the return r of an individual asset j through its factor loading, β, also called "factor beta". The systematic risk factors are the asset classes, for which proxies are used, such as the MSCI U.S. equities index, J.P. Morgan U.S. Government Bond index, the gold price, etcetera.

$$(3) \qquad R_t = \sum_{j=1}^{J} \left(w_{j,t} r_{j,t}\right) + u_t$$

The return on a portfolio R at time t is determined as in Equation (3), in which w is the weight each asset j has in the portfolio and r is the return on the individual asset. The error term u_t is the sum of the individual assets' error terms ε. Using Equation (2), Equation (3) can be rewritten as

$$(4) \qquad R_t = \sum_{k=1}^{K} \left(b_{k,t} F_{k,t}\right) + u_t$$

$$\text{where} \qquad b_{k,t} = \sum_{j=1}^{J} \left(w_{j,t} \beta_{j,k}\right)$$

From Equation (4), the return of a hedge fund is a weighted average of the return of a small number of asset classes. The investment style of a hedge fund involves both the choice which asset classes to invest in, referred to as the "location choice", and the direction and quantity invested in the asset classes, referred to as the "trading strategy" or "exposure". In Equation (4), the location choice can be deducted from the values of F, whereas the trading strategy is reflected in b. A lot of authors use the term "strategy" for the combination of location choice and trading strategy, since both are the consequence of a strategic choice. The terms "style" and "strategy" are therefore often used interchangeably, though "strategy" is most commonly used.

This linear multifactor model has some shortcomings, however. The multifactor model is very suitable for style analysis of mutual funds, since mutual funds largely employ buy-and-hold strategies. By contrast, hedge fund tend to use highly dynamic strategies and change their positions over time. When a trading strategy involves changing portfolio positions over time, the correlation between the asset class return and hedge fund return is not constant over time. In other words, the coefficient *b* in Equation (4) reflects only the average of the changing style. It may even be the case that no correlation is found between the return of a hedge fund and a particular asset class, even though the hedge fund under consideration has a directional exposure to the asset class. This is the case, for example, when a hedge fund alternates between a long and a short position in the asset. Moreover, hedge funds buy securities with non-linear pay-offs, such as options, making a linear model a somewhat questionable tool for style analysis. The above leads to the conclusion that the regression model of (4) poorly reflects the style of hedge funds when their trading strategies are highly dynamic and their portfolios comprise non-linear securities. Investors may erroneously believe that hedge funds have no systematic risk components because linear models do not capture them. Adapting the style analysis may provide a solution.

Authors solve the non-linearity problem in a variety of ways. To capture the investment style of hedge funds, Fung and Hsieh (1997) perform a factor analysis on 409 hedge fund returns and extract five principal components. They construct five "style factors" by creating investable portfolios of hedge funds that are closely related to the principal components. Each style factor represents a trading style. The style factors are then regressed on the asset class model of (4) to find correlations between hedge fund returns and asset class returns. For some styles, they indeed find strong correlations with higher explanatory power.[11] This implicates that hedge funds trading styles are based on common strategies. They also use a non-parametric method to analyse the trading styles. By sorting asset class returns in five states of the world and comparing the returns on the style factors, they find that the regression correlations do not reflect buy-and-hold strategies, but rather dynamic trading strategies. They conclude that their style factors can be useful additions to a regression model, so that the model accounts for trading strategies as well as location choices of hedge fund managers.

The style analyses of Agarwal and Naik (2000a, 2000c) in fact do not offer a solution to the non-linearity problem that occurs when applying a standard multifactor model to hedge funds. Nonetheless, they find significant results when regressing hedge fund style index returns on several asset class returns. They find that their eight style regressions have R^2s between 38 and 83 percent, with slightly higher explanatory power for directional styles. This is to be expected by the very definition of non-directional styles: they are supposed to be only weakly correlated with the market. The exposures they find are consistent with the style classifications. For example, the short style

[11] Three regressions have an R^2 higher than 50 percent and one or more significant coefficients.

exhibits a negative weight on U.S. equities and the global/macro style has a positive exposure to currency. They also find the remarkable result that non-directional styles have significant exposures to market factors. For instance, the equity hedge style has a significant positive exposure to both U.S. equities and non-U.S. equities.

Fung and Hsieh (2001) focus on one specific trading style, called “trend following”, which is the strategy that the majority of commodity trading advisors (CTAs) employ. CTAs are structured quite the same as hedge funds, but only trade in futures and/or futures options. Traditionally, these instruments have commodities as underlying assets, but the growth in the financial derivatives markets has enabled CTAs to take on exposures to other risks such as interest rates, currencies and stock indices. The trend following style appears to exhibit large positive returns in both bull and bear markets, which is similar to the pay-offs on an option straddle. The authors argue that returns of funds employing a trend following style should resemble the pay-offs on a lookback straddle, consisting of a lookback put and call option. The owner of a lookback call option can buy the underlying asset for the lowest price over the life of the option and the owner of a lookback put option can sell for the highest price over the life of the option. The authors form a so-called asset-based style factor by creating empirical returns on a dynamic lookback straddle strategy, and find that the returns on this strategy replicate the returns of trend following CTAs better than buy-and-hold regressions. This means that trend following hedge funds have a diversifying effect on a portfolio, since they offset stock and bond price declines during extreme market downturns. The more important implication of this, for the purposes of this study, is that trend following CTAs do have systematic risks in their portfolio, even though linear models would suggest they do not.

Mitchell and Pulvino (2001) conduct a similar research into risk arbitrage strategies. They find that the returns on a risk arbitrage strategy are largely uncorrelated with the market, except during severe market downturns. During market downturns, the correlation of risk arbitrage returns and market returns increases dramatically. This means that risk arbitrage returns are similar to written put options on market indices. A linear model does not capture this characteristic of hedge fund returns. This is an important lesson to investors. The excess return that is earned under most market circumstances may represent the premium they earn for providing liquidity in market downturns. Analyzing hedge fund returns with a straightforward linear multifactor model would not deliver this information, however.

In a recent publication, Patton (2009) investigates the dependence of “market neutral” hedge funds, which are hedge funds that classify themselves as funds adopting non-directional styles. Using a polynomial model, he finds that 28 percent of "market-neutral" hedge funds are in fact statistically dependent of equity market indices.

Agarwal and Naik (2004) recognize the importance of taking option-like features into account when analysing hedge fund returns. They broaden the scope of Fung and Hsieh (2001) and Mitchell and Pulvino (2001) by analysing multiple hedge fund styles. However, they do not create "asset-based style factors" by replicating a dynamic trading strategy as Fung and Hsieh (2001) propose. Instead, they build on Glosten and Jagannathan (1994) and regress hedge fund returns on excess returns of option portfolios and standard asset classes in a linear model as in Equation (4). They find that option-like features are not restricted to risk arbitrage and trend following styles, but that they are a feature of many hedge fund styles available. Apart from some linear exposures to market factors, they find that the pay-offs of event arbitrage, restructuring, event driven, relative value arbitrage and convertible arbitrage styles all resemble written put options on the S&P 500 index. The short selling style resembles a written call option on the same index.

Style analysis has shown that, on a closer look, hedge funds do exhibit significant risk exposures. This conclusion is not only valid for funds adopting a directional style, but also for those adopting a non-directional style. Style indices that are based on self-classification of hedge funds do appear to be reliable since the exposures are in line with expectations on the basis of the classification. Hedge fund trading strategies are highly dynamic, which gives return series option-like features. This makes it harder to find a suitable model that captures the risk exposures reliably. This is reflected in the fact that the explanatory power of hedge fund models is lower than those of mutual fund models. Many authors tried to get around this problem by adapting their style analysis in such a way that the dynamics of hedge fund exposures are captured.

This study proposes a different method to unveil the risk exposures of hedge funds. Since hedge funds trade dynamically and in non-linear products, their location choices and exposures change over time. Despite the useful adaptations of the aforementioned models, the resulting equations are still only capable of capturing average exposures to the chosen risk factors over the research period. They do not capture any time-variation in the exposures. It can very well be argued that allowing for time-varying exposures may be a better way of grasping hedge fund exposures. The remainder of this chapter is dedicated to the treatment of research on the time-variation of hedge funds' risk exposures.

3.2 Time-variation

Before proceeding to the methodology of this model, the previous literature on time-variation of hedge fund risk exposures is discussed. This study aims to find the risk exposures of hedge funds by using a highly dynamic time-varying model. From the next subsection it will become clear that no such study has been conducted yet. The methodology used to facilitate time-variation is derived from a branch of behavioural finance: the heterogeneous agents literature. In order to introduce this methodology, some of the heterogeneous agents literature is treated in Section 3.2.2.

3.2.1 Time-variation in hedge fund research

Fung and Hsieh (2004b) continue their research from Fung and Hsieh (2001) with asset-based style factors to analyse various composite hedge fund return indices. This means they do not account for different trading styles that are employed by the different hedge funds included in the index. This may explain why they find different significant risk exposures than Agarwal and Naik (2004). They find statistically significant positive exposures to lookback straddle option portfolios for two out of three indices investigated. All composite hedge fund indices have a positive exposure to the S&P 500 index and a Wilshire small cap-minus-big cap index. An important finding is that some exposures change over time. By using a cumulative sum of recursive residuals method, they construct time frames and identify September 1998 and March 2000 as breakpoints. This means that the cumulative recursive residuals cross the confidence band at the demise of Long-Term Capital Management and at the end of the Internet bubble, respectively.

In bear market circumstances during the 2000-2002 period, the indices have an enormous negative exposure to the change in the Federal Reserve's ten year constant maturity yield, whereas this factor shows no statistical significance over the bullish 1994-1998 period. The exposures are quite similar across the three different data vendors: HFR, TASS and MSCI. The change in credit spread between Baa bonds and the Federal Reserve's ten year constant maturity yield shows an opposite pattern.

Fung, Hsieh, Naik and Ramadorai (2008) investigate whether risk exposures of hedge funds change over time by running regressions over different time intervals. The breakpoints are determined on the basis of the above-mentioned research by Fung and Hsieh (2004b), but the most recent period includes two more years of data. The resulting intervals are roughly 1995-1998, 1998-2000 and 2000-2004. Also, the same risk factors are used. They find that coefficients are statistically different between periods (which indicates time-variation), though the location choices remain mostly the same. The exception here is the change in the Federal Reserve's ten year constant maturity yield, as could be expected considering the aforementioned findings of Fung and Hsieh (2004b). This exposure is significant only in het latest period, beginning in 2000. Interestingly, the difference in this exposure between the three periods is not as stunning as it was in the previous study.[12] Moreover, the sign of the exposure in the latest period is positive as opposed to a negative exposure in the 2004 study. As it appears, the two extra years of the third interval has greatly increased the exposure of hedge fund indices to this particular risk factor. Another remarkable difference between the 2004 and 2008 study is the exposure to the change in credit spread between Baa bonds and the Federal Reserve's ten year constant maturity yield in the period up to 1998. The 2004 study shows a negative exposure as low as -4 percentage points per point change in the credit spread, whereas the 2008 study shows a positive exposure of 0.7 percentage point. The intervals do not exactly coincide (1994-1998 and 1995-1998 for the 2004 and 2008 study, respectively), but the comparison of these two studies is a good indication that short-term fluctuations in hedge fund exposures have an important influence on long-term averages. Not only can time-variation of exposures be spotted between time frames within a single study, but the slight adaptation of time frames in a different study also yields different results. With respect to these studies, this appears to be especially true for bond market exposures.

Bollen and Whaley (2009) attempt to find time-variation in hedge fund risk exposures in two different ways. Both methods try to find the exposures on risk factors also used in other studies of hedge fund returns. The research includes 5 Fama and French factors and 7 Fung and Hsieh factors, derived from a number of studies by Fung and Hsieh mentioned earlier in this review. The sample period comprises 144 months, from January 1994 to December 2005.

The first methodology is to find discrete moments in time where the strategies of individual hedge funds change. Fung and Hsieh (2004b) applied a different procedure to establish relevant time frames, although the assumption of discrete shifts in hedge fund strategies is inherent in their methodology as well. It is assumed that a hedge fund has a certain combination of exposures at the start of its operations. At one particular point in time, a hedge fund shifts its strategy and the exposures change accordingly. Only one change per fund is allowed due to the limited sample history for most funds. By simulation, the so-called *changepoints* are identified. This involves running regression *F*-tests on each of the possible changepoints. They find that about 40 percent of hedge

[12] The exposure in the 1995-1998 period is insignificant in both studies, but in the 2000-2002 (Fung and Hsieh (2004b)) and 2000-2004 (Fung, Hsieh, Naik and Ramadorai (2008)) intervals, the exposure is approximately -2 and 0.16 percentage points per point change in the yield, respectively. A critical note can be made, which is that the databases of both studies are not identical. The 2008 study uses a consolidated database of three data vendors (HFR, TASS and CISDM) and the 2004 study uses three separate databases. However, the 2004 study has treated two out of three of the databases also used in the 2008 study (HFR and TASS) and all three separate analyses of 2004 give comparable results to the one of 2008.

funds experience a significant shift in factor loadings, but they do not find a common switching moment. The switch predominantly occurs early in the life of a hedge fund and switching funds outperform the non-switching ones.

The second methodology to test for time-varying exposures does not assume one discrete strategy shift, but a smooth continuous process of changing exposures. The factor loadings are each assumed to follow a first-order autoregressive process around a long-term mean. The simulations ran with this model have a lower power than the changepoint regression. The reason for this is that the underlying return generating process is not known, the authors argue. Therefore, this methodology is not continued further and no conclusions are drawn from the results. It is worth noting this effort, however. It is the first attempt in the hedge fund literature to model a continuous strategy changing process.

Overall, there has only been little research into the time-variation of hedge fund risk exposures. It is clear that some time-variation does occur, however. This statement can be made because all empirical studies, including those not mainly or explicitly focused on time-variation, point toward that fact. Pure linear multifactor models do not suffice to uncover the risk exposures of hedge funds, which is made clear by the low explanatory power of these models. Some adaptations, such as factor analysis and the addition of option components, indeed teach us a bit more about hedge fund exposures. It is recognised that these models do not fully capture the true exposures of hedge funds over a certain period of time. This is mostly due to the dynamic trading strategies: any linear multifactor model can only capture the average exposure. Subdividing the regression equations into several time frames indeed shows that hedge fund risk exposures change over time. However, it can be expected that exposures change more than once or every now and again. This study is an attempt to reveal this continuously changing behaviour of hedge fund managers.

Time-variation in hedge fund returns is not only empirically but also theoretically very well founded. This study will try to shed a new light on the dynamics of hedge fund risk exposures. In order to do so, a methodology different from Bollen and Whaley (2009) is used to try and uncover some of the strategy changing behaviour of hedge fund managers. Details on the actual methodology of this study can be found in Section 4.1. In the next subsection, an introduction to this methodology is provided by reviewing some of the previous literature upon which this methodology is based.

3.2.2 Time-variation in heterogeneous agents literature

The aforementioned literature sheds some light on the time-variation of hedge fund index returns. There are some studies that allow for some kind of switching behaviour of hedge fund managers. This study is an attempt to determine the time-variation in hedge fund returns more accurately by allowing hedge fund managers to switch strategies each month. The methodology to do so is derived from the literature on behavioural heterogeneity of agents. The following section gives a short summary of the literature in this field as far as it has a close link to the methodology employed in this study. LeBaron (2006) and Hommes (2006) provide a more elaborate overview of heterogeneous agents models in general.

The heterogeneous agents literature attempts to explain market prices and stylized facts under the assumption of groups of boundedly rational agents who base their expectations on different types of information. Examples of stylized facts that have been mimicked by heterogeneous agents models are persistence and fluctuation of market prices, clustered volatility and fat tails in asset returns.

Many models consist of two groups of agents, fundamentalists and chartists. Fundamentalists expect the future asset price to move towards the "true" asset value, whereas chartists base their expectation of asset price movements upon observed historical price patterns. It is assumed that both groups of agents apply trading strategies in accordance with their expectations, so that the resulting market prices are a weighted average of the expectations. Early work in this field has been done by Zeeman (1974).

Frankel and Froot (1990) apply a heterogeneous agents model with regard to the exchange rate. They model portfolio managers who form their expectations as a weighted average of fundamentalists' and chartists' expectations. The respective weights depend on the predictive power of the forecasts in the previous period. By means of simulation they find that the exchange rate may exhibit a temporary bubble, driving the fundamentalists' weight to zero, which accelerates the appreciation. However, external deficits turn the trend and more weight is assigned again to fundamentalists' forecasts, now leading to an accelerated depreciation.

