A Quantitative Analysis of Hedge Fund Style and Performance

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Abstract
In this analysis we identify dynamic hedge fund strategies quantitatively pursuing a Principal Component Analysis following Fung & Hsieh (1997). We extract five dominant hedge fund strategies each representing similar investment styles and analyse the performance of each strategy by employing a multi-factor model comprising both market indices and passive option strategies along the lines of Agerwal & Naik (2000). We find that that such passive option strategies play an important role in explaining hedge fund returns. Moreover we show that the majority of the five homogenous strategies show neutral performance, but this result turns out to be sensitive to any potential survivorship biases.

Keywords: Hedge funds, dynamic strategies, performance.

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1. Introduction

Since the near collapse of Long-Term Capital Management in 1998 an increasing focus has been directed to the performance of hedge funds. In particular, recent research has been concentrated on identifying dynamic trading strategies in order to mimic the actual trades of hedge funds. Contrary to mutual funds, performance analyses of hedge funds are quite different because the returns of hedge funds usually have low correlations with market indices, and therefore a traditional CAPM analysis using the Jensen measure is typically not appropriate. Moreover, hedge funds pursue many different styles, see Brown, Goetzmann & Ibbotson (1999), and as shown by Fung & Hsieh (1997) these hedge fund styles often generate option-like returns[1].

While Fung & Hsieh (1997) were primarily interested in identifying the hedge funds styles, the study by Brown et al. (1999) was mainly concerned with the performance of hedge funds including performance persistence. The research into the performance of hedge funds is, however, sparse compared to the performance literature on mutual funds and pension funds and at present there is no general conclusion as to whether hedge funds are able to generate positive risk-adjusted returns.

Brown et al. (1999) analyse the performance of 399 offshore hedge funds for the period 1989 to 1995. They conclude that hedge funds for this period have been able to outperform the S&P 500 index in terms of higher Sharpe ratios and positive Jensen alphas. Furthermore, they confirm their conclusion using various self-determined benchmarks based on industry classifications.

Ackermann, McEnally & Ravenscraft (1999) analyse a sample of 547 hedge funds using monthly observations for the period 1988 to 1995, but they are not able to confirm the Brown et al. (1999) evidence that hedge funds have outperformed standard market indices. However, comparing hedge funds and mutual funds Ackermann et al. find that hedge funds have been able to systematically outperform mutual funds.

Liang (1999) formulates a multi-factor model comprising 8 different factors that represent various market indices within equities, bonds, exchange rates, commodities and the money market. He analyses 385 funds for the period 1994 to 1996 and finds that out of 16 different strategy classifications, 7 hedge fund groups show a significantly positive performance, whereas 2 hedge funds show a significantly negative performance, thus leaving the remaining 7 funds with a neutral performance. Further, Liang confirms the Ackermann et al. (1999) finding that on average hedge funds provide better risk-to-reward ratios than mutual funds in terms of Sharpe ratios. In Liang (2001) the sample is extended to cover a longer period from 1990 to 1999, and Liang confirms that hedge funds on average provide higher Sharpe ratios (0.41) than the S&P 500 index (0.27) during this period.

Similarly, Edwards & Caglayan (2001a) estimate a multi-factor model comprising 6 factors, and estimate the model for eight different strategy classifications for a total sample of 836 hedge funds for the period 1990 to 1998. They find that 25% of the funds have yielded significantly positive Jensen measures.

A similar conclusion is reached by Capocci & Hubner (2003), who analyse the performance of nearly 2,800 hedge funds for a period as long as 1984 to 2000. They find that approximately 25% of the funds have obtained significantly positive Jensen alphas using a multi-factor model comprising 11 different factors.