Brock and Hommes (1997, 1998) take a different approach to modelling trading behaviour. In their approach, agents can choose and switch between a number of forecasts. The fraction of agents choosing a particular forecast at any particular time depends on the historical performance of the particular forecast and the sensitivity of agents to select the optimal forecast, the latter commonly referred to as the "intensity of choice". As the distribution of agents over the different forecast strategies changes over time, the state of the economy changes along. In Brock and Hommes (1997) costly rational expectations are modelled versus cheap naïve expectations. They find that both types can co-exist in a system with fluctuating fractions. Brock and Hommes (1998) create a few financial market applications of a behavioural model. Among other things, they find that fundamentalists and biased traders can co-exist causing asset prices to fluctuate around an unstable fundamental steady state.

De Jong, Verschoor and Zwinkels (2009) combine the approaches of both Frankel and Froot (1990) and Brock and Hommes (1997, 1998). In their setup a portfolio manager can choose between three forecasts, rather than two as in Frankel and Froot (1990). An internationalist forecast is added to the fundamentalist and chartist forecasts in order to investigate the phenomenon of contagion: why extreme financial events appear to be linked to similar events in other markets while these markets are otherwise not closely related. The Asian crisis is used to investigate linkages between the Hong Kong and Thailand stock exchanges.

The realised log-price changes are modelled as a weighted average of the three available forecasts plus a random innovation

$$(5) \qquad \Delta p_{t+1} = \sum_{h=1}^{H} w_{h,t} S_{h,t}(\Delta p_{t+1}) + \varepsilon_t$$

in which Δp_{t+1} is the price change in the following period $(t+1)$, w is the relative weight of forecast h and $S_{h,t}(\Delta p_{t+1})$ is the price change induced by forecast h.[13]

Agents can switch between forecasts and that is where the model of Brock and Hommes (1997, 1998) comes in. To determine the weights for each of the three forecasts at a particular time, their procedure is applied. The weights are defined as the probability of choosing a particular forecast in a multinomial logit model considering past fitness of a particular forecast

$$(6) \qquad w_{h,t} = \frac{\exp\left[\gamma \pi_{h,t-1}\right]}{\sum_{i=1}^{H} \exp\left[\gamma \pi_{i,t-1}\right]} = \frac{1}{1 + \sum_{i \neq h} \exp\left[\gamma(\pi_{i,t-1} - \pi_{h,t-1})\right]}$$

[13] Here it is important that the general idea of a switching mechanism is introduced to the reader. The formal definitions of the forecasting rules $S_{h,t}(\Delta p_{t+1})$ are not part of this section since it is not relevant to the methodology that is put forward in the next chapter. For more details on the forecasting rules, the original work of the authors can be consulted (De Jong, Verschoor and Zwinkels (2009), page 1932).

The intensity of choice is defined as γ and $\pi_{h,t-1}$ is the forecasting inaccuracy of a particular forecast in the previous period. As already mentioned, the intensity of choice captures the sensitivity of the portfolio managers to the performance of the various forecasts available to them. Therefore, when the intensity of choice equals zero, portfolio managers would be absolutely insensitive to past fitness of forecasts and would always assign a value of $1/H$ to each forecast. As the absolute value of γ increases, portfolio managers become more sensitive to the performance of the available forecasts.

In the particular model of De Jong, Verschoor and Zwinkels (2009), $\pi_{h,t-1}$ is a measure of forecasting *inaccuracy.* Therefore, γ needs to be negative in order to serve as a feedback rule that is economically sound. When this is the case, the portfolio manager will shift weights in favour of the best performing forecast. The magnitude of weight shifts depends on the values of the intensity of choice and the performance of a particular forecasts relative to the others.

It can be seen that the sum of the weights in (6) is always equal to one since the denominator equals the sum of the three numerators. This implies that the three forecasts are exhaustive. Also, since the numerator is always positive, weights are always positive. This means that all forecasts are relevant to the manager since he or she will not assign a negative weight to any particular forecast.[14]

The authors reach a number of notable conclusions. Firstly, they find significant coefficients for the different forecasts, leading to the conclusion that portfolio managers indeed use a combination of fundamentalist, chartist and internationalist forecasts. Moreover, the intensity of choice parameters are significantly negative for both the Hong Kong and Thailand market and the switching models have significantly higher explanatory power than the non-switching models. This means that switching between forecasts indeed occurs. An analysis of the weights provides evidence that the importance of the three different forecasts changes heavily over time, pointing towards a time-varying correlation between markets. It appears that crises are triggered by fundamentalism and chartism rather than internationalism. The crises are subsequently aggravated by the increased internationalists weight, though. This research therefore provides evidence against the argument that contagion in financial markets is triggered by an increase in correlation between markets. It is aggravated by it, however.

This chapter has provided an overview of previous literature that is related to this study because of its study object and/or its methodology. In the next chapter, the data and methodology of this study are put forward in detail.

[14] And, as a result of the first two statements, nor can a weight be higher than 1.

4 Data and Methodology

This study attempts to uncover the time-variation in hedge fund risk exposures. The methodology entails adapting a style analysis by adding time-varying weights to the equation. Section 4.1 discusses the manner in which this study is conducted. Section 4.2 elaborates on the inputs of the model.

4.1 Methodology

Markowitz (1952) laid the foundations of modern portfolio theory and paved the way for Sharpe (1964) and Lintner's (1965) capital asset pricing model (CAPM) and Ross' (1976) arbitrage pricing theory (APT). The methodology and terminology in this study are also based on these established theories which are both widely used by investors and academics. Unsystematic risk is defined as the specific volatility of a particular asset. Since an investor can diversify away unsystematic risk by holding a portfolio of assets, unsystematic risk components are not priced in the market. Systematic risk, on the other hand, can be defined as the volatility of a particular asset which is attributable to overall volatility in the market. This risk, also called market risk, cannot be diversified away and so investors will want to be compensated for their exposure to this risk. Market risk can be broken down into various different risk factors which influence the movement of asset prices. Since these risk factors are the only priced factors in the market, the return on a particular asset must then be determined by these factors.

In accordance with the results of the CAPM and APT, multifactor models usually estimate a linear relationship between the excess return on an asset and the excess return that a risk factor yields; excess returns being the returns in excess of the risk-free rate. The general formula in Equation (7) represents the multifactor model which forms the basis of this study.

(7) $$R_i = \alpha_i + \sum_{j=1}^{J} (b_{ij} F_j) + \varepsilon_i$$

Each of the returns F on the J risk factors independently impacts the net-of-fee return R of a hedge fund style index i through its factor loading, b. In other words, the factor loading represents the sensitivity of the hedge fund style index return to the risk factor return. The intercept is represented by α, which is perceived as the level of outperformance of a hedge fund in performance evaluation.[15] The error term ε can be regarded to represent unsystematic risk that is present in the index.

The hedge fund style indices are each constituted by a number of hedge fund managers. The asset classes in which these hedge fund managers have invested (their "location choices") are represented by F. Factor loading b captures both the factor loadings of the individual assets in the total hedge fund portfolio and the weights that are assigned to these individual assets. Due to the dynamic nature of hedge fund trading styles, the actual loadings can be expected to shift during the regression period. Thus b reflects the average factor loading resulting from the hedge funds trading strategies. The results of Fung and Hsieh (2001) and Agarwal and Naik (2004) suggest that hedge fund exposures are better approximated when factors are inserted that replicate returns on option trading strategies. Therefore, option-based risk factors are added to the regression as well. Section 4.2 will elaborate on the data that are used for the construction of the risk factors.

There has not been much research into the time-variation of risk exposures in the hedge fund industry. It has been noticed, though, that the correlation of hedge fund returns with market returns seems to be time-varying due to the use of dynamic trading strategies.[16] In this study, a model is constructed in which hedge fund managers are allowed to switch between strategies on a monthly basis. This may shed light on the behaviour of hedge fund returns over time. The change in correlation with risk factors may be explained by shifts in strategy. This is shown in Equation (8). The methodology is derived from De Jong, Verschoor and Zwinkels (2009).[17]

$$(8) \qquad R_{i,t} = \alpha_i + \sum_{j=1}^{J} (w_{j,t} b_j F_{j,t}) + \varepsilon$$

All variables are defined as in (7). The monthly return on a hedge fund style index is not only determined by the average exposures to the different risk factors ($b_j F_{j,t}$), but also by the weight ($w_{j,t}$) that is put on a particular factor loading at a particular time.

A "strategy" is defined as a combination of various exposures to various asset classes. A "strategy shift" occurs when the weights change.[18] In this framework, hedge fund managers can change their strategy each month. If all managers within the index choose to adhere to a certain

[15] Alternatively, of course, the level of underperformance if α is negative. See Section 2.4.
[16] See Chapter 3.
[17] See also Section 3.2.2.
[18] As can be seen from (8), the factor loadings (b_j) are fixed throughout the regression period.

strategy, the weights stay approximately the same throughout the sample period. When a number of managers within the index want to switch to a different strategy, the weights will change and so will the exposures.

There is no weight attached to alpha, since outperformance cannot be part of any trading strategy. It makes no sense to "put more weight" on outperformance. Alpha's are not even a result of styles in general. It may be the case that, on average, convertible arbitrage strategies outperform the market, but still many convertible arbitrage funds will underperform. Alpha very much belongs to a particular fund rather than a particular style. That is why studies related to performance evaluation consider outperformance at the individual fund level rather than at the index level. Still, an intercept is included in the equation to facilitate an unbiased regression.

When will hedge fund managers want to change their strategy? Probably when they find that other strategies are more profitable. A mechanism must therefore be implemented which augments the weights in such a way that hedge fund managers switch weights depending on the performance of other possible strategies. Weights are determined as in (9).

$$w_{j,t} = \frac{\exp\left[\gamma \cdot \pi_{j,t}\right]}{\sum_{j=1}^{J} \exp\left[\gamma \cdot \pi_{j,t}\right]} \tag{9}$$

In this formula, γ denotes the intensity of choice. This can be interpreted as the willingness of managers to change their strategy in reaction to the comparison of their own results with that of other possible strategies. As the absolute value of γ gets very large, managers are very sensitive to the performance of other strategies and shift the weights accordingly. Alternatively, if γ tends to zero, managers do not change strategies at all, but rather choose equal and constant weights to all risk factors.

It is assumed that all relevant strategies can be obtained by changing exposures to the risk factors in this model. For that reason, the weights add up to one. Furthermore, the weights are in a range between zero and one. This may not be intuitive since hedge funds have the ability to borrow money and take short positions in certain asset classes. It should be noted that the coefficients (b_j) can be negative, however. For instance, a style with a short exposure to the U.S. equity market will have a negative coefficient. The weight, then, fine tunes the magnitude of this short exposure at a certain time. A strategy that involves switching from a short to a long exposure to a certain risk factor, is not accounted for in this model, however. The assumption is that a shift in strategy will not be such that the sign of the exposure changes.

The performance measure of a particular risk factor j is denoted by π. From Equation (8), the weights are multiplied by a factor loading (b_j) that is either positive (for long exposures) or negative (for short exposures). Good performance of a long-exposed risk factor should lead to an increased weight to that particular risk factor. By the same token, good performance of a short-exposed risk factor should lead to a decreased weight. The reverse holds for weights attached to bad performing risk factors. A weight to a risk factor should move closer to zero in cases that a long-exposed risk factor performed badly and in cases that a short-exposed risk factor performed well. This means that the impact that risk factor performance has on a weight also depends on the sign of the accompanying factor loading. This is incorporated in the definition of the performance measure π in (10.a) for risk factors with a long exposure and in (10.b) for risk factors with a short exposure.

$$(10.a) \quad \pi_{j,t} = \frac{1}{4} \sum_{T=t-4}^{t-1} F_{j,T} \;\; for \; b_j \geq 0$$

$$(10.b) \quad \pi_{j,t} = -\frac{1}{4} \sum_{T=t-4}^{t-1} F_{j,T} \;\; for \; b_j < 0$$

So when a risk factor yields returns that are favourable to the hedge fund style index, taking the sign of its factor loading into consideration, the performance measure will increase. Hence, γ in Equation (9) needs to be positive in order for the weights to increase for good performing risk factors and decreasing for bad performing ones. Since hedge funds are after absolute returns, it is assumed that their managers disregard the risk that is involved in trading strategies when evaluating them. The performance of a particular risk factor is therefore simply measured by the average return over the last four months. For each of the six styles, all monthly intervals between one and twelve months were tested in order to see which interval produced the highest log-likelihood for the time-varying model. No interval consistently yielded the highest log-likelihood, but all were improvements to the linear model.[19] Nor can any consistency be found in this area among studies using heterogeneous agent models. Boswijk, Hommes and Manzan (2007) use a period of 1 year for their dynamic asset pricing model concerning U.S. stock prices, Chavas (2000) finds significant heterogeneous behaviour for prices in the U.S. beef market with actors using historic information of at least one year back. Westerhoff and Reitz (2003) analyse exchange rate fluctuations using 1-day historic performances. De Jong, Verschoor and Zwinkels (2009) use returns of the previous quarter. Hommes (2006) recognises that more research needs to be done in this respect. The choice of any kind of interval is

[19] The time-varying model is estimated using maximum likelihood; see page 31.

inevitably arbitrary. The four month horizon is chosen because it is about the average interval of the best scoring intervals in terms of log-likelihood and it yields relatively high log-likelihoods for all styles.

It follows from (9) and (10) that hedge fund managers evaluate their style on a risk factor basis. The performance of each of the risk components in the portfolio is assessed. The strategy is shifted towards the risk factors that were profitable in the past. Since the decision rule is not forward looking, its reliability can be questioned. It can be argued that hedge funds managers are not naïve traders: surely they do not invest in an asset class solely on the basis of a recent good performance? Here it is important to point out one final important assumption of this model. When the strategies of a style do not perform as well as other possible strategies, hedge fund managers may be inclined to adopt different trading strategies, or maybe enter a few trades that are more common to a more successful strategy. For instance, when non-directional styles are outperformed by directional styles, the managers may be inclined to create more exposure to certain markets. It is not uncommon for hedge funds to have exposures to markets that do not belong to their style category.[20] It is naïve to bet on asset classes that performed well over the last period. Yet it is reasonable to assume that hedge fund managers are likely to follow *strategies* that were successful in the recent past. The strategies, although not directly observable, are proxied by exposures to risk factors. The important underlying assumption of this model is therefore that the best performing strategies have exposures to the best performing risk factors. A shift towards a better performing strategy then automatically leads to a shift towards the better performing risk factors. This assumption is valid when the risk factors are indeed capable to capture all relevant strategies (i.e. the risk factors are exhaustive).

The estimation procedure is as follows. First of all, an ordinary least squares regression will be run in order to mimic the study by Agarwal and Naik (2004). It will be tested whether the inclusion of option-based risk factors can indeed show time-variation in hedge fund risk exposures and whether the results are different from Agarwal and Naik (2004). In the second place, the time-varying model will be tested. For all styles, the model in (8) is estimated. An equation-by-equation maximum likelihood is used with a normal distribution as likelihood function. To find appropriate starting values and coefficients in the simulation, the model is first estimated with $\gamma = 0$, which is equal to the estimation of a linear model (i.e. no switching will occur). The model that allows for switching is estimated thereafter. A comparison can then be made between the linear and dynamic case, eventually leading to conclusions about the time-varying behaviour of hedge fund risk exposures.

[20] See Chapter 3.

4.2 Data

This study aims to find the risk exposures of hedge funds by means of an adapted style analysis. In order to do so, the returns of several hedge fund style indices are regressed on both buy-and-hold risk factors and option-based risk factors.[21] The analyses are conducted for both the HFR and CS/Tremont hedge fund indices. Three reasons can be mentioned for the use of these two databases. The first reason is that no database spans the entire hedge fund universe. Conclusions that are drawn from results using only a single database could prove to be valid for a particular part of the hedge fund universe only. Secondly, both databases use a different methodology to construct the index. The CS/Tremont indices are asset-weighted whereas the HFR indices are equally weighted. Lastly, hedge fund indices are prone to data biases, such as survivorship bias and backfill bias.[22] Robustness demands that the analysis is conducted on more than one database in order to account for the differences and shortcomings in the various hedge fund indices. The chosen style indices are the ones that have a comparable counterpart in the other database. The non-directional trading styles under investigation are convertible arbitrage, equity market neutral and event driven. The directional styles are emerging markets, global macro and short bias.[23] The sample consists of monthly net-of-fee returns on the indices from May 1996 to August 2009. All indices include only U.S. hedge funds with more than $50 million in assets under management and having at least a one year track record.

Table 4.1
Hedge fund style indices

In this table the hedge fund style indices under investigation are summed up. For both data providers 6 styles are chosen. Each style of one database has a counterpart in the other database which has similar selection criteria for addition to the index. The definitions of the styles can be found on the respective websites (www.hfr.com for the HFR indices and www.hedgeindex.com for the CS/Tremont indices). The HFR terminology is used throughout this study.

Hedge Fund Research (HFR)	Credit Suisse/Tremont (CS/Tremont)
Convertible arbitrage	Convertible arbitrage
Equity market neutral	Equity market neutral
Event driven	Event driven
Emerging markets	Emerging markets
Global/macro	Global macro
Short bias	Dedicated short bias

[21] The terminological distinction between buy-and-hold risk factors and option-based risk factors is also used by Agarwal and Naik (2004).
[22] See Section 2.2.
[23] The HFR terminology of hedge fund styles is used throughout this study. The trading styles are also summed up in Table 4.1. For a brief description of the various styles: see Appendix A.

Buy-and-hold risk factors and option-based risk factors are used to measure the risk exposures of hedge funds. The buy-and-hold risk factors are a collection of eight asset classes and three zero-investment strategies. Indices are used to proxy for asset classes. For the equity markets, the following three market-capitalisation weighted indices are used. The Russell 3000 index represents the U.S. equity market. The MSCI emerging markets index represents equity market performance of emerging markets. Lastly, the MSCI World index excluding the U.S. represents the equity markets of developed countries apart from the United States. In order to capture exposures to the bond market, three bond indices are used. The Barclay Capital U.S. Aggregate Index represents government and investment-grade corporate bonds in the U.S., whereas the J.P. Morgan Global Aggregate Index excluding the U.S. represents government and investment-grade corporate bonds outside the U.S. The Barclays Capital Global High Yield Index represents high-yield bonds trading at global markets. In order to capture currency exposure, the U.S. Federal Reserve Broad Dollar Index is used. Commodity exposure is proxied by the Merrill Lynch Commodity Index. All return series were available through Thomson Datastream.

Apart from the asset classes representing the location choices of hedge fund managers, three zero-investment strategies are also added as risk factors. After all, if hedge funds use these kinds of strategies within an asset class, there is no exposure to that particular asset class. The returns on three of such commonly used strategies are therefore calculated and added as a risk factor. The first two strategies are derived from Fama and French (1993) who found that a “size” factor and a “book-to-market equity” factor, in combination with the excess market return, explain average returns on stocks quite well. In this study it is researched whether hedge funds are exposed to these risk factors as well. The returns on the two factors are calculated as follows. All NYSE, AMEX and NASDAQ stocks for which market equity data are available for at least half a year are used to construct six portfolios. The stocks are first divided into three groups sorted by book-to-market value, breakpoints being the 30th and 70th percentile. These three groups are each divided into two smaller groups: a group with small stocks and one with big stocks in terms of market capitalisation, with the median size as breakpoint. The first strategy that can be created using the resulting six portfolios is denoted HML (high minus low). The return on this strategy is calculated by averaging the returns on the two high book-to-market portfolios and subtracting the average return on the two low book-to-market portfolios. This risk factor will be referred to as the “value” factor. The second strategy is denoted SMB (small minus big) and is calculated by subtracting the average return on the three big size portfolios from the average return on the three small size portfolios. The six portfolios are rebalanced each year at the end of June. This risk factor is referred to as the “size factor”.

Jegadeesh and Titman (1993) found that past winning stocks continued to outperform losing stocks over a three to twelve month horizon. Carhart (1997) finds that this effect explains the performance persistence of mutual funds. In order to investigate hedge fund exposure to this trading strategy, a third zero-investment strategy is used as risk factor, denoted WML (winners minus losers). This factor is called the "momentum" factor and is constructed using the same data as for the construction of the size and value factors. Instead of stocks being categorized by book-to-market value, they are divided into three groups by sorting them on their performance over the last year. Intersecting these three groups with the two size groups again gives six portfolios. The monthly return of the WML factor is obtained by calculating this month's average return of previous year's good performers and subtracting this month's average return of the previous year's bad performers (averaging the samples of the big and the small firms). The six portfolios are rebalanced each month instead of each year. This risk factor can therefore be characterized as somewhat dynamic in nature. The returns on the size, value and momentum factors were available through K.R. French's Tuck MBA School of Business online data library.[24]

Four option-based risk factors are added to the buy-and-hold risk factors to capture non-linear exposures that occur due to the derivative trading and dynamic trading strategies of hedge funds. The return on a risk factor is gained by trading either an out-of-the-money call option (OMC), an at-the-money call option (AMC), an out-of-the-money put option (OMP) or an at-the-money put option (AMP) on the S&P 500 composite index. The options are traded at the Chicago Board Options Exchange and expire on the third Saturday of each month. The reason for using these particular options is that they are a frequent and exchange-traded derivative. This liquidity provides reliable market prices. The reason that no in-the-money option factors are used, is because of put-call parity. The pay-off on such an option can be replicated by using risk-free assets, underlying assets and an out-of-the-money option.

The returns on the option factors need also be calculated using the prices at month's end to match the return series of the hedge fund index returns. The return on the option factors for any particular month is computed as follows. An option is bought at the first trading day of the month before it expires. It is then sold at the first trading day of the following month, being the month in which the option expires. For instance, the return on the AMC factor in February 1998 is computed by buying an AMC that expires in March 1998 on the first trading day of February 1998 and then selling it on the first trading day of March 1998. The strike price of the AMC is of course determined by the value of the S&P 500 composite index at the time of purchase. The call and put option with the present value of its strike price nearest to the value of the S&P 500 composite index are chosen

[24] http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html

as the AMC and AMP, respectively. The OMC (or OMP) is the option with a next higher (or lower) strike price than the at-the-money option. Option prices were available through the Ivy DB OptionMetrics database.

Table 4.2 contains the descriptive statistics of this sample. The directional styles generally have higher volatilities than the non-directional styles, indicating that directional styles indeed take larger risks. The null hypothesis of normal distribution of returns was rejected for all hedge fund style indices, but also for all of the risk factor returns except the non-U.S. bonds.[25] The hedge fund indices all have positive excess kurtosis (fat tails), which indicates that the standard deviation underestimates the risk run by the hedge funds. Most indices also have negative skewness, indicating that especially negative risks are underestimated. The convertible arbitrage suffers most from these distributional characteristics.

In Table 4.3 the correlations between the style indices are given. Most correlations between the styles are moderately high. The highest correlation is found between the emerging market style and the event driven style in both the HFR and CS/Tremont database. All correlations are positive except for the correlations of the short bias style with the other styles. It can be also seen that most style indices correlate heavily with their counterpart in the other database. The exception to this is the equity market neutral style.

Table 4.4 shows the correlations of the risk factors. Correlations between the developed equity markets and emerging equity markets and are quite high. High-yield bonds correlate with equity markets as well. It should be no surprise that high correlation exists between the equity markets and the (S&P 500) option factors. U.S. bonds have a high correlation with non-U.S. bonds but have very low correlation with other risk factors. The three zero-investment strategies also have very low correlations with other risk factors.

[25] Jarque-Bera tests were performed at a 1% significance level.

Table 4.2
Descriptive statistics

This table contains the means, medians, standard deviations, minimum, maximum, skewness and kurtosis of monthly returns for 6 HFR hedge fund style indices (panel A), 6 CS/Tremont hedge fund style indices (panel B), 11 buy-and-hold risk factors and 4 option-based risk factors (panel C) during May 1996 to August 2009.

Panel A: HFR indices	**Mean**	**Median**	**Std. Dev.**	**Min.**	**Max.**	**Skewness**	**Kurtosis**
Non-directional							
Convertible arbitrage	0.66	0.91	2.25	-16.01	9.74	-3.02	27.25
Equity market neutral	0.50	0.48	0.95	-2.87	3.59	-0.14	4.56
Event driven	0.83	1.22	2.09	-8.90	5.13	-1.39	7.24
Directional							
Emerging markets	0.93	1.59	4.36	-21.02	14.80	-1.06	7.10
Global/macro	0.75	0.63	1.88	-3.77	6.82	0.43	3.69
Short bias	0.30	-0.17	5.71	-21.21	22.84	0.26	5.67
Panel B: CST indices	**Mean**	**Median**	**Std. Dev.**	**Min.**	**Max.**	**Skewness**	**Kurtosis**
Non-directional							
Convertible arbitrage	0.66	1.03	2.18	-12.59	5.81	-2.78	17.97
Equity market neutral	0.77	0.82	1.05	-5.61	3.63	-1.90	13.92
Event driven	0.82	1.03	1.82	-11.77	4.22	-2.70	17.03
Directional							
Emerging markets	0.83	1.57	4.25	-23.03	15.34	-1.26	9.32
Global/macro	1.03	1.20	2.94	-11.55	10.46	-0.18	6.54
Short bias	-0.11	-0.69	5.06	-9.57	22.71	0.79	4.57
Panel C: Risk factors	**Mean**	**Median**	**Std. Dev.**	**Min.**	**Max.**	**Skewness**	**Kurtosis**
U.S. Equities	0.58	0.91	5.08	-17.43	16.18	-0.52	4.57
Emerging markets	0.91	1.11	6.40	-24.76	16.63	-0.55	4.46
non-U.S. Equities	0.45	1.03	4.69	-15.44	10.79	-0.84	3.82
HML factor	0.37	0.33	3.76	-12.41	13.84	-0.01	4.94
SMB factor	0.26	-0.08	3.93	-16.83	21.99	0.79	9.92
WML factor	0.44	0.78	6.20	-34.66	18.39	-1.43	10.31
U.S. Bonds	0.50	0.62	1.07	-3.34	3.37	-0.37	3.65
High-yield bonds	0.70	1.08	3.23	-16.46	11.36	-1.56	11.12
non-U.S. Bonds	0.50	0.59	2.49	-5.41	8.11	0.21	3.31
Commodities	1.16	1.58	6.76	-27.44	20.41	-0.36	4.36
Dollar	0.06	0.13	1.53	-4.75	6.59	0.36	4.96
Option-based factors							
At-the-money Call	-13.03	-29.93	75.54	-99.76	203.55	0.78	2.63
At-the-money Put	-25.03	-57.23	79.73	-97.13	271.43	1.56	4.92
Out-of-the-money Call	-15.72	-41.28	82.73	-100.00	259.18	1.03	3.28
Out-of-the-money Put	-29.93	-65.52	80.98	-97.80	287.42	1.75	5.63

Table 4.3
Hedge fund indices correlation matrix

The correlations between the various HFR and CS/Tremont hedge fund style indices are shown. The 6 styles under investigation are three non-directional styles: convertible arbitrage (CA), equity market neutral (EN) and event driven (ED) and three directional styles: emerging markets (EM), global/macro (GM) and short bias (SB).

	HFR						CS/Tremont					
	CA	EN	ED	EM	GM	SB	CA	EN	ED	EM	GM	SB
HFR												
CA	1											
EN	0.28	1										
ED	0.64	0.41	1									
EM	0.53	0.27	0.81	1								
GM	0.18	0.35	0.51	0.57	1							
SB	-0.29	-0.14	-0.67	-0.63	-0.41	1						
CS/Tremont												
CA	0.92	0.36	0.63	0.50	0.20	-0.22	1					
EN	0.44	0.30	0.52	0.45	0.33	-0.30	0.40	1				
ED	0.62	0.46	0.91	0.80	0.51	-0.53	0.65	0.50	1			
EM	0.47	0.29	0.75	0.96	0.59	-0.60	0.46	0.43	0.77	1		
GM	0.28	0.37	0.37	0.43	0.69	-0.19	0.34	0.23	0.42	0.52	1	
SB	-0.31	-0.16	-0.69	-0.62	-0.40	0.83	-0.26	-0.34	-0.58	-0.57	-0.12	1

Table 4.4
Risk factors correlation matrix

The correlations of the buy-and-hold and option-based risk factors are shown. The abbreviations represent the Russell 3000 index (RUS), the MSCI emerging markets index (EMK), the MSCI World index excluding the U.S. (MSW), the Fama and French "value" factor (HML), the Fama and French "size" factor (SMB), the Fama and French "momentum" factor (WML), the Barclays Capital U.S. Aggregate index to represent U.S. bonds (USB), the Barclays Capital Global High Yield index to represent high-yield bonds (HYB), the J.P. Morgan Global Aggregate index to represent the global bond markets excluding the U.S. (JPG), the Merrill Lynch Commodity index (COM), the Federal Reserve Broad Dollar index (DOL), the at-the-money call option on the S&P 500 index (AMC), the out-of-the-money call option on the S&P 500 index (OMC), the at-the-money put option on the S&P 500 index (AMP) and the out-of-the-money put option on the S&P 500 index (OMP).

	RUS	EMK	MSW	HML	SMB	WML	USB	HYB	JPG	COM	DOL	AMC	OMC	AMP	OMP
RUS	1														
EMK	0.75	1													
MSW	0.87	0.81	1												
HML	-0.20	-0.26	-0.18	1											
SMB	0.16	0.30	0.22	-0.40	1										
WML	-0.38	-0.31	-0.31	-0.17	0.08	1									
USB	0.05	-0.06	-0.08	0.05	-0.07	0.004	1								
HYB	0.69	0.71	0.68	-0.10	0.24	-0.38	0.25	1							
JPG	0.10	0.03	-0.09	0.05	0.04	-0.05	0.54	0.17	1						
COM	0.29	0.38	0.28	-0.01	0.16	-0.05	-0.01	0.33	0.19	1					
DOL	-0.49	-0.47	-0.34	0.01	-0.17	0.17	-0.20	-0.46	-0.73	-0.45	1				
AMC	0.82	0.59	0.68	-0.22	-0.01	-0.30	0.06	0.45	0.02	0.11	-0.30	1			
OMC	0.79	0.55	0.65	-0.21	-0.03	-0.29	0.06	0.42	0.02	0.10	-0.29	0.995	1		
AMP	-0.87	-0.70	-0.80	0.27	-0.15	0.30	-0.02	-0.63	0.02	-0.22	0.32	-0.72	-0.67	1	
OMP	-0.85	-0.69	-0.79	0.27	-0.16	0.29	-0.01	-0.63	0.02	-0.23	0.31	-0.69	-0.64	0.997	1

5 Results

First of all, the results of the linear regression model are treated in Section 5.1. Since this model is similar to the one employed by Agarwal and Naik (2004), differences and similarities in the results are also investigated. This study goes one step further by attempting to find out what time-variation exists in hedge fund risk exposures. The time-varying maximum likelihood model is treated in Section 5.2.

5.1 Linear regression model

In Table 5.1 the ordinary least squares regression results are given for the HFR style indices. In the following subsections the results on the HFR style indices are treated. To check whether the results on the HFR sample are robust, the results are compared with those of the CS/Tremont sample in Section 5.1.7. In Section 5.1.8 a short summary is provided. The trading styles are explained in Appendix A.

5.1.1 Convertible arbitrage

The trading strategy applied by convertible arbitrage hedge funds is to purchase undervalued convertible bonds (or to sell overvalued convertible bonds) and to hedge out the risk components, such as interest rate risk, equity risk and credit risk. This trading style can therefore be characterised as a non-directional style. The results show exposures to many risk factors, however. The relatively large positive exposure to high-yield bonds indicates that credit risk is particularly not hedged away completely. Also, negative exposures to the U.S. equity market, non-U.S. bond markets and dollar remain. A slight positive exposure to commodities is found as well.

In a sense, these results are comparable with those of Agarwal and Naik (2004) since they, too, find many exposures despite the (alleged) non-directional character of this trading style. They find different and even contrary exposures, however. A negative exposure to the at-the-money put option is found along with slightly positive exposures to the U.S. equity market, the U.S. bond market, emerging equity markets and the SMB portfolio. Contrary to the current findings, they find a significant intercept.