However, the studies by Brown et al. (1999), Ackermann et al. (1999), Liang (1999, 2001), Edwards & Caglayan (2001a) and Capocci & Hubner (2003) do not explicitly consider dynamic trading strategies in terms of options. Agerwal & Naik (2000) define a number of different passive option strategies based on standard market indices and include these option strategies as well as the passive market indices into a multi-factor style model along the lines of Sharpe (1992). Studying the period 1990 to 1998 for 586 hedge funds they are able to confirm that the option strategies play a significant role in determining the fund returns. The increase in the goodness-of-fit is remarkable, when passive option strategies are included, and based on the extended multi-factor model they conclude that hedge funds generally have not been able to generate abnormal returns. Only 35% of the funds analysed obtain significantly positive Jensen measures, while 13% of the funds yield significantly negative Jensen measures. Also Fung & Hsieh (2002) incorporate option strategies into a Sharpe style model, but they are primarily interested in exploring the risk of fixed income hedge fund styles and do not consider performance explicitly. But as opposed to the Agerwal & Naik (2000) finding, Fung & Hsieh find that in most cases their option strategies only play a marginal role, which may be due to the fact that they use active and advanced straddle strategies.

Compared to other related analyses our study differs in a number of respects. Firstly, we determine the classification of hedge funds endogenously applying a Principal Component Analysis. With Fung & Hsieh (1997, 2002) and Brown & Goetzmann (2003) as the only exceptions, previous studies rely purely on qualitative (exogenous) classifications, which are ad hoc and often reported by the hedge funds themselves. However, Fung & Hsieh (1997, 2002) do not explicitly consider the performance of hedge funds, and further Fung & Hsieh (2002) only consider the risk in fixed income hedge funds as well as only including a few option strategies. In our study we analyse the influence on hedge fund performance including 10 different market indices and 36 different passive option strategies. Secondly, we identify five principal components as do Fung & Hsieh (1997), but we are able to explain more than 60% of the cross-sectional variation in hedge fund returns compared to the 43% explanation in Fung and Hsieh[2]. Thirdly, following Agerwal & Naik (2000) we apply a multi-factor model comprising buy-and-hold strategies as well as passive option strategies to identify the performance of hedge funds on relatively new data from 1999 to 2002. Finally, we carefully examine the dataset in order to eliminate potential biases. The main extension of our analysis to the existing literature on hedge fund style and performance is therefore the combination of the quantitative classification approach and the inclusion of dynamic option strategies in the multi-factor model.

The paper is organised as follows. In Section 2 we describe our data and discuss a number of potential biases, which are common in hedge fund datasets. Starting out by a sample of 1,014 hedge funds, we describe how this sample must be reduced due to potential biases leaving us with a final sample of 185 hedge funds. Section 3 presents the quantitative Principal Component Analysis methodology, and we identify five dominant investment styles that are able to account for more than 60% of the return variance. Section 4 describes the multi-factor model applied and in particular the section discusses the many different factors in terms of buy-and-hold market indices and passive option strategies included in the performance analysis. Finally, Section 5 presents the empirical results on the performance of hedge funds, and Section 6 concludes.

2. Data selection

The data used in this analysis is taken from the Zürich Alternative Investment Performance Database CISDM (the former MAR database), which contains 1,014 individual funds[3]. This database gives details of each fund in relation to returns and a number of qualitative properties as e.g. degree of leverage, financial instruments used and the actual assets invested in. The sample period is June 1999 to June 2002 amounting to 37 monthly observations.

Today, a number of different companies and institutions collect data on hedge funds, e.g. TASS Investment Research, Hedge Fund Research, Inc. (HFR) and Center for International Securities and Derivatives Markets (CISDM), which is the former Managed Account Reports, Inc. (MAR) database. However, none of these vendors are comprehensive, since it is up to the individual hedge funds whether they report their data or not[4].

However, not all of the 1,014 funds will be included in the analysis. In fact, this sample will be reduced in order to take account of a number of potential biases. Fung & Hsieh (2000) consider four different potential biases in hedge fund datasets: survivorship bias, selection bias, instant history bias, and multi-period sampling bias. It is well-recognised that survivorship bias can have important implications for the performance evaluation, see e.g. Malkiel (1995) and Carhart, Carpenter, Lynch & Musto (2002), who analyse the consequences of survivorship bias on mutual fund performance. For hedge funds survivorship bias may play an even bigger role, as seen during the 1998 crisis when a number of hedge funds collapsed. Based on the TASS database Fung & Hsieh (2000) estimate the survivorship bias to be 3.00% annually, and likewise Brown et al. (1999) find an approximate survivorship bias of 3.00% annually for off-shore hedge funds. These numbers are to some extent supported by Liang (2000, 2001), who finds that on average the annual survivorship bias is 2.2% and 2.4%, respectively, based on the HFR and TASS databases, whereas Edwards & Caglayan (2001a) estimate the survivorship bias to 1.85% annually in the MAR database[5]. As opposed to these estimates, Ackerman et al. (1999) combine the MAR and the HFR databases, and find that positive and negative survival-related effects offset each other and their estimate of the survivorship bias is only 0.16% on an annual basis. However, Liang (2000) argues that the estimate of the survivorship bias in hedge funds data is very sensitive to the estimation period used and the actual estimation method applied.

Whereas some authors find a statistically significant survivorship bias of around 2-3% annually, i.e. the return of surviving funds is up to 3% higher than the return of all (surviving and defunct) funds, the same authors argue that the selection bias tend to be much smaller. Fung & Hsieh (2000) argue that this may be due to two opposing effects. Firstly, only those funds with a good performance will have an incentive to report their performance to the databases and secondly some funds, even with good performance, may not want to report their performance to the databases, because they are not interested in attracting new investors. In sum these effects may offset each other, and the selection bias becomes negligible. This observation is consistent with Ackermann et al. (1999), who find that the selection bias in the MAR database is very small.

The instant history bias[6] appears in the database, if the database vendor incorporates the full history of returns, including the first period of the fund's existence. Based on the TASS database Fung & Hsieh (2000) find that the returns of the first 12 months give a positive bias and suggest that the returns of the first 12 months should be excluded from the database. Fung & Hsieh (2000) estimate the instant history bias to be approximately 1.4% annually in the TASS database. Similarly, Edwards & Caglayan (2001a) estimate the instant history bias to be 1.17% annually in the MAR database. Since our performance analysis is based on portfolio returns, an instant history bias is probably not present.

Finally, a multi-period sampling bias may occur if the funds history is short. However, this potential bias has nothing to do with the data vendors, but rather concerns the fact that investors may only want to invest in funds with a sufficient history. To overcome this bias Ackermann et al. (1999) argue in favour of an estimation period of at least 24 monthly observations, whereas Fung & Hsieh (2000) require at least 36 historical returns for each fund in their analysis, although they argue that this type of bias is very small.

Based on the survivorship bias estimates referred to above, we will analyse the sensitivity of hedge fund performance in Section 5. Unfortunately, our sample does not include defunct hedge funds and we are not able to determine the actual survivorship bias in our sample, which motivates the sensitivity analysis in Section 5. To take account of an instant history bias we only include funds that have been in operation for at least a 12 month longer period than our estimation period. Furthermore, we follow Ackermann et al. (1999) in relation to a multi-period sampling bias and restrict the number of funds in our sample to funds with a return history of at least 24 months. The corrections for the instant history bias and the multi-period sampling bias mean that the total sample of 1,014 funds is reduced by 146 funds leaving us with 868 remaining funds.

Besides the four different types of biases suggested by Fung & Hsieh (2000), we will consider another potential bias, which may invalidate our data. Weisman (2001) argues that hedge funds often invest in assets with a low liquidity, and that this aspect has not to date been given a satisfactory consideration in the hedge fund literature[7]. Since our dataset may be exposed to an illiquidity bias, we have considered the different strategies in the CISDM dataset, and we find that based on the qualitative grouping of strategies, a strategy called Global Emerging will tend to be more illiquid than the rest of the strategies. The Global Emerging strategy is focussed on Eastern Europe, which is typically less liquid than e.g. the European markets. Also Fung & Hsieh (1997) exclude emerging market funds from their sample arguing that there are only limited possibilities of employing dynamic trading strategies in emerging markets[8]. We have identified 62 funds in the Global Emerging group, and these are excluded from the sample. Our sample is then reduced to 806 hedge funds.