Table 5.1
Regression results (HFR)

This table shows the results of the regression model in Equation (7) for the six HFR style indices during the sample period from May 1996 to August 2009. The table shows the intercept (α) and the following slope coefficients (factor loadings) for buy-and-hold factors: the Russell 3000 index (RUS), the MSCI emerging markets index (EMK), the MSCI World index excluding the U.S. (MSW), the Fama and French "value" factor (HML), the Fama and French "size" factor (SMB), the Fama and French "momentum" factor (WML), the Barclays Capital U.S. Aggregate index to represent U.S. bonds (USB), the Barclays Capital Global High Yield index to represent high-yield bonds (HYB), the J.P. Morgan Global Aggregate index to represent the global bond markets excluding the U.S. (JPG), the Merrill Lynch Commodity index (COM) and the Federal Reserve Broad Dollar index (DOL). Option-based risk factors are options on the S&P 500 composite index: an at-the-money call option (AMC), an out-of-the-money call option (OMC), an at-the-money put option (AMP) and an out-of-the-money put option (OMP). Standard deviations are in parentheses. Significance is represented by * (10% level), ** (5% level) and *** (1% level).

	Convertible arbitrage	*Equity market neutral*	*Event driven*	*Emerging markets*	*Global/macro*	*Short bias*
α	0.107 (0.167)	0.218*** (0.079)	0.370*** (0.110)	0.035 (0.200)	0.517*** (0.151)	0.035 (0.298)
RUS	-0.184** (0.081)	-0.035 (0.039)	-0.123** (0.053)	-0.402*** (0.097)	-0.207*** (0.074)	-0.316** (0.145)
EMK	-0.062 (0.040)	-0.041** (0.019)	0.044 (0.026)	0.500*** (0.048)	0.143*** (0.036)	-0.061 (0.072)
MSW	0.079 (0.067)	0.032 (0.032)	0.031 (0.044)	0.025 (0.080)	0.048 (0.061)	-0.196 (0.119)
HML	-0.009 (0.039)	0.032* (0.019)	0.031 (0.026)	0.007 (0.047)	-0.005 (0.035)	0.457*** (0.070)
SMB	-0.015 (0.037)	0.005 (0.017)	0.135*** (0.024)	0.036 (0.044)	0.093*** (0.033)	-0.484*** (0.065)
WML	-0.024 (0.023)	0.087*** (0.011)	0.029* (0.015)	0.102*** (0.027)	0.088*** (0.021)	-0.053 (0.041)
USB	0.279 (0.169)	-0.015 (0.080)	-0.218* (0.111)	0.019 (0.202)	0.082 (0.153)	0.536* (0.302)
HYB	0.501*** (0.068)	0.096*** (0.032)	0.345*** (0.044)	0.440*** (0.081)	0.070 (0.061)	-0.119 (0.120)
JPG	-0.364*** (0.109)	-0.077 (0.052)	-0.053 (0.072)	-0.267** (0.130)	0.247** (0.099)	-0.332* (0.194)
COM	0.053** (0.021)	0.021** (0.010)	0.018 (0.014)	-0.007 (0.025)	0.043** (0.019)	0.040 (0.038)
DOL	-0.634*** (0.189)	-0.170* (0.090)	-0.082 (0.124)	-0.530** (0.226)	0.378** (0.171)	-0.305 (0.337)
AMC	-0.004 (0.026)	0.032** (0.013)	0.033* (0.017)	0.016 (0.032)	0.016 (0.024)	0.102** (0.047)
OMC	0.006 (0.022)	-0.024** (0.010)	-0.020 (0.014)	0.002 (0.026)	-0.001 (0.020)	-0.097** (0.039)
AMP	-0.006 (0.029)	0.017 (0.014)	0.028 (0.019)	0.081** (0.035)	0.022 (0.026)	0.025 (0.052)
OMP	0.005 (0.027)	-0.014 (0.013)	-0.029* (0.018)	-0.082** (0.032)	-0.020 (0.024)	-0.015 (0.048)
$\bar{R}^2$	0.551	0.370	0.773	0.830	0.438	0.777

5.1.2 Equity market neutral

Hedge funds adopting this trading style try to buy undervalued and sell overvalued stocks and hedge away the market risk involved. The found exposures are statistically significant but small in comparison with the exposures that other styles exhibit. Negative exposures to emerging market equities and the U.S. dollar are found along with positive exposures to the value factor, momentum factor, high-yield bonds and commodities. This finding indicates that the equity market is not the only market in which trades are made by equity market neutral hedge funds. Also, significant exposures to the S&P 500 at-the money and out-of-the-money call options are found. These exposures have similar magnitude but have an opposite sign, however. Since the returns on the at-the-money options are not very different from the returns on the out-of-the-money counterparts, the effects largely offset each other. This is also observed in the results of the emerging markets and short bias styles indices. It could be stated that the hedge funds are involved in some sort of bull spread. But since there is no economic intuition behind this, especially not for three out of six hedge fund styles, this phenomenon is most probably due to the high correlation between the at-the-money and out-of-the money options.[26] The coefficients on the option factors are therefore concluded not to be of any relevance, despite the statistical significance.

The significant intercept suggests that this style is able to outperform the market. Agarwal and Naik (2004) find much larger and more specific exposures, namely to the U.S. equity market and the size factor. The $\bar{R}^2$ they find is much larger, which is about 73% compared to 38% in this sample.

5.1.3 Event driven

Event driven strategies try to exploit mispricing of securities before the occurrence of an event such as a merger or a restructuring. The risk involved in these strategies is that the event is not realised. Agarwal and Naik (2004) argue that since this is more likely to happen during market downturns, one would expect some kind of positive exposure to the equity market. On the other hand, it can also be argued that events related to financial distress will be realised exactly because of market downturns. This may be an explanation for the fact that a negative exposure to the U.S. equity market and investment-grade bond market is found, contrary to the result of Agarwal and Naik (2004). A long exposure to high-yield bonds is also found. This exposure is not surprising since many events will

[26] This should not come as a surprise because of the close relatedness of the options. The correlation between the at-the-money call and the out-of-the-money call is 0.995, the correlation between the at-the-money put and the out-of-the-money put is 0.997. See Table 4.4 for the correlation matrix of risk factors.

concern the companies that have issued these bonds. Agarwal and Naik (2004) do not find any exposure to bond markets. Similarly to the current results, they do find a positive exposure to the size factor and a positive intercept.

One more remark should be made about the results of the event driven style. It is the only style with a significant net exposure to option-based risk factors. Apart from the short out-of-the-money put exposure, the event driven style appears to have a long exposure to the at-the-money call option as well. This is inconsistent with Agarwal and Naik (2004), who only find a short position in a put option. The option component was added to find out if the absolute return objective in fact leads hedge funds to be insuring against negative tail events in return for a premium. A long exposure to a call option in no way leads to such an "absolute return". Rather, it produces the opposite effect. The economic interpretation of this result would be that event driven styles pay a premium to benefit from upswings in the market. There is no intuition as to why it would be so. It does protect them from negative returns on the short U.S. equity exposure, so this could be the reason. The returns of Agarwal and Naik (2004) are more intuitive. It has to be concluded that their results are not persistent, though.

5.1.4 Emerging markets

The emerging markets style index is constituted by hedge funds that invest in a multitude of securities in emerging markets by using several investment strategies. It is a directional style and investors can therefore typically expect a lot of emerging equity market, emerging bond market and currency exposures. The results indicate that this is indeed the case. The exposure to emerging equity markets is positive with an accompanying negative exposure to the U.S. dollar. The exposure to global high-yield bonds is positive whereas the exposure to non-U.S. investment-grade bond markets is negative. A positive exposure to the momentum factor and a negative exposure to the U.S. equity market exist as well.

As it was in the case of the equity market neutral index, the emerging markets index exhibits offsetting exposures to option-based risk factors. This means there is no real non-linear exposure. Reference is made to Section 5.1.2 for a more elaborate explanation. Agarwal and Naik (2004) did not include any emerging market trading styles in their study.

5.1.5 Global/macro

The global/macro trading style index includes hedge funds that adopt a broad range of strategies predicated on movements of economic variables rather than company-specific characteristics. It appears that significant exposures exist to many risk factors as can be expected from a directional style with many investment strategies and trading techniques. The style has a negative exposure to the U.S. equity market, but a positive one to emerging equity markets. The exposures to the non-U.S. bond market and U.S. dollar are also positive. To the value factor, momentum factor and commodities only small positive exposures are found. The intercept is also positive, indicating a market outperformance. Agarwal and Naik (2004) did not include global/macro trading styles in their study.

5.1.6 Short bias

The short bias trading style is characterised by a consistent short exposure to the equity market. Still its primary investment strategy is to take advantage of undervaluation or overvaluation of companies in the market, as equity market neutral styles do. This is confirmed by the results. A short exposure to the U.S. equity market exists along with short exposures to the size factor and non-U.S. bond factor. A positive exposure is found with respect to the value factor and U.S. bond factor. Offsetting exposures are found with regard to the option factors, similar to the equity market neutral and emerging markets styles. In Section 5.1.2 this was made clear more elaborately.

5.1.7 Results of the CS/Tremont sample

Table 5.2 shows the regression results for the CS/Tremont style indices. There are some key similarities between the results of the HFR database and the CS/Tremont database. For instance, the convertible arbitrage, event driven and emerging markets styles have a very similar risk profile. The direction and magnitude of the corresponding coefficients are very much alike. The intercepts are also similar with the exception of the short bias style. The convertible arbitrage and emerging markets styles do not have significant intercepts, whereas the equity market neutral, event driven and global/macro styles all have a positive intercept. The resemblance between the $\bar{R}^2$'s is also quite striking. The emerging markets, short bias and event driven styles have relatively high $\bar{R}^2$'s in comparison with the other three styles.

Table 5.2
Regression results (CS/Tremont)

This table shows the results of the regression model in Equation (7) for the six CS/Tremont style indices during the sample period from May 1996 to August 2009. The table shows the intercept (α) and the following slope coefficients (factor loadings) for buy-and-hold factors: the Russell 3000 index (RUS), the MSCI World index excluding the U.S. (MSW), the MSCI emerging markets index (EMK), the Fama and French "value" factor (HML), the Fama and French "size" factor (SMB), the Fama and French "momentum" factor (WML), the Barclays Capital U.S. Aggregate index to represent U.S. bonds (USB), the Barclays Capital Global High Yield index to represent high-yield bonds (HYB), the J.P. Morgan Global Aggregate index to represent the global bond markets excluding the U.S. (JPG), the Merrill Lynch Commodity index (COM) and the Federal Reserve Broad Dollar index (DOL). Option-based risk factors are options on the S&P 500 composite index: an at-the-money call option (AMC), an out-of-the-money call option (OMC), an at-the-money put option (AMP) and an out-of-the-money put option (OMP). Standard deviations are in parentheses. Significance is represented by * (10% level), ** (5% level) and *** (1% level).

	Convertible arbitrage	*Equity market neutral*	*Event driven*	*Emerging markets*	*Global/macro*	*Short bias*
α	0.094 (0.170)	0.408*** (0.090)	0.394*** (0.116)	-0.183 (0.239)	0.584** (0.269)	-0.553* (0.322)
RUS	-0.313*** (0.083)	0.139*** (0.044)	-0.162*** (0.056)	-0.342*** (0.116)	-0.236* (0.131)	-0.183 (0.159)
EMK	-0.100** (0.041)	0.006 (0.022)	0.054* (0.028)	0.480*** (0.057)	0.029 (0.065)	-0.151* (0.078)
MSW	0.109 (0.068)	-0.050 (0.036)	0.052 (0.046)	0.003 (0.096)	0.071 (0.108)	-0.055 (0.130)
HML	0.008 (0.040)	0.022 (0.021)	0.035 (0.027)	-0.014 (0.056)	0.045 (0.063)	0.202*** (0.076)
SMB	0.015 (0.037)	-0.022 (0.020)	0.042* (0.025)	0.020 (0.052)	0.034 (0.059)	-0.323*** (0.071)
WML	-0.012 (0.023)	0.009 (0.012)	0.061*** (0.016)	0.157*** (0.033)	0.137*** (0.037)	-0.034 (0.045)
USB	0.244 (0.172)	-0.050 (0.091)	-0.307*** (0.117)	0.213 (0.242)	0.662** (0.272)	0.547* (0.326)
HYB	0.540*** (0.069)	0.080** (0.036)	0.379*** (0.047)	0.450*** (0.097)	0.270** (0.109)	-0.313** (0.131)
JPG	-0.391*** (0.111)	-0.049 (0.058)	-0.032 (0.076)	-0.256 (0.156)	-0.130 (0.175)	-0.275 (0.213)
COM	0.056** (0.022)	0.020* (0.011)	0.023 (0.015)	-0.022 (0.031)	0.060* (0.034)	0.048 (0.041)
DOL	-0.580*** (0.193)	-0.099 (0.101)	0.019 (0.131)	-0.329 (0.271)	0.228 (0.304)	-0.440 (0.369)
AMC	-0.007 (0.027)	-0.005 (0.014)	0.008 (0.018)	0.008 (0.038)	0.034 (0.042)	0.017 (0.049)
OMC	0.011 (0.022)	0.005 (0.012)	0.001 (0.015)	0.007 (0.031)	-0.015 (0.035)	-0.026 (0.041)
AMP	-0.002 (0.030)	0.009 (0.016)	0.017 (0.020)	0.094** (0.042)	0.026 (0.047)	0.043 (0.056)
OMP	-0.002 (0.027)	-0.006 (0.014)	-0.019 (0.019)	-0.095** (0.038)	-0.026 (0.043)	-0.038 (0.051)
$\bar{R}^2$	0.502	0.358	0.664	0.739	0.234	0.649

There are some key differences to be noted, too, however. The CS/Tremont regressions typically have less significant variables. All $\bar{R}^2$'s are lower, although the difference is not large. The regressions that have the lowest $\bar{R}^2$'s in both samples differ the most. For the equity market neutral style, high-yield bond and commodity risk factors correspond with the risk factors resulting from the HFR regression. The risk factors found for the global/macro style are also very different. The exposures to the U.S. equity market, momentum and commodity factors are similar, but no exposure is found to emerging market equities, size factor, non-U.S. bonds or U.S. dollar. Another point of interest is that there is no significant currency exposure found for the emerging markets style.

It appears that the exposures are quite similar for some styles, but very different for others. It is of particular interest that the styles which do not exhibit a lot of resemblance with the counterpart in the other sample, have much lower explanatory power than the other styles. The style regressions with high explanatory power do have similar exposures. This indicates that the risk exposures found for a certain style in one database are robust under the condition that the linear nature of the regression fits the data quite well and the appropriate risk factors are included in the regression. Conclusions drawn on the basis of a sample from only one database remain liable to give inaccurate generalisations of the entire hedge fund universe, however.

5.1.8 Summary on the linear regression results

There are three important reasons for conducting these linear regressions in this study. Firstly, the option-based risk factors can shed some light on the non-linear nature of hedge fund returns. The second reason is that a comparison can be made with Agarwal and Naik (2004). Since Agarwal and Naik (2004) employ a different time frame, this comparison may reveal information on the time-variation of hedge fund risk exposures. Thirdly, in relation to this, a comparison can be made between the linear regression model and a model that explicitly allows for time-varying risk exposures. This latter model will be the subject of the next section. In this section, the first two issues are treated.

The first issue is whether the option-based risk factors provides any understanding of the non-linear exposures of hedge funds. It appears that the option-based risk factors are not capable of showing a non-linear pay-off since most styles have no exposure to an option-based risk factor. In cases where a significant exposure to an option-based risk factors is found, an offsetting exposure is found as well. For instance, a positive exposure to the out-of-the-money call is offset by a negative exposure to the at-the-money call of similar magnitude.[27] Regressions run without the option-based

[27] This is only different for the HFR event driven style. See Section 5.1.3.

risk factors do not affect the $\bar{R}^2$ much. Regressions run with only at-the-money options do not yield significant results on the option components either. Therefore it can be safely stated that the relations found between hedge fund style indices and option-based risk factors are spurious. This is even more likely because of the high positive correlation between the two option-based risk factors.[28] In this light it is somewhat surprising that Agarwal and Naik (2004) do find significant and non-offsetting exposures to the option-based risk factors, since their methodology is the same.