Although the total sample of hedge funds must be reduced by more than 200 funds due to potential biases, further reductions are needed. Firstly, in the CISDM dataset a qualitative strategy measure is missing for a number of funds (24 funds), and therefore it is difficult to identify to which specific strategy the fund should be located. Secondly, we exclude fund of funds (204 funds) from the sample as opposed to most previous studies of hedge fund performance. The main reason is that fund of funds represent multiple strategies, and obviously it is hard to identify specific trading strategies for fund of funds due to their investments in other funds[9]. Moreover in Section 3, we construct five specific portfolios each representing one trading strategy, and this exercise is not possible if the sample includes fund of funds. Thirdly, the dataset includes some (17) benchmarks, which are also excluded. Forthly, we identify that one manager may control more than one fund, and the sample includes a number of funds, which are indistinguishable from each other regarding returns and qualitative strategy. We therefore exclude such funds (157 funds) so that one manager is represented by only one fund in the sample. In total these exclusions amount to 402 funds/benchmarks, and the reduced sample now contains 404 funds.

Finally, we want an analysis period of at least three years, and since our data ends by June 30th, 2002, our estimation period is from June 1st, 1999 to June 30th, 2002 amounting to 37 months. This means that some funds (219 funds) in the sample that have not been operating for the whole analysis period must be excluded. This leaves us with a final sample of 185 hedge funds and a total of 6,845 observations. However, a sample consisting of 37 observations is usually too small for empirical analyses, but due to data limitations it is customary in the hedge fund literature to operate with few observations, e.g. Brown et al. (1999), who use annual observations for the period 1989 to 1995, i.e. 7 observations, and Ackermann et al. (1999), who use monthly observations in a sample of 2 years (24 observations) and a sample of 8 years (96 observations). One exception is, however, Capocci & Hubner (2003) who use 198 monthly observations.

Also a sample of only 185 hedge funds is small compared to previous analyses of the performance of hedge funds, e.g. Fung & Hsieh (1997) analyse 297 hedge funds, Brown et al. (1999) analyse 399 hedge funds, Ackermann et al. (1999) analyse 547 hedge funds, Liang (1999) analyses 385 funds, Edwards & Caglayan (2001a) analyse 836 funds and Capocci & Hubner (2003) analyse 2,796 funds[10]. However, we find that the above-mentioned reductions in the dataset are necessary in order to obtain valid and robust results that can be compared to other analyses of hedge funds styles and performance. In particular, we have excluded funds of funds as opposed to most previous analyses, which accounts for a major difference to other studies[11].

In Table I the 185 hedge funds analysed in this study are classified into 9 groups/styles corresponding to specific self-reported industry classifications[12].

TABLE I here

Table I reports mean and median annual total returns based on net-of-fees asset values corrected for dividends as well as the annual standard deviation of the returns. The net asset values have been corrected for all fees including incentive fees that have been deducted in the hedge funds.

3. Identifying trading strategies

As mentioned in the previous section, the major data vendors have defined their own qualitative classification of hedge funds into which they locate the specific funds. In the CISDM dataset a number of qualitative properties of each hedge fund are available, but since hedge funds typically pursue a dynamic investment style, a grouping based purely on qualitative characteristics, which are often defined a priori when the fund was established, will not solve the classification problem.

In this analysis we will determine endogenously a number of homogeneous groups of hedge fund strategies based on a statistical Principal Component Analysis (PCA). The central hypothesis in this quantitative analysis follows Fung & Hsieh (1997, 1999), who observe that if two funds follow the same strategy and trade on the same markets, i.e. buy and sell the same assets, a correlation exists between the returns of the two funds even if their returns are not correlated to a market return.

The PCA is particularly relevant in this case, because it provides us with a statistical classification of the dominating components in terms of investment strategies, and we will be able to identify the minimum number of components that best explain the return variance. Compared to the nine different classifications in Table I, we would expect a smaller number of components in the PCA, e.g. the analysis in Fung & Hsieh (1997) results in only five orthogonal principal components.