The analysed six style indices are not identical to the ones used by Agarwal and Naik (2004). This is because the six style indices used in this study are comparable between databases, whereas some used by Agarwal and Naik (2004) are not. A comparison with the Agarwal and Naik (2004) results can be made nevertheless. Some obvious exposures are similar: short exposures are found in the short bias style and emerging market and dollar exposures are found in the emerging markets style. Other exposures are completely different, however. The most striking difference is that Agarwal and Naik (2004) find many exposures to the option-based risk factors. The differences emphasize the changing nature of hedge fund risk exposures. It is therefore necessary to investigate time-variation in hedge fund risk exposures more thoroughly. The following section deals with the estimation of the time-varying model which was set forth in Section 4.1.

5.2 Time-varying model

The model in equation (8) is estimated for both the HFR and CS/Tremont database. The results are given in Tables 5.3 and 5.4 for the HFR sample and in Tables 5.5 and 5.6 for the CS/Tremont sample. When conclusions are drawn without reference to a database, the HFR results are used. When the CS/Tremont sample is used, this is mentioned explicitly. This is usually the case for robustness checks.

The model is estimated without the use of option-based risk factors as explanatory variables. The option-based risk factors formed a mechanism to implement a non-linear element in an otherwise linear regression model. The time-varying weights should be able to sufficiently capture the non-linearities present in hedge fund risk exposures. Therefore, non-linear explanatory variables such as options-based risk factors are not necessary. In addition to this, the option-based risk factors were not able to explain non-linearities in the linear case (Section 5.1), so there are no theoretical grounds to assume they will do better in this time-varying model.

[28] This was already mentioned in footnote 24.

Table 5.3
Estimation results non-directional styles (HFR)

This table shows the results of the model in Equation (8) for the three non-directional HFR style indices during the sample period from May 1996 to August 2009. Convertible arbitrage, equity market neutral and event driven styles are the non-directional styles. For each style, both the linear case ($\gamma = 0$) and the switching case is shown. The table shows the intercept (α) and the following slope coefficients (factor loadings) for buy-and-hold factors: the Russell 3000 index (RUS), the MSCI emerging markets index (EMK), the MSCI World index excluding the U.S. (MSW), the Fama and French "value" factor (HML), the Fama and French "size" factor (SMB), the Fama and French "momentum" factor (WML), the Barclays Capital U.S. Aggregate index to represent U.S. bonds (USB), the Barclays Capital Global High Yield index to represent high-yield bonds (HYB), the J.P. Morgan Global Aggregate index to represent the global bond markets excluding the U.S. (JPG), the Merrill Lynch Commodity index (COM) and the Federal Reserve Broad Dollar index (DOL). The intensity of choice is denoted by γ. LogL is the log likelihood. Standard deviations are in parentheses. Significance is represented by * (10% level), ** (5% level) and *** (1% level).

	Convertible arbitrage		*Equity market neutral*		*Event driven*	
	Linear	Switch	Linear	Switch	Linear	Switch
α	0.061 (0.143)	0.041 (0.156)	0.138** (0.066)	0.111* (0.065)	0.377*** (0.109)	0.362*** (0.115)
RUS	-1.438** (0.631)	-1.386** (0.640)	0.125 (0.281)	0.471 (0.291)	0.494 (0.400)	0.675 (0.463)
EMK	-0.619 (0.507)	-0.685 (0.518)	-0.327 (0.249)	-0.400* (0.236)	0.687** (0.335)	0.592* (0.336)
MSW	0.813 (0.790)	0.835 (0.813)	0.381 (0.399)	0.171 (0.374)	0.496 (0.571)	0.404 (0.617)
HML	-0.187 (0.398)	-0.194 (0.406)	0.375* (0.222)	0.411** (0.198)	0.164 (0.342)	0.109 (0.330)
SMB	-0.266 (0.477)	-0.258 (0.495)	0.026 (0.210)	0.000 (0.197)	1.273*** (0.303)	1.205*** (0.276)
WML	-0.272 (0.283)	-0.295 (0.276)	0.949*** (0.123)	0.925*** (0.135)	0.324** (0.165)	0.352** (0.166)
USB	3.376* (1.934)	3.455* (2.067)	0.009 (0.924)	0.006 (0.946)	-1.952 (1.684)	-1.960 (1.712)
HYB	5.332*** (0.669)	5.393*** (0.673)	0.768** (0.349)	0.865** (0.391)	3.375*** (0.539)	3.450*** (0.531)
JPG	-4.061*** (1.12)	-4.185*** (1.312)	-0.831 (0.573)	-1.005* (0.555)	-0.607 (1.086)	-0.823 (1.049)
COM	0.558** (0.275)	0.559** (0.273)	0.185* (0.111)	0.184* (0.108)	0.125 (0.204)	0.123 (0.220)
DOL	-6.88*** (1.889)	-7.201*** (2.069)	-1.701* (1.024)	-2.027* (1.043)	-0.257 (1.790)	-0.559 (1.720)
γ	-	0.010 (0.009)	-	0.045*** (0.014)	-	0.020 (0.014)
LogL	-286.1	-285.7	-172.3	-167.2***	-230.7	-230.4

Table 5.4
Estimation results directional styles (HFR)

This table shows the results of the model in Equation (8) for the three directional HFR style indices during the sample period from May 1996 to August 2009. Emerging markets, global/macro and short bias styles are the directional styles. For each style, both the linear case ($\gamma = 0$) and the switching case is shown. The table shows the intercept (α) and the following slope coefficients (factor loadings) for buy-and-hold factors: the Russell 3000 index (RUS), the MSCI emerging markets index (EMK), the MSCI World index excluding the U.S. (MSW), the Fama and French "value" factor (HML), the Fama and French "size" factor (SMB), the Fama and French "momentum" factor (WML), the Barclays Capital U.S. Aggregate index to represent U.S. bonds (USB), the Barclays Capital Global High Yield index to represent high-yield bonds (HYB), the J.P. Morgan Global Aggregate index to represent the global bond markets excluding the U.S. (JPG), the Merrill Lynch Commodity index (COM) and the Federal Reserve Broad Dollar index (DOL). The intensity of choice is denoted by γ. LogL is the log likelihood. Standard deviations are in parentheses. Significance is represented by * (10% level), ** (5% level) and *** (1% level).

	Emerging markets		*Global/macro*		*Short bias*	
	Linear	Switch	Linear	Switch	Linear	Switch
α	0.148 (0.179)	0.105 (0.184)	0.326** (0.142)	0.184 (0.139)	0.080 (0.248)	0.157 (0.235)
RUS	-1.931*** (0.748)	-1.763** (0.770)	-0.266 (0.653)	0.811* (0.451)	-5.556*** (0.974)	-6.84*** (1.234)
EMK	5.589*** (0.519)	5.426*** (0.543)	1.786*** (0.444)	0.159 (0.184)	-0.684 (0.718)	0.000 (0.001)
MSW	0.637 (0.837)	0.591 (0.868)	0.451 (0.759)	1.497*** (0.528)	-1.438 (1.227)	-1.266 (1.122)
HML	-0.216 (0.589)	-0.235 (0.554)	-0.252 (0.412)	-0.430 (0.281)	5.099*** (0.729)	4.888*** (0.685)
SMB	0.005 (0.424)	0.004 (0.177)	0.687 (0.425)	0.548** (0.249)	-4.035*** (0.573)	-3.698*** (0.497)
WML	1.090*** (0.399)	1.107*** (0.411)	0.932*** (0.230)	0.347** (0.144)	-0.293 (0.330)	-0.278 (0.405)
USB	0.926 (2.753)	0.828 (2.747)	1.929 (2.017)	2.831** (1.159)	5.452* (3.306)	6.519** (3.145)
HYB	4.210*** (0.890)	4.530*** (0.837)	-0.069 (0.821)	0.419 (0.441)	-0.989 (1.086)	-1.460 (1.116)
JPG	-3.295* (1.719)	-3.442* (1.770)	2.460** (1.111)	1.479*** (0.515)	-2.831 (2.225)	-2.857 (2.253)
COM	-0.113 (0.338)	-0.118 (0.347)	0.362 (0.235)	0.361*** (0.133)	0.437 (0.435)	0.313 (0.406)
DOL	-5.596* (2.968)	-6.072** (3.079)	4.284** (1.897)	1.171* (0.700)	-3.103 (4.392)	-2.355 (4.667)
γ	-	0.011 (0.007)	-	0.349*** (0.081)	-	-0.039** (0.020)
LogL	-325.1	-324.0	-281.5	-270.5***	-371.3	-368.2**

For each style, a linear and a switching case is provided. The linear case involves no switching and puts an equal and constant weight on all eleven risk factors. This is established by having the portfolio managers be completely insensitive to the performance of the various risk factors ($\gamma = 0$). The results should be identical to the linear regression method of Section 5.1 except that no option-based risk factors are included this time. And, of course, the coefficients are 11 times as large because they are each multiplied by a weight in Equation (8) to find the exposure to a particular risk factor.[29] It can be seen from comparing the linear cases in Tables 5.3 and 5.4 with the results in Table 5.1 that the omission of option-based risk factors has little effect on the results. Most styles do not exhibit a lot of changes in significant risk factors. For the global/macro style, the number of significant exposures is reduced. No "new" exposures appear, however, in the sense that no insignificant exposures turn significant when option-based risk factors are left out. One exception to this is formed by the event driven style in the HFR database: a positive exposure to the emerging equity markets emerges. A positive exposure to U.S. bonds appears in the convertible arbitrage style. Similar effects are also present in the CS/Tremont results.[30]

5.2.1 Factor loadings

If the time-varying model is able to capture the time-variation of hedge fund risk exposures, then more or other exposures should be observed and the model should have a significantly higher explanatory power. This appears to be the case for three out of six styles: the equity market neutral style, the global/macro style and the short bias style.[31] The managers adopting these styles are indeed sensitive to the returns of their own strategies relative to the returns of other strategies and adapt their own style accordingly. The value for gamma is much higher for the global/macro style than for the equity market neutral and short bias styles. This means that global/macro managers are more keen to switch weights to more successful strategies. The reason behind this may be that global/macro managers are very free in their choice of markets to invest in and the financial instruments employed. As it is a directional style, they do not have to worry as much about their exposures as equity market neutral managers do. A switch is easily made. Equity market neutral managers can only trade equity products and, at the same time, they are not allowed to have major exposures to the equity market. Recall that much of this is true for short bias managers as well. Even though it is classified as a directional style, the purpose of the short bias style is to conduct the same strategies as the equity market neutral style whilst keeping a net negative exposure to the market.

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[29] The weights being 1/11 since the number of risk factors employed is 11 and $\gamma = 0$. See equation (9).

[30] Compare the linear cases in Table 5.5 and 5.6 with the results in Table 5.2.

[31] To test whether the time-varying model has a higher explanatory power, a likelihood ratio test was conducted.

It can be seen from Table 5.3 that the equity market neutral style displays two more exposures in the switching case than it does in the linear case. Apart from the factors that had significant exposures in the linear case, negative exposures to the emerging equity markets and global investment-grade bond market are found. It appears that the equity market neutral style experiences periods during which the exposure to these factors are very much present. The short bias style has no changes in exposures, nor do the values of the factor loadings change much. The changes in exposures of the global macro style are more remarkable. When managers are allowed to switch between exposures, the positive exposures to the emerging equity markets disappears, whereas positive exposures appear to the U.S. equity market, the global equity market, the size factor, the U.S. bond market and commodities. The intercept is no longer significant. The styles that do not have a significant increase in log-likelihood have no exposure changes. The values of their factor loadings change only slightly.

The results of the analysis conducted on the CS/Tremont database also point to the global/macro and short bias styles for significant time-varying behaviour of hedge fund managers. The equity market neutral style does not show a significant improvement in log-likelihood, however. The log-likelihood of the event driven style increases significantly at the 10% significance level. The intensity of choice is again highest for the global/macro style. The CS/Tremont styles show much less changes to the factor loadings than the HFR styles. The types of exposures of the global/macro and short bias styles stay more or less the same. The results on the HFR database appear quite robust, since two out of three significant time-varying styles display significant time-variation in the CS/Tremont database results as well. The exposures found in the CS/Tremont database are different altogether, though. For example, regarding the global/macro style, more exposures are found in the results of the HFR database. In general, it can be stated that the discrepancy between the HFR and CS/Tremont databases that was found in the standard linear regression model in Section 5.1, is not reduced by using a time-varying model. Therefore it is still very important to draw conclusions on the basis of various databases when conducting hedge fund research. The time-varying model is able to explain the hedge fund index returns for some styles better than a linear model, however.

Table 5.5
Estimation results non-directional styles (CS/Tremont)

This table shows the results of the model in equation (8) for the three non-directional CS/Tremont style indices during the sample period from May 1996 to August 2009. Convertible arbitrage, equity market neutral and event driven styles are the non-directional styles. For each style, both the linear case ($\gamma = 0$) and the switching case is shown. The table shows the intercept (α) and the following slope coefficients (factor loadings) for buy-and-hold factors: the Russell 3000 index (RUS), the MSCI emerging markets index (EMK), the MSCI World index excluding the U.S. (MSW), the Fama and French "value" factor (HML), the Fama and French "size" factor (SMB), the Fama and French "momentum" factor (WML), the Barclays Capital U.S. Aggregate index to represent U.S. bonds (USB), the Barclays Capital Global High Yield index to represent high-yield bonds (HYB), the J.P. Morgan Global Aggregate index to represent the global bond markets excluding the U.S. (JPG), the Merrill Lynch Commodity index (COM) and the Federal Reserve Broad Dollar index (DOL). The intensity of choice is denoted by γ. LogL is the log likelihood. Standard deviations are in parentheses. Significance is represented by * (10% level), ** (5% level) and *** (1% level).

	Convertible arbitrage		*Equity market neutral*		*Event driven*	
	Linear	Switch	Linear	Switch	Linear	Switch
α	0.096 (0.154)	0.065 (0.157)	0.384*** (0.075)	0.384*** (0.077)	0.390*** (0.110)	0.358*** (0.113)
RUS	-2.029*** (0.766)	-1.888** (0.764)	1.124*** (0.288)	1.125*** (0.352)	-0.320 (0.456)	-0.360 (0.475)
EMK	-0.989* (0.543)	-1.057** (0.534)	-0.005 (0.221)	-0.005 (0.232)	0.709** (0.336)	0.453 (0.339)
MSW	1.197 (0.904)	1.161 (0.941)	-0.562 (0.350)	-0.562 (0.366)	0.635 (0.555)	0.814 (0.600)
HML	-0.117 (0.425)	-0.066 (0.425)	0.294 (0.262)	0.294 (0.290)	0.210 (0.341)	0.087 (0.317)
SMB	-0.059 (0.375)	0.000 (0.003)	-0.221 (0.227)	-0.221 (0.241)	0.249 (0.311)	0.169 (0.268)
WML	-0.129 (0.288)	-0.132 (0.269)	0.083 (0.164)	0.083 (0.164)	0.669*** (0.172)	0.655*** (0.170)
USB	3.182 (2.074)	3.279 (2.062)	-0.568 (0.998)	-0.568 (1.002)	-2.895* (1.625)	-2.794 (1.713)
HYB	5.677*** (0.668)	5.759*** (0.704)	0.855** (0.384)	0.855** (0.388)	3.814*** (0.477)	4.006*** (0.443)
JPG	-4.398*** (1.282)	-4.576*** (1.305)	-0.618 (0.746)	-0.618 (0.760)	-0.470 (1.013)	-0.885 (1.063)
COM	0.566** (0.251)	0.567** (0.250)	0.239 (0.159)	0.238 (0.160)	0.207 (0.185)	0.209 (0.199)
DOL	-6.013*** (2.112)	-6.437*** (2.249)	-1.442 (1.299)	-1.443 (1.348)	0.536 (1.549)	-0.414 (1.652)
γ	-	0.012 (0.009)	-	0.000 (0.019)	-	0.027* (0.015)
LogL	-291.0	-290.3	-187.1	-187.1	-234.2	-232.8*

Table 5.6

Estimation results directional styles (CS/Tremont)

This table shows the results of the model in equation (8) for the three directional HFR style indices during the sample period from May 1996 to August 2009. Emerging markets, global/macro and short bias styles are the directional styles. For each style, both the linear case ($\gamma = 0$) and the switching case is shown. The table shows the intercept (α) and the following slope coefficients (factor loadings) for buy-and-hold factors: the Russell 3000 index (RUS), the MSCI emerging markets index (EMK), the MSCI World index excluding the U.S. (MSW), the Fama and French "value" factor (HML), the Fama and French "size" factor (SMB), the Fama and French "momentum" factor (WML), the Barclays Capital U.S. Aggregate index to represent U.S. bonds (USB), the Barclays Capital Global High Yield index to represent high-yield bonds (HYB), the J.P. Morgan Global Aggregate index to represent the global bond markets excluding the U.S. (JPG), the Merrill Lynch Commodity index (COM) and the Federal Reserve Broad Dollar index (DOL). The intensity of choice is denoted by γ. LogL is the log likelihood. Standard deviations are in parentheses. Significance is represented by * (10% level), ** (5% level) and *** (1% level).