Technically, we have set the confidence level at 0.385 for the factor loadings, which means that if a factor explains less than 15% (0.385^2) of the variance of a specific fund, it is insignificant. This confidence level is consistent with a 95% t-statistic with 37 degrees of freedom yielding a correlation coefficient (factor loading) of 0.325. Based on this the PCA identifies 5 orthogonal components that are able to explain more than 60% of the total variance. This is a satisfactory degree of determination and much higher than the 43% explained in Fung & Hsieh (1997). The main difference between the Fung & Hsieh findings and our results concerns the first factor. In their analysis the first component explains 11.87%, whereas in our analysis the first component explains 24.92%. This finding is mainly due to the fact that we include a smaller number of funds than do Fung & Hsieh. The remaining four components explain 10.00%, 9.42%, 6.35% and 4.93%, respectively in the Fung & Hsieh analysis, and equivalently we find that the remaining four components explain 12.65%, 10.80% 7.04% and 4.65%, respectively.

By restricting the number of components to exactly five, we find that out of 185 hedge funds, the return variance for 142 of these funds can be explained by one single factor, thus clearly indicating that there is an unambiguous connection between this one factor and the return variance. For most of the remaining 43 hedge funds two components were required to explain the hedge fund variance and in only a few cases, no components could be identified. In the remaining analyses only the 142 funds will be considered.

In Table II we present for each of the five components, the number of funds, the average factor loading, and the maximum and the minimum factor loadings.

TABLE II here

To relate each of these components to specific hedge fund strategies we compare the funds in each category to their qualitative characteristics and based on these comparisons we try to assign meaningful names to each component thus recognising that such names will not give a comprehensive description of the strategies[13].

The first component we term "Opportunistic/Sector", but this component is by far the most difficult component to classify. All of the nine qualitative strategies in Table I are represented among the 58 funds related to component 1[14], but especially two strategies dominate; Global Established (GE) and Sector fund (S). The Global Established funds operate on the established equity markets in the US and in Europe and their style is opportunistic, whereas the Sector funds focus on technology and the medical industry.

The second component, which we term "Event Driven", is much more clearly identified, since 21 of the 29 funds related to component 2 classify themselves as Event Driven funds. According to Table I Event Driven funds can be separated into Distressed and Risk Arbitrage, where a Distressed strategy concerns investments in bonds, equities and debt in companies that are being re-structured or are close to being bankrupt, and a Risk Arbitrage strategy concerns exploring informational inefficiencies related to mergers and acquisitions.

The third component is termed "Global Macro". The Global Macro (GM) strategy is based on macroeconomic and political analyses of the global financial markets and the degree of leverage is typically high. Global Macro funds engage in arbitrage strategies in equities, fixed income and currencies.

The forth component is termed "Value", and the funds related to this component are dominated by Established funds. These funds primarily invest in the US market, and this component can be characterised by market neutral strategies mainly based on long/short equity. The long/short strategy in its pure form seeks to neutralise the systematic risk focusing on the idiosyncratic risk and therefore these funds often invest in few assets rather than in well-diversified portfolios.

Finally, the fifth component is termed "Market Neutral Arbitrage", because all of the 9 funds related to this component are market neutral arbitrage funds. Pursuing this strategy the funds try to exploit marginal differences in prices of financial products that in terms of risk are almost equivalent. Since such inefficiencies are typically small, market neutral arbitrage funds usually have a high degree of leverage.

Further, the five strategies can be categorised into Directional and Non-directional strategies following Agerwal & Naik (2000); the Directional strategies are the Opportunistic/Sector, the Global Macro and the Value strategies, since these are characterised by active positions directed to specific movements in the market, whereas the Non-directional strategies are the Event Driven and the Market Neutral Arbitrage strategies, since these strategies are not directed at any specific market movement, i.e. they have a market-neutral focus.

We are now able to construct five portfolios, where each portfolio comprises the funds related to each of the five strategies identified. All funds appear in the portfolios with equal weights and according to the definitions above the five portfolios are termed P1: Opportunistic/Sector, P2: Event Driven, P3: Global Macro, P4: Value, and P5: Market Neutral Arbitrage, respectively. In Table III we present summary statistics for the five portfolios and for the S&P 500 index, which is included for comparison purposes.

TABLE III here

Table III documents that all the portfolios have obtained a positive return, and compared to the S&P 500 index, each of the five portfolios dominates the S&P 500 index in terms of both the return and the risk. Table III also presents the Jacque-Bera statistic for normality, and for a 5% critical significance value of 5.99, we infer that normality cannot be rejected for portfolio 3 and portfolio 4 as well as for the S&P 500 index. However, rejection of normality may lead one to overestimate the significance of traditional performance measures. In this case normality is rejected for three out of five portfolios, and we therefore have to be careful interpreting the results on performance in Section 5.

4. A multi-factor model with buy-and-hold and option strategies

As mentioned in the Introduction an analysis of hedge funds style and performance must take a different starting point compared to mutual fund analyses, since hedge fund strategies are typically dynamic trading strategies. This means that the return on hedge funds often has no or only little correlation to standard market indices and appropriate benchmarks are therefore not available.

Fung & Hsieh (1997) illustrate why a dynamic hedge fund strategy even in assets closely related to a market index may not result in a high correlation between the fund return and the market index return. If a hedge fund engages in leveraged positions in S&P 500 futures, say, which are changed continuously between short and long positions, the net effect may be zero and therefore the correlation between the fund return and the S&P 500 return will be nil[15]. Consequently, there need not be a linear relationship between the fund and standard market indices used as benchmarks[16]. Hence traditional performance models such as the standard CAPM security market model or Sharpe's style-based factor model, see Sharpe (1992) become invalid. However, non-linear relationships have been applied in the mutual funds literature to test for the mutual fund manager's ability to time the market, e.g. Treynor & Mazuy (1966) suggest a quadratic equation and Merton (1981) and Henriksson & Merton (1981) develop an option-based model.

There are a number of potential explanations why hedge fund returns may show an option-like pattern. Firstly, as opposed to most mutual funds, hedge funds are allowed to and do employ option strategies. Secondly, hedge fund managers are typically paid according to the returns obtained by the hedge fund, which mimics a call option. Finally, Agerwal & Naik (2000) argue that hedge funds have an opportunistic nature of trading implying state-contingent bets, and returns from option strategies may to some extent capture such state-contingent bets. To validate this, Agerwal & Naik observe that for 54% of a sample of 586 hedge funds, call or put options are the most significant individual factors in a multi-factor model. Especially for the non-directional market neutral funds, passive option strategies explain a significant part of the fund returns. In fact the Agerwal and Naik evidence is consistent with the observation that β in a CAPM security market line model is time-varying.

To infer whether the identified strategy components in this analysis have option-like features, we illustrate in Figures 1, 2, and 3 the monthly return on portfolio 3, portfolio 4 and portfolio

5, respectively. The 37 monthly returns are on an ex-post basis sorted and grouped into five states, where state 1 contains the 20% lowest returns, i.e. the most bearish months and state 5 contains the 20% highest returns, i.e. the most bullish months[17].

FIGURE 1 here

Figure 1 compares the return on portfolio 3 to the return from the Salomon Brothers Government and Corporate Bond index, and we see that the return on portfolio 3 mimics the return on a straddle with the Salomon Brothers Government and Corporate Bond index as the underlying index.

In Figure 2 we compare the return on portfolio 4 to the Russell 3000 index, and we see that the return on portfolio 4 can be characterised as the return on a long call option with the Russell 3000 index as the underlying index. The choice of the Russell 3000 index is based on the fact that the portfolio 4 funds are Value funds that focus on long positions in undervalued stock hedged by short positions in overvalued stocks.

FIGURE 2 here

Finally, Figure 3 illustrates that the return on portfolio 5 is equivalent to the return on a long put option with a low exercise price and with the MSCI World ex. US index as the underlying index. Portfolio 5 funds are market-neutral funds.

FIGURE 3 here

Based on these preliminary comparisons of the portfolio return and the return of relevant marked indices, we would expect that passive option strategies play a significant role explaining portfolio returns, see also Fung & Hsieh (1997, 1999).