	Emerging markets		*Global/macro*		*Short bias*	
	Linear	Switch	Linear	Switch	Linear	Switch
α	0.036 (0.207)	0.022 (0.216)	0.460* (0.247)	0.336 (0.212)	-0.156 (0.264)	-0.048 (0.262)
RUS	-1.874** (0.923)	-1.850* (0.971)	-0.029 (1.052)	1.257 (0.849)	-4.745*** (1.125)	-6.477*** (1.218)
EMK	5.253*** (0.626)	5.190*** (0.638)	0.615 (0.795)	0.000 (0.523)	-2.269*** (0.870)	-1.418 (0.871)
MSW	0.516 (0.937)	0.533 (0.977)	0.815 (1.147)	0.787 (0.969)	-0.010 (1.476)	0.526 (1.256)
HML	-0.389 (0.665)	-0.392 (0.664)	0.243 (0.867)	0.473 (0.477)	2.383** (0.937)	2.120** (0.940)
SMB	-0.094 (0.552)	-0.079 (0.565)	0.021 (0.780)	0.021 (0.548)	-2.889*** (0.805)	-2.739*** (0.668)
WML	1.687*** (0.448)	1.689*** (0.465)	1.500*** (0.471)	1.219*** (0.376)	-0.452 (0.462)	-0.331 (0.513)
USB	2.733 (3.229)	2.738 (3.286)	8.240** (4.119)	9.862*** (2.520)	3.357 (3.801)	4.838 (3.604)
HYB	4.570*** (0.957)	4.664*** (1.064)	2.166 (1.639)	1.423 (1.159)	-2.614** (1.229)	-3.358*** (1.135)
JPG	-3.181 (2.049)	-3.271 (2.056)	-1.582 (2.229)	-2.875 (1.754)	-2.612 (2.578)	-2.612 (2.467)
COM	-0.223 (0.431)	-0.228 (0.443)	0.536 (0.393)	0.543* (0.326)	0.818* (0.472)	0.727 (0.458)
DOL	-3.589 (3.683)	-3.812 (3.692)	3.108 (3.860)	0.901 (2.590)	-5.624 (4.795)	-4.634 (4.602)
γ	-	0.003 (0.009)	-	0.152** (0.065)	-	-0.041*** (0.014)
LogL	-349.8	-349.7	-366.0	-359.1***	-396.2	-392.2***

It is hard to explain why particular styles exhibit significant time-varying exposures and others do not. Both the global/macro style and short bias style are directional styles. The common denominator of global/macro hedge funds is that they invest on the basis of macro-economic changes. This does not contain a limitation on the exposures they may choose. For example, convertible arbitrage hedge funds are bound to both the instruments used (i.e. convertible bonds) as to the employed strategies (i.e. arbitrage). An explanation for the time-varying behaviour of global/macro hedge funds may therefore be their ability to use a (world)wide range of different instruments and strategies, resulting in very dynamic exposures. The same can be said of the emerging markets and short bias styles, be it to a lesser extent.

It may be argued that the equity market neutral style suffers from the same limitation as do convertible arbitrage and event driven styles, since it is also a non-directional style. So why does this style in particular exhibit a significant intensity of choice, albeit only in the HFR database? The reason for this may be that equity market neutral hedge funds have more areas to find arbitrage opportunities in. The strategies employed may entail trades in domestic and foreign markets, or value, size and momentum strategies, depending of where profit opportunities arise. This leads to switches between risk factors. An event driven fund has much less freedom to do so, since the strategy is to anticipate events. It is reasonable to assume that the risk of non-occurrence of an event (which is the major risk for the event driven style) does not change in favour of any kind of stock (whether it be small, large, winning, losing, value or growth stocks). Therefore it makes no sense for event driven funds to shift from, say, investing in small stocks to investing in winning stocks or growth stocks at any point in time. It is much more plausible that the exposures to the risk factors remain relatively stable over time. It is likely that many events occur with financially distressed firms, irrespective of the time frame investigated. Therefore an exposure to the high-yield bond market in both the linear and the switching case is observed. The reason why the exposures of the convertible arbitrage style are very stable over time was already mentioned: the instruments and strategies used are inherently fixed in this style.

It is observed that some types of exposures change when the time-varying model is applied to the equity market neutral and global/macro styles. The magnitudes of the exposures in the time-varying model typically are not very different compared to the magnitudes of the exposures that were already significant in the linear model. In the case of the equity market neutral style, the factor loadings of the significant exposures are at approximately the same level in the time-varying model as in the linear one. In the global/macro style, the momentum exposure and non-U.S. bond market exposure change only a bit. Slight changes are also present in the CS/Tremont results. There are no large changes, such as sign changes. This indicates that the average exposures over the length of the research period are similar in both models, as should be expected.

When comparing the magnitude of the coefficients in Tables 5.3 and 5.4 with those in Tables 5.1 and 5.2, it needs to be kept in mind that the coefficients are eleven times as large in the time-varying model as in the linear regression model such as employed by Agarwal and Naik (2004). This is because in the time-varying model all coefficients are multiplied by a weight which is, on average, 1/11. Taking this into account, the magnitude of the coefficients of the time-varying model are not very different from the ones found in the linear model.

5.2.2 Switching behaviour

The log-likelihood significantly increases for the global/macro style and short bias style in both the HFR and CS/Tremont sample. This means that these hedge fund managers adapt their strategies based on the past performance of risk factors. Some indication for this also exists for equity market neutral and event driven managers. In order to grasp the switching behaviour of the hedge fund managers, the weights attached to the risk factors need to be studied. The value of gamma is usually not very high, even for the styles for which the time-varying model is an improvement compared to the linear model. This means that managers do not react very strongly on information on the performance of risk factors. This is different for the global/macro styles. The high values of gamma mean that the global/macro managers react strongest to the prior performance of strategies. This style is therefore chosen to study the switching behaviour.

The descriptive statistics of the weights of the global/macro style are given in Table 5.7. The mean and median weights of the respective risk exposures of this style are mostly around 1/11 and so do not differ much. The commodity index and emerging market index have performed better in terms of absolute returns,[32] so one would expect these weights to be higher on average. This is indeed observable for the weights of the global/macro style in both the HFR and CS/Tremont sample.[33] The mechanism of the model is clear. A risk factor with a high absolute performance makes hedge fund managers put more weight on strategies related to that particular risk factor.

[32] See Table 4.2 for the sample descriptive statistics.
[33] The descriptive statistics of the CS/Tremont weights are given in Appendix B.

Table 5.7
Descriptive statistics on weights of global/macro style (HFR)

The descriptive statistics (mean, median, standard deviation, minimum and maximum) of the weights in the time-varying model (8) are shown for the global/macro style of the HFR database. The abbreviations represent the Russell 3000 index (RUS), the MSCI emerging markets index (EMK), the MSCI World index excluding the U.S. (MSW), the Fama and French "value" factor (HML), the Fama and French "size" factor (SMB), the Fama and French "momentum" factor (WML), the Barclays Capital U.S. Aggregate index to represent U.S. bonds (USB), the Barclays Capital Global High Yield index to represent high-yield bonds (HYB), the J.P. Morgan Global Aggregate index to represent the global bond markets excluding the U.S. (JPG), the Merrill Lynch Commodity index (COM) and the Federal Reserve Broad Dollar index (DOL).

	Global/macro (HFR)				
	Mean	Med.	SD.	Min.	Max.
w_{RUS}	0.088	0.079	0.053	0.003	0.309
w_{EMK}	0.121	0.091	0.102	0.002	0.497
w_{MSW}	0.083	0.080	0.046	0.005	0.255
w_{HML}	0.078	0.067	0.057	0.006	0.460
w_{SMB}	0.074	0.064	0.045	0.018	0.317
w_{WML}	0.107	0.081	0.088	0.000	0.513
w_{USB}	0.076	0.075	0.03	0.009	0.157
w_{HYB}	0.082	0.075	0.038	0.005	0.231
w_{JPG}	0.082	0.071	0.048	0.006	0.323
w_{COM}	0.139	0.128	0.105	0.000	0.456
w_{DOL}	0.071	0.060	0.048	0.005	0.380

This also has its effect on the degree to which the weights change. Some weights have a higher standard deviation than others, which is especially true of the exposures to the momentum factor, commodity factor and emerging markets factor. It is the result of higher volatility in the returns of these risk factors.[34] This pattern is therefore consistent across both databases. This is also reflected in the minimum and maximum values the weights reach. The weights of the emerging markets, momentum and commodities factors reach both lowest and highest values compared to the other risk factors.

[34] See Table 4.2 for the sample descriptive statistics.

Table 5.8
Weight correlations of global/macro style (HFR)

The correlations of the weights in the time-varying model (8) are shown for the global/macro style in the HFR database. In Panel A, the correlations between the weights are displayed. In Panel B, the correlations between the weights and the absolute performance history of the risk factors over the previous 4 months is provided. The abbreviations represent the Russell 3000 index (RUS), the MSCI emerging markets index (EMK), the MSCI World index excluding the U.S. (MSW), the Fama and French "value" factor (HML), the Fama and French "size" factor (SMB), the Fama and French "momentum" factor (WML), the Barclays Capital U.S. Aggregate index to represent U.S. bonds (USB), the Barclays Capital Global High Yield index to represent high-yield bonds (HYB), the J.P. Morgan Global Aggregate index to represent the global bond markets excluding the U.S. (JPG), the Merrill Lynch Commodity index (COM) and the Federal Reserve Broad Dollar index (DOL).

Panel A: Correlations between weights

	w_{RUS}	w_{EMK}	w_{MSW}	w_{HML}	w_{SMB}	w_{WML}	w_{USB}	w_{HYB}	w_{JPG}	w_{COM}	w_{DOL}
w_{RUS}	1										
w_{EMK}	0.195	1									
w_{MSW}	0.656	0.376	1								
w_{HML}	-0.071	-0.177	-0.195	1							
w_{SMB}	-0.205	-0.102	-0.199	-0.067	1						
w_{WML}	-0.462	-0.478	-0.425	0.121	0.067	1					
w_{USB}	-0.223	-0.644	-0.369	0.028	0.014	0.238	1				
w_{HYB}	0.300	0.069	0.181	-0.199	-0.064	-0.484	0.092	1			
w_{JPG}	-0.219	-0.460	-0.448	0.055	-0.109	0.231	0.633	0.025	1		
w_{COM}	-0.312	-0.115	-0.234	-0.336	-0.187	-0.134	-0.199	-0.069	-0.118	1	
w_{DOL}	-0.231	-0.460	-0.244	0.119	0.211	0.195	0.593	-0.199	0.112	-0.256	1

Panel B: Correlations between performance history of risk factors and weights

	w_{RUS}	w_{EMK}	w_{MSW}	w_{HML}	w_{SMB}	w_{WML}	w_{USB}	w_{HYB}	w_{JPG}	w_{COM}	w_{DOL}
RUS	0.789	0.540	0.665	-0.212	-0.180	-0.529	-0.612	0.319	-0.443	-0.038	-0.616
EMK	0.334	0.859	0.483	-0.133	-0.096	-0.500	-0.780	0.212	-0.493	0.023	-0.733
MSW	0.606	0.623	0.795	-0.237	-0.147	-0.492	-0.715	0.222	-0.604	0.013	-0.594
HML	-0.125	-0.105	-0.020	-0.774	0.037	-0.064	0.440	0.216	0.189	0.231	0.240
SMB	-0.080	0.298	-0.030	-0.076	0.759	-0.054	-0.513	0.001	-0.36	-0.046	-0.264
WML	-0.285	-0.474	-0.223	0.236	0.116	0.747	0.095	-0.551	0.129	-0.025	0.084
USB	-0.027	-0.334	-0.345	0.070	-0.195	0.196	0.539	0.271	0.521	-0.123	0.011
HYB	0.433	0.478	0.374	-0.212	-0.143	-0.505	-0.495	0.708	-0.317	0.104	-0.707
JPG	-0.034	-0.163	-0.310	0.017	-0.219	0.083	0.166	0.179	0.758	0.011	-0.306
COM	-0.052	0.245	0.019	-0.443	-0.127	-0.207	-0.473	0.142	-0.234	0.757	-0.694
DOL	-0.163	-0.320	-0.097	0.237	0.208	0.176	0.332	-0.256	-0.222	-0.207	0.821

Table 5.8 shows a number of correlation coefficients. In Panel A of Table 5.8 the correlations between the weights are given for the global/macro style. Analysing these correlations between the weights gives a general picture on the switching behaviour of hedge fund managers. In general, it must be noted that the correlations between weights tend to be negative, since the weights must add up to one. But since shifts in weights are largely determined by differences in performance of the risk factors, it can be expected that the weights correlate in a way similar to the corresponding risk factors. This is indeed the case.[35]

The sign of the correlation between weights also depends on the signs of the factor loadings (b_j) under consideration, however. For example, the correlation between the momentum and value factor is negative, but the correlation between the *weights* for the global/macro managers is positive. The reason behind this, is that the global/macro style has a negative exposure to the value factor, but a positive exposure to the momentum factor (see Table 5.4). Since both the correlation between these risk factors is negative and the signs of the factor loadings to these risk factors are opposite, hedge fund managers will tend to simultaneously increase or decrease the weights on these two risk factors. Switching is defined as increasing the magnitude of one exposure while simultaneously decreasing the magnitude of the other. Put differently, hedge fund managers have a tendency to switch between risk factors if the correlation between the weights is negative. Since the magnitudes of the value and momentum factor exposures increase (or decrease) simultaneously, there is no switching between these risk factors.[36] Each style has its own switching mechanisms, because of the different signs of the exposures and different intensities of choice. Another reason is that the weight to a risk factor is not determined by a bilateral comparison of risk factor performance, but in relation to the movement of *all* other risk factors. Correlation coefficients between weights therefore do not tell the entire switching story. Rather, they are a result of a more complicated process.

It can be seen from Table 5.8 that the weights on U.S. and global equity markets move in tandem for the global/macro hedge funds. When these hedge fund managers increase the weight on the U.S. equity market, they increase the weights on other developed equity markets as well. The reason for this is that the performance of these two risk factors are also very closely correlated. The correlations between the high-yield bond market and the several equity markets are also positive. This is reflected in the positive correlations between the weights. The weights on the zero-

[35] The correlation matrix for risk factors is found in Table 4.4.

[36] It can be argued that switching should be defined differently, namely as redistributing funds over different risk factors. In that sense, switching does occur between the high-yield bond market and U.S. dollar. After all, when the long high-yield bond exposure becomes “longer”, the short dollar exposure becomes “shorter”. However, switching must be regarded as switching between strategies. Increasing (decreasing) a long and a short position at the same time should therefore not be regarded a switch, but rather as taking a larger (smaller) stake in an already existing strategy.

investment strategies have very low correlations with one another. Hedge fund managers apparently do not switch between these strategies. To some extent, they do switch between these strategies and equity exposures. Hardly any switching occurs between the zero-investment strategies, the U.S and global bond markets and the U.S. dollar. The weight on the commodity market has very low correlations with all other weights and all correlations are negative. Apparently, hedge fund managers switch from commodity exposures to other exposures and back. An increase in the weight of commodities leads to a decrease in all other weights.

The paragraphs above served to illustrate the switching mechanism at work. It serves no purpose to elaborate specifically on each bilateral switching possibility by treating each cell in the matrix. Some attention must yet be given to the relation between the performance of risk factors and the weights, because weight changes are driven by changes in performance of the risk factors. This is shown for the global/macro style in Panel B of Table 5.8. The correlations are given between the weights and the 4-month absolute performance history of risk factors. It shows how weights change as a result of the performance history of all risk factors in the model. Both the sign of the exposures and the correlation between the risk factors produce the effect that is displayed in these matrices. The elements on the diagonal have very high values, illustrating the importance of the performance history of the weight's "own" risk factor. A negative correlation is found between the performance of the value factor and its weight since the exposure to the value factor is negative. Where other risk factors are also influential on a weight, this is a result of the close correlation between that particular risk factor and the weight's "own" risk factor.[37]

In Figures 5.1 and 5.2 scatter plots are displayed in order to show the relation between the weights on a risk factor and its performance in more detail. In Figure 5.1 the weights on the commodity factor are plotted having the performance of the commodity factor relative to the sum of the risk factor performances along the horizontal axis. In Figure 5.2 a similar picture is obtained when the performance of the commodity factor is related to the best performing risk factor. It is observed that the weight on the commodity factor increases with a better performance of the commodity risk factor relative to other factors. The steepness of the increase is determined by the intensity of choice. For other smooth transition models, Van Dijk, Teräsvirta and Franses (2002) and Teräsvirta (1998) have shown that the observations in such scatter plots are less of a cloud and more of a fixed line. The reason for this difference is that the value of the weight of a risk factor in this model depends not only on its performance relative to the sum of risk factor performances, it also depends on the distribution of the performance of the other risk factors. This follows from Equation (9).

[37] See Table 4.4 for the correlations between risk factors.

Figure 5.1
The commodity weight vis-à-vis the performance of the commodity risk factor relative to the total performance

This scatter plot shows the 160 observations (from May 1996 to August 2009) of the weight on the commodity risk factor (w_{COM}) versus the performance of the commodity risk factor (π_{COM}) relative to the sum of the risk factor performance ($\sum_{j=1}^{11} \pi_j$) using the HFR database.

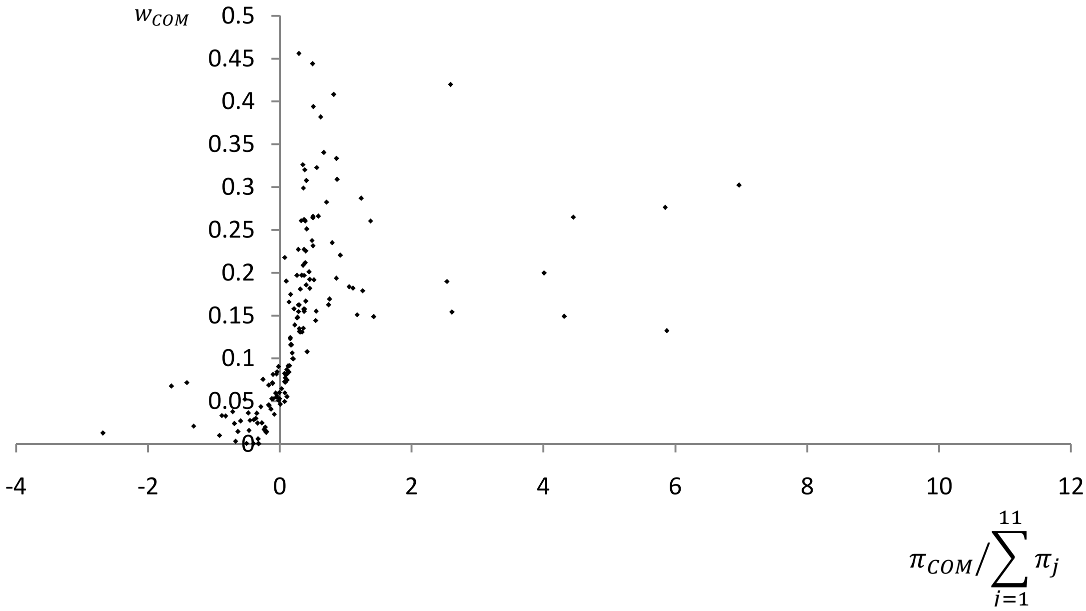
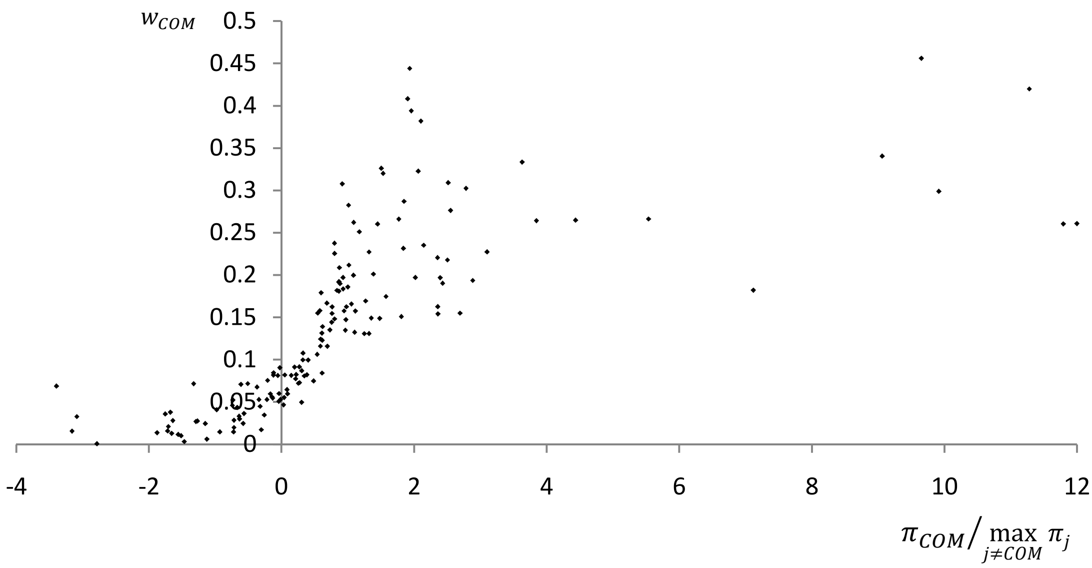


Figure 5.2
The commodity weight vis-à-vis the performance of the commodity risk factor relative to the performance of the best performing risk factor

This scatter plot shows the 160 observations (from May 1996 to August 2009) of the weight on the commodity risk factor (w_{COM}) versus the performance of the commodity risk factor (π_{COM}) relative to the best performing risk factor excluding the commodity risk factor ($\max_{j \neq COM} \pi_j$) using the HFR database.



Something that can also be observed from the figures is that the weight appears to rapidly increase when the performance measure on the horizontal axis passes the 0 threshold. Below this threshold the weight remains between 0 and 0.10, whereas weights surge to as high as 0.45 even slightly above this threshold. So for low values of relative risk factor performance, weights of a risk factor do not change much even when its relative performance increases substantially. The same is true for a substantial decline of the relative risk factor performance when this performance is high, even though this is less visible in Figure 5.1 and 5.2.[38] Teräsvirta (1998) shows that this effect can cause a transition model to fit the data better than a linear model, but yield an intensity of choice that is not statistically significant.

Table 5.9
Correlations between HFR and CS/Tremont weights of global/macro style

The correlations between the HFR and CS/Tremont weights in the time-varying model (8) are shown for the global/macro style. The abbreviations represent the Russell 3000 index (RUS), the MSCI emerging markets index (EMK), the MSCI World index excluding the U.S. (MSW), the Fama and French "value" factor (HML), the Fama and French "size" factor (SMB), the Fama and French "momentum" factor (WML), the Barclays Capital U.S. Aggregate index to represent U.S. bonds (USB), the Barclays Capital Global High Yield index to represent high-yield bonds (HYB), the J.P. Morgan Global Aggregate index to represent the global bond markets excluding the U.S. (JPG), the Merrill Lynch Commodity index (COM) and the Federal Reserve Broad Dollar index (DOL).

Panel A: Correlations between HFR and CS/Tremont weights

HFR / CST	w_{RUS}	w_{EMK}	w_{MSW}	w_{HML}	w_{SMB}	w_{WML}	w_{USB}	w_{HYB}	w_{JPG}	w_{COM}	w_{DOL}
w_{RUS}	0.956	0.329	0.636	-0.034	-0.256	-0.507	-0.361	0.310	-0.219	-0.260	-0.392
w_{EMK}	0.272	0.960	0.411	-0.072	-0.132	-0.500	-0.723	0.130	-0.443	-0.099	-0.600
w_{MSW}	0.710	0.510	0.937	-0.119	-0.237	-0.486	-0.556	0.195	-0.489	-0.185	-0.430
w_{HML}	-0.290	-0.395	-0.258	-0.459	0.100	0.141	0.732	0.079	0.398	0.088	0.490
w_{SMB}	-0.275	-0.091	-0.302	0.156	0.918	0.143	-0.076	-0.132	-0.028	-0.224	0.146
w_{WML}	-0.452	-0.542	-0.442	0.330	0.055	0.940	0.245	-0.570	0.303	-0.144	0.226
w_{USB}	-0.274	-0.632	-0.497	0.376	-0.099	0.337	0.849	-0.056	0.739	-0.272	0.528
w_{HYB}	0.349	0.161	0.157	-0.001	-0.192	-0.478	-0.072	0.916	0.050	-0.074	-0.394
w_{JPG}	-0.166	-0.277	-0.017	0.205	0.188	0.111	0.391	-0.243	-0.233	-0.197	0.774
w_{COM}	-0.280	0.008	-0.229	-0.344	-0.183	-0.121	-0.317	-0.009	-0.089	0.944	-0.454
w_{DOL}	-0.288	-0.523	-0.340	0.392	0.102	0.277	0.621	-0.266	0.257	-0.302	0.914

[38] Some effect of it is visible since the extreme values of relative performance do not produce extreme weights.

In the discussion of the model results in Tables 5.3 to 5.6 it was mentioned that the HFR and CS/Tremont databases gave different exposures in significance, sign and magnitude. The switching behaviour of HFR and CS/Tremont global/macro managers are not very different from one another, however.[39] This is to be expected because the signs of the exposures are quite similar. In Table 5.9 the correlations are given between the weights of the global/macro managers from the two databases. From this table it can be seen that the correlations between corresponding weights on the diagonal are very high. Since weights are a function of risk factor performance and intensity of choice, the difference between the intensities of choice drives these correlations. Negative signs are found for the value factor and non-U.S. bonds factor, since these factors have a different sign in both models. A good performance of these risk factors therefore leads to a weight increase in one model and to a decrease in the other. Since the switching mechanisms depend on both the correlation of the risk factors and the value of the factor loadings of particular styles in particular databases, it is important to recognise that no statements can be made regarding the switching behaviour of hedge fund managers in general.

Now that the mechanisms have been displayed and explained, the path of the weights can be analysed through time. Figure 5.3 shows the evolution of the weights of the global/macro style in the HFR database. Again, the reason for choosing this particular style is the high intensity of choice which implies pronounced weight changes. It is important to note that the weights along the vertical axis are measured as relative to the average weight. This means that the average weight (1/11) is denoted as 1. This is done in order to gain a better insight into the magnitude of the weight changes. Some general characteristics of the graphs can be deduced from the data that were already treated. For instance, it is clear that the volatilities of the U.S. bond and U.S. dollar weights are lower than those of the commodity and emerging market weights.

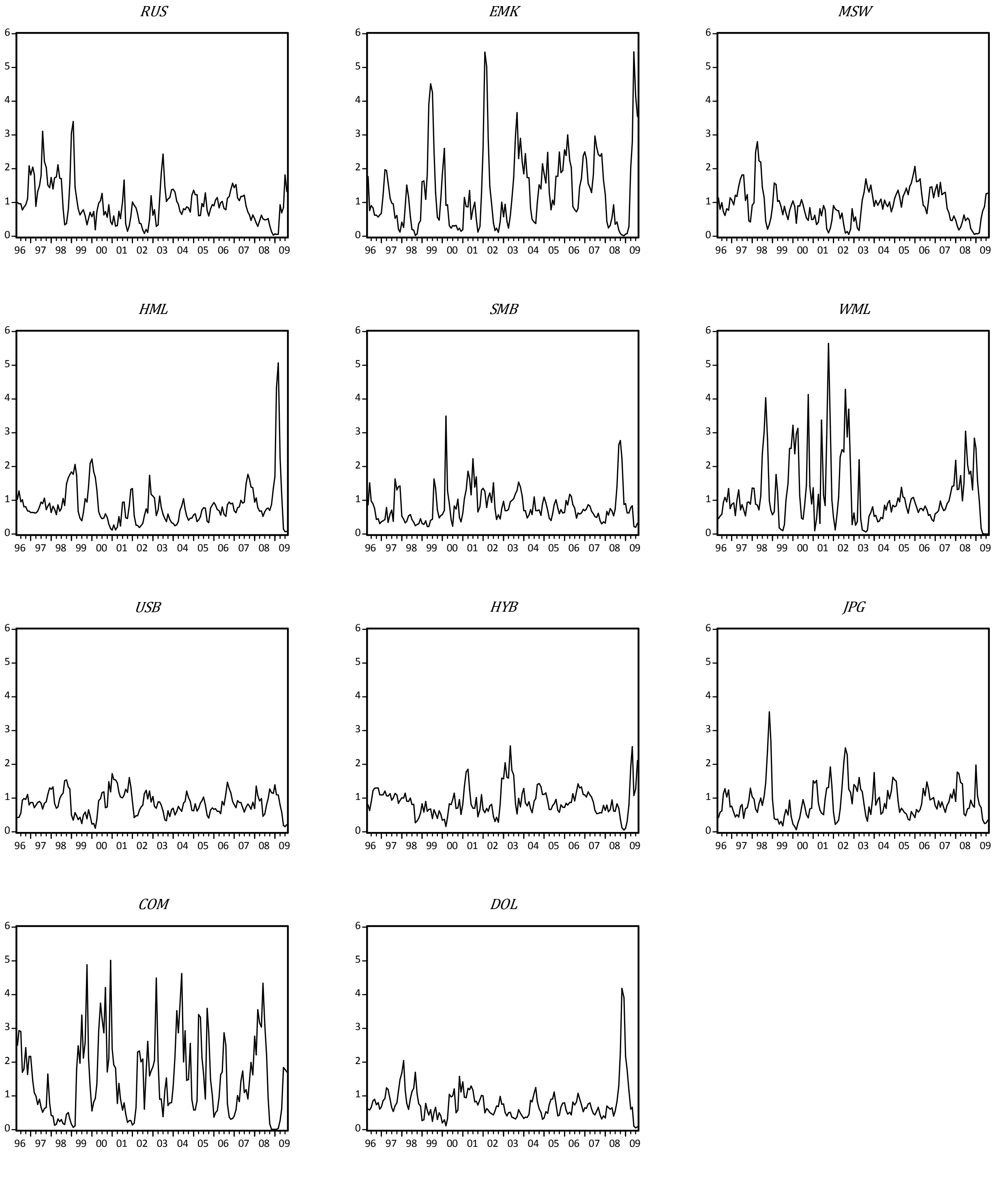
It is especially interesting to investigate the weights of the significant exposures.[40] Of the significant risk factors, the weight of the commodity exposure is the most volatile one. Since the factor loading of this factor is not very large, the exposure itself does not reach high values. The same holds for the weight of the momentum factor, which is also quite volatile. The weight of the developed equity markets does not have a lot of steep increases or declines, with a few exceptions. Within the first four months of 1998, the weight surges to four times the value it had by the end of 1997, to quickly decline again during the Russian debt crisis. The weight peaks during the first six months of 2009 as well.

[39] The correlations as they are displayed for the HFR database in Table 5.8 are given for the CS/Tremont database in Appendix C.

[40] Significant risk factors for the global/macro style in the HFR database are: U.S. equity, non-U.S. equity, size factor, momentum factor, U.S. bonds, non-U.S. bonds, commodities and U.S. dollar. See Table 5.4.

Figure 5.3
Weights global/macro style (HFR)

The graphs show the weights attached to the various risk factors of the global/macro style in the HFR database. The sample period is May 1996 - August 2009. The abbreviations represent the Russell 3000 index (RUS), the MSCI emerging markets index (EMK), the MSCI World index excluding the U.S. (MSW), the Fama and French "value" factor (HML), the Fama and French "size" factor (SMB), the Fama and French "momentum" factor (WML), the Barclays Capital U.S. Aggregate index to represent U.S. bonds (USB), the Barclays Capital Global High Yield index to represent high-yield bonds (HYB), the J.P. Morgan Global Aggregate index to represent the bond market excluding the U.S. (JPG), the Merrill Lynch Commodity index (COM) and the Federal Reserve Broad Dollar index (DOL).