In order to include option strategies we apply the methodology suggested by Agerwal & Naik (2000). Along the lines of Fung & Hsieh (1997), who argue that the return from hedge funds can be separated into Location factors (buy-and-hold strategies), Trading Strategy factors (option-like strategies) and Leverage factors (return from gearing), Agerwal & Naik suggest that Sharpe's multi-factor style model can be extended to include these various factors. In this analysis the leverage factor will not be considered, partly because the CISDM database does not give details of leverage for all of the funds in the database and partly because we believe that the leverage effect may produce a potential bias, because the information on the degree of leverage has been provided by the hedge funds themselves.

Therefore, the focus will be on the Location and the Trading Strategy factors. We define 46 factors in all of which 10 factors are Location factors and the remaining 36 factors are Trading Strategy factors. Some of the 10 Location factors are equivalent to the Location factors used in the studies by Agerwal & Naik (2000) and Liang (1999) but differences exist. We include three equity indices: The Russell 3000 index, the MSCI World ex. US index and the MSCI Emerging Market index. Together these indices represent the major equity markets including 95% of the US market. Similarly, we include three bond indices: the Salomon Brothers Government and Corporate Bond index, the Salomon Brothers World Government Bond index and the Lehman High Yield (US) index. Again we would argue that together these three indices represent the major global bond markets including US corporate bonds and US high yield bonds. Further, we include an exchange index: the US Nominal Effective Trade-Weighted Exchange Rate index and a commodity index: the Goldman Sachs Commodity index to reflect positions in exchange rates and commodities. Finally, we include the famous SMB and HML indices suggested by Fama & French (1996), which measure a Size factor and a Value-Growth factor, respectively.

The 36 Trading Strategy factors are based on 6 of the Location factors. We determine 6 different passive option strategies related to: the Russell 3000 index, the MSCI World ex. US index, the MSCI Emerging Market index, the Salomon Brothers World Government Bond index, the Lehman High Yield index and the US Nominal Effective Trade-Weighted Exchange Rate index. The 6 option strategies for each of the 6 market indices are separated into at-the-money, out-of-the-money and deep-out-of-the-money options as well as into call and put options following Agerwal & Naik (2000). This gives a total of 36 different option strategies. It is worth pointing out, however, that these option strategies are passive simply representing buying and writing call and put options, i.e. option strategies that are common knowledge to investors in the market. We do not, however, include advanced option strategies as e.g. butterflies, strangles etc., as opposed to Fung & Hsieh (2002), because such strategies are not generally common to market participants, and therefore a hedge fund manager employing such advanced strategies with success should be identified through the Jensen measure, see Equation (1) below.

To price these options we use the Black and Scholes model, which gives us European option prices, thus recognising that these prices may be lower than the actual market prices[18]. The out-of-the-money options have an exercise price that is one half standard deviation away from the at-the-money exercise price and the exercise price of the deep-out-of-the-money options are one standard deviation away from the at-the-money exercise price. We assume that all options expire after 1 month and that the 37 months historical volatility on the underlying index will approximate the 1 month future volatility.

Obviously, we cannot formulate a multi-factor model, which includes 46 factors, since only 37 observations are available. To solve this problem we use the step-wise procedure in Liang (1999) and in Agerwal & Naik (2000). They suggest that in order to have sufficient degrees of freedom and to mitigate potential problems of multicollinearity, the independent variables are entered into the model one at a time based on their individual correlation with the portfolio return. The single best factor variable is chosen first, and then this is paired with each of the other independent factor variables one at a time. The second variable with the highest correlation to the portfolio return is then included and this procedure continues and ends when only significant variables enter the equation. An important drawback of the step-wise procedure is, however, that the resulting regression equation is not optimal in terms of producing the highest goodness-of-fit for a given number of independent variables, see Malhotra (1999), as is e.g. the case using the general-to-specific approach suggested by Hendry (1997). But as argued by Aczel (1996) the step-wise regression procedure minimises the risk of excluding significant factors and including insignificant factors. However, the step-wise regression may tend to overfit the factors in which case the performance measure becomes biased towards zero. To account for this potential bias, relevant robustness analyses will be provided.