The weight of the U.S. bond exposure is not very volatile. The influence that the weight has on the exposure is not negligible, however. For instance, the relative weight takes values between 0.1 and 1.5 between March and November of the year 2000, which is a 15 fold increase of the exposure in 8 months time. The exposure is doubled from January to February 2008. The weight of the global bond markets is moderately volatile throughout the sample period, but has a large peak in November 1998 due to the good performance of global investment-grade bond strategies relative to most other asset classes, which suffered from the Russian debt crisis. The final interesting observation is the large spike of the U.S. dollar weight in the second half 2008. Due to its very strong performance, it rose to more than 4 times the average weight in November starting from only one third in June. By the end of the second quarter in 2009 it had returned to nearly zero.

6 Summary and conclusions

This study focuses on the risk exposures of hedge funds. In particular, it is investigated whether hedge funds exhibit time-varying risk exposures. Earlier studies on hedge funds have indicated that hedge funds returns exhibit non-normal distributions. The same holds for hedge fund style indices. The mean-variance framework is therefore unsuitable for risk assessment and performance evaluation. To be able to fairly evaluate the performance of hedge funds, it is necessary that the risk exposures of hedge funds are carefully assessed. Many authors have used a multifactor model in a so-called style analysis. Usually, the correlation between hedge fund returns and the market is quite low, which points towards low risk systematic risk exposures and high diversification benefits. Moreover, researchers are often confronted with large intercepts which lead them to conclude that hedge funds are capable of outperforming the market. These results are distorted, however. The explanatory power of the multifactor models is consistently low. Fung and Hsieh (1997) were first to establish that linear multifactor models in fact do not capture the risk exposures of hedge funds in a satisfactory manner. Hedge funds frequently use derivatives and dynamic trading strategies, causing their exposures to market factors to be far from linear.

Subsequent research focused on adapting the style analysis in order to handle the non-linear risk exposures. One way in which non-linearities can be captured is by implementing option-based risk factors. Agarwal and Naik (2004) analyse multiple hedge fund styles using a standard multifactor model, but including the returns on option components as well. Their analysis showed that the returns on many hedge fund styles exhibit a risk profile that is similar to a short put option on the S&P 500 index. Since the non-linearities largely stem from the dynamic trading strategies that hedge funds employ, some authors have tried to determine the hedge fund risk exposures over different time frames. By comparing the results of these studies it appears that the resulting exposures depend heavily on the chosen interval. This is a good indication that hedge fund risk exposures are indeed time-varying. Bollen and Whaley (2009) are first to try and determine the time-variation of risk exposures in a dynamic fashion. In a model that allows for one shift only, they find that about 40 percent of hedge funds experience a significant shift in factor loadings.

This study involves two separate analyses. The first analysis is a replication of the Agarwal and Naik (2004) study. A ordinary least squares regression is run on eleven buy-and-hold risk factors and four option-based risk factors. This linear model can capture only the average exposure over the length of the regression period. The second analysis takes it one step further by allowing hedge fund managers to make shifts in their trading strategies each month. In this way the changes in risk exposures can be measured more accurately. When hedge fund managers find that their strategies are not as profitable as alternative strategies, they may decide to put more emphasis on investing in these alternative strategies. A behavioural finance approach is used to accommodate this. Since all possible strategies are not directly observable, risk factors are used as proxies. Each risk factor has an accompanying factor loading. To each factor loading a weight is added with a value between 0 and 1. Each month the value of each weight is determined by two elements: the performance of the matching risk factor and the intensity of choice. The former is measured by the average return of the risk factor over the prior 4 months and the latter is defined as the sensitivity of hedge fund managers to shift weights on the basis of the prior performance of the risk factors. The model is estimated using maximum likelihood. The analysis is conducted on two datasets from different data vendors in order to check for robustness.

Both the linear OLS and the time-varying maximum likelihood estimation are conducted for six hedge fund style indices: convertible arbitrage, equity market neutral, event driven, emerging markets, global/macro and short bias. The sample consists of monthly returns on the HFR and CS/Tremont indices from May 1996 to August 2009. The risk factors employed include eight proxies for the U.S. equity market, the emerging equity markets, the developed equity markets excluding the U.S., the U.S. bond market, the global high-yield bond markets, the global investment-grade bond markets, the commodity markets and the U.S. dollar. The risk factors also include three zero-investment strategies: a "value" factor, a "size" factor and a "momentum" factor. The option-based risk factors are left out of the time-varying model since they do not add any value to the linear model.

The OLS model gives results that differ from Agarwal and Naik (2004). Some risk exposures are the same, but many exposures are not. This is again an indication that hedge fund risk exposures are very time-varying. The option-based risk factors are not able to capture the non-linearities, which is contrary to the findings of Agarwal and Naik (2004). Of the non-directional styles, the equity market neutral style manages best to maintain low exposures.

The time-varying model is able to capture the time-variation for the global/macro style and short bias style. Both styles have a significant intensity of choice and a significant increase in log-likelihood. This indicates that these hedge fund managers indeed switch their strategies on the basis of prior performance of alternative strategies. This is found in both the HFR and the CS/Tremont database. For the equity market neutral style, this result was found in the HFR database but not in the CS/Tremont database. Conversely, the managers of the event driven style show time-varying behaviour in the CS/Tremont database but not in the HFR database. It appears that the time-varying model can add value to the analysis of hedge fund risk exposures. The risks to which the hedge fund managers are exposed are different across datasets, however. It is therefore important to recognise that conclusions about the nature of risk exposures of a style should be drawn with care. The results on the HFR styles indicate that new exposures appear. The time-varying model is apparently able to capture exposures that remain hidden in a linear model. This effect is not present in results of the CS/Tremont style indices, however. The magnitudes of the factor loadings are not very different from the ones found in the linear model. This indicates that the average exposures over the length of the research period are similar in both models, as should be expected.

Switching is heaviest for the global/macro style since it has the highest intensity of choice. This is directly reflected in the volatility of the weights. Hedge fund managers determine to increase or decrease a weight on the basis of the performance of the corresponding risk factor relative to all other risk factors. They also take into account the sign of the factor loading since it is only wise to increase weight on a good performing strategy if the exposure is long. Some weights are more volatile than others, but the effects on the exposures are clearly visible. Analysing the weights of the risk factors with significant factor loadings, it is observed that most risk exposures of hedge funds vary substantially during the sample period. Weight can have values near zero and as high has 0.5, depending on the intensity of choice. Even when not taking into account large spikes or drops, exposures regularly move from low to high values and back, having doubled, tripled or quadrupled in the process.

Altogether it can be concluded that a time-varying model provides a better understanding of the nature of hedge fund risk exposures. The time-varying model shows consistencies across the different databases, since it points towards the same styles for significant switching behaviour and it yields higher explanatory values than a linear model. It is capable of discovering risk exposures that remain hidden in a linear context. For the short bias and global/macro style it can be concluded that hedge fund managers change their exposures significantly through time based on the performance of alternative strategies available.

Even though this time-varying model has shed some more light on the risk exposures of hedge funds, it may be the case that some time-varying behaviour of hedge fund managers is still not captured. Some suggestions can be made for further research in this area. This study was necessarily conducted at an aggregate level. It is likely that individual hedge fund managers who constitute a style index all behave differently. This may be one of the reasons why different exposures are found in different datasets. An analysis conducted at the individual fund level may therefore give additional understanding of strategy changing behaviour of hedge funds. Furthermore, some adaptations to the model may also add value to the already existing literature. For instance, it will be interesting to see whether a model that allows for switching between short and long exposures can give more insights on time-variation. Also, the exposures to asset classes are proxied by a number of market indices. It may be useful to try and find more appropriate risk factors by means of a factor analysis, for example. A final suggestion would be to devise a switching mechanism which is based on the expected performance of various strategies rather than on the realised performance.

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Appendices

Appendix A.1
Non-directional trading styles

Below are short descriptions of the non-directional hedge fund trading styles that are mentioned in this study. Non-directional styles claim to be uncorrelated with the market. The descriptions are derived from the definitions given by the data providers HFR and CS/Tremont.

Style	Description
Convertible arbitrage	The convertible arbitrage style includes strategies in which the investment thesis is predicated on realisation of a spread between related instruments in which one or multiple components of the spread is a convertible fixed income instrument.
Distressed (Distressed/restructuring)	The distressed style focuses primarily on corporate credit instruments of companies trading at significant discounts to their value as a result of either formal bankruptcy proceeding or financial market perception of near term proceedings.
Equity market neutral (Equity hedge)	This is the style that hedge funds owe their name to. These hedge funds predominantly trade equities or equity instruments while keeping the net exposure to the equity market near zero. The investments can be global, but also with a focus on a particular industry of geographical area.
Event arbitrage	The event arbitrage style entails taking a long position in the securities of the acquired company and a short position in the securities of the acquiring company.
Event driven	Hedge funds adopting this style take positions in securities they expect to rise in value because of an upcoming event such as a merger, restructuring, shareholder buybacks, security issuance, et cetera. It frequently involves trading additional derivatives as well. The main risk is non-realisation of the event.
Fixed income arbitrage	Hedge funds maintain positions in which the investment thesis is predicated on realization of a valuation discrepancy in the relationship between multiple fixed income instruments.
Restructuring	See *Distressed*.

Appendix A.2
Directional trading styles

Below are short descriptions of the directional hedge fund trading styles that are mentioned in this study. Directional styles attempt to earn returns by creating market exposures. The descriptions are derived from the definitions given by the data providers HFR and CS/Tremont.

Style	Description
Emerging markets	There exist no investment strategy criteria for inclusion in the emerging market index. The constituents are selected according to the regional investment focus, such as Asia, Eastern Europe or Latin America.
Global/macro	This style comprises investing (globally) in securities, commodities, interest rates and currencies, depending on the expected rise or decline in values, mainly on the basis of macroeconomic forecast.
Long ("value" or "growth")	Hedge fund managers take positions in securities of companies which are determined by the manager to be undervalued or overvalued. These analyses are based on the characteristics of the firm's financial statements, both in an absolute sense and relative to other similar securities and market indicators. The market risks are not hedged
Short	The short style aims at selling short overvalued securities and repurchasing them in the future at a lower price.
Short bias	Hedge funds try to buy undervalued or sell overvalued securities, hedging out the market risk. The manager maintains consistent short exposure, however. The investment level or the level of short exposure may very over market cycles.
Trend following	This style involves trading all kinds of securities in order to profit from long-term and short-term trends in the macroeconomic environment.

Appendix B
Weights descriptive statistics global/macro style (CS/Tremont)

The descriptive statistics (mean, median, standard deviation, minimum and maximum) of the weights in the time-varying model (8) are shown for the global/macro style of the CS/Tremont database. The abbreviations represent the Russell 3000 index (RUS), the MSCI emerging markets index (EMK), the MSCI World index excluding the U.S. (MSW), the Fama and French "value" factor (HML), the Fama and French "size" factor (SMB), the Fama and French "momentum" factor (WML), the Barclays Capital U.S. Aggregate index to represent U.S. bonds (USB), the Barclays Capital Global High Yield index to represent high-yield bonds (HYB), the J.P. Morgan Global Aggregate index to represent the global bond markets excluding the U.S. (JPG), the Merrill Lynch Commodity index (COM) and the Federal Reserve Broad Dollar index (DOL).

	Global/macro				
	Mean	Med.	SD.	Min.	Max.
w_{RUS}	0.091	0.089	0.026	0.025	0.192
w_{EMK}	0.100	0.096	0.043	0.021	0.242
w_{MSW}	0.088	0.090	0.023	0.032	0.149
w_{HML}	0.089	0.087	0.032	0.015	0.260
w_{SMB}	0.085	0.082	0.021	0.047	0.209
w_{WML}	0.097	0.089	0.041	0.006	0.228
w_{USB}	0.088	0.086	0.017	0.045	0.144
w_{HYB}	0.090	0.088	0.019	0.033	0.152
w_{JPG}	0.083	0.084	0.018	0.032	0.154
w_{COM}	0.106	0.108	0.042	0.011	0.216
w_{DOL}	0.083	0.080	0.023	0.032	0.210

Appendix C
Weight correlations global/macro style (CS/Tremont)

The correlations of the weights in the time-varying model (8) are shown for the global/macro style in the CS/Tremont database. In Panel A, the correlations between the weights are displayed. In Panel B, the correlations between the weights and the absolute performance history of the risk factors over the previous 4 months is provided. The abbreviations represent the Russell 3000 index (RUS), the MSCI emerging markets index (EMK), the MSCI World index excluding the U.S. (MSW), the Fama and French "value" factor (HML), the Fama and French "size" factor (SMB), the Fama and French "momentum" factor (WML), the Barclays Capital U.S. Aggregate index to represent U.S. bonds (USB), the Barclays Capital Global High Yield index to represent high-yield bonds (HYB), the J.P. Morgan Global Aggregate index to represent the global bond markets excluding the U.S. (JPG), the Merrill Lynch Commodity index (COM) and the Federal Reserve Broad Dollar index (DOL).

Panel A: Correlations between weights

	w_{RUS}	w_{EMK}	w_{MSW}	w_{HML}	w_{SMB}	w_{WML}	w_{USB}	w_{HYB}	w_{JPG}	w_{COM}	w_{DOL}
w_{RUS}	1										
w_{EMK}	0.429	1									
w_{MSW}	0.768	0.588	1								
w_{HML}	-0.441	-0.539	-0.461	1							
w_{SMB}	-0.296	-0.089	-0.299	-0.099	1						
w_{WML}	-0.503	-0.534	-0.503	0.035	0.182	1					
w_{USB}	-0.369	-0.670	-0.625	0.402	-0.004	0.431	1				
w_{HYB}	0.421	0.268	0.251	-0.180	-0.164	-0.532	-0.060	1			
w_{JPG}	-0.303	-0.418	-0.197	0.281	0.062	0.126	0.269	-0.438	1		
w_{COM}	-0.178	0.054	-0.128	-0.064	-0.203	-0.152	-0.365	0.033	-0.392	1	
w_{DOL}	-0.432	-0.638	-0.512	0.339	0.152	0.374	0.729	-0.365	0.719	-0.494	1

Panel B: Correlations between performance history of risk factors and weights

	w_{RUS}	w_{EMK}	w_{MSW}	w_{HML}	w_{SMB}	w_{WML}	w_{USB}	w_{HYB}	w_{JPG}	w_{COM}	w_{DOL}
RUS	0.892	0.639	0.835	-0.512	-0.249	-0.579	-0.695	0.421	-0.437	0.092	-0.719
EMK	0.479	0.949	0.656	-0.567	-0.077	-0.532	-0.777	0.334	-0.513	0.186	-0.786
MSW	0.703	0.708	0.927	-0.495	-0.221	-0.548	-0.828	0.282	-0.348	0.111	-0.722
HML	-0.242	-0.258	-0.197	0.866	-0.203	-0.238	0.071	-0.024	0.078	0.128	0.024
SMB	-0.034	0.335	0.061	-0.321	0.826	-0.085	-0.496	0.016	-0.259	0.047	-0.333
WML	-0.354	-0.438	-0.295	-0.03	0.176	0.864	0.188	-0.562	0.115	-0.051	0.181
USB	-0.073	-0.297	-0.369	0.241	-0.107	0.191	0.625	0.339	-0.325	-0.103	0.137
HYB	0.546	0.593	0.529	-0.362	-0.162	-0.602	-0.563	0.816	-0.616	0.261	-0.764
JPG	0.040	-0.060	-0.226	0.029	-0.050	0.135	0.390	0.352	-0.738	0.127	-0.159
COM	0.071	0.311	0.153	-0.163	-0.201	-0.295	-0.613	0.184	-0.53	0.895	-0.785
DOL	-0.322	-0.454	-0.269	0.221	0.181	0.219	0.316	-0.405	0.796	-0.407	0.819

Appendix D
Weights global/macro style (CS/Tremont)

The graphs show the relative weights attached to the various risk factors of the global/macro style in the CS/Tremont database. The sample period is May 1996 - August 2009. The abbreviations represent the Russell 3000 index (RUS), the MSCI emerging markets index (EMK), the MSCI World index excluding the U.S. (MSW), the Fama and French "value" factor (HML), the Fama and French "size" factor (SMB), the Fama and French "momentum" factor (WML), the Barclays Capital U.S. Aggregate index to represent U.S. bonds (USB), the Barclays Capital Global High Yield index to represent high-yield bonds (HYB), the J.P. Morgan Global Aggregate index to represent the bond market excluding the U.S. (JPG), the Merrill Lynch Commodity index (COM) and the Federal Reserve Broad Dollar index (DOL).