The extended multi-factor model reads as:

$$R_{pt} = \alpha_p + \sum_{k=1}^{K} b_{pk} \cdot F_{kt} + u_{pt} \tag{1}$$

where:

- R_{pt} is the net-of-fees excess return[19] on hedge fund portfolio p for month t
- α_p is the value added of hedge fund portfolio p, i.e. the equivalent to the Jensen measure in the simple CAPM security market line model
- b_{pk} is the average factor loading of hedge fund portfolio p on the k^{th} factor
- F_{kt} is the excess return on the k^{th} factor for month t
- u_{pt} is a white noise error term for month t

Equation (1) is estimated for each of the five portfolios created in Section 3 using the step-wise method described above contrary to Agerwal & Naik (2000), who estimate Equation (1) for all of the individual funds in their sample. Since we have classified the funds quantitatively into five independent style groups, we are allowed to analyse performance for the five portfolios only rather than for each fund separately. Below we will, however, perform some sensitivity tests in terms of individual fund regressions in order to validate our portfolio results.

5. Empirical results of performance

We are now ready to present the estimation results obtained from the step-wise regressions of Equation (1) for each of the five portfolios. We only present the final model, and as will be clear shortly, only a few of the 46 different factors turn out to be significant, thus explaining the excess return on the five portfolios. The estimation results are presented in Table IV. Figures in parentheses are Newey-West corrected t-statistics, the R^2-adj gives the adjusted goodness-of-fit, SE is the standard error of the regression, Q(12) and $Q^2(12)$ are the Ljung-Box Q-statistics for 12^{th} order serial correlation in the residual levels and squares, respectively, ARCH(12) is an LM-test for 12^{th} order conditional heteroskedasticity, and J-B is the Jacque-Bera statistic testing for normality. Figures in parentheses below test statistics are probability values.

TABLE IV here

For the first portfolio, P1: Opportunistic/Sector, Table IV shows that the excess return is positively related to a bought at-the-money call option with the MSCI World ex. US index as the underlying index (MSCIWCATM) and the SMB size factor. The positive influence of the size factor on the portfolio excess return is consistent with the fact that Opportunistic/Sector funds invest in small companies. But besides the influence of the size factor, we infer that the portfolio return is also affected by the excess return of one of the option strategies. In fact the marginal increment in the R^2-adj of including the passive option strategy amounts to 0.12 (from 0.26 to 0.38), indicating that the option strategy improves the regression equation. Concerning performance we see that α is positive but not statistically significant. Apparently funds in the Opportunistic/Sector portfolio have not on average been able to generate abnormal excess returns.

For the second portfolio P2: Event Driven, we infer from Table IV that again only two factors turn out being significantly different from zero, and also in this case one of the passive option strategies enters the regression equation. In this case the option strategy is a written (the negative sign) out-of-the-money put option with the Lehman High Yield index as the underlying index (LEHPOTM). The other significant factor is the Goldman Sachs Commodity (GSC) index. The goodness-of-fit is 0.51, whereas excluding the option factor, the goodness-of-fit falls to 0.28. It is also interesting to observe that in this regression α becomes positive and significantly different from zero at the 5% level. Consequently, the Event Driven funds seem on average to have obtained a positive abnormal excess return.

For the third portfolio P3: Global Macro, the results in Table IV distinguish itself from the two previous regression equations in a number of areas. Firstly, because three factors now become significant; the Russell 3000 index, the Lehman High Yield index and the SMB size factor, where the size factor also appeared in portfolio 1, and secondly because none of the passive option strategies appear in the model, i.e. only Location factors determine the excess return on the Global Macro funds. Finally, this model is characterised by a much higher goodness-of-fit of 0.88. In this case we must conclude that on average Global Macro funds do not pursue dynamic trading strategies. Considering α we find that this is positive but insignificant at a strict 5% level, but it is close to being significantly different from zero (at a 5.78 % level) indicating neutral to positive performance.

Turning to the fourth portfolio P4: Value, we see from Table IV that the excess return is influenced by only one factor, which is a bought out-of-the-money call option based on the Russell 3000 index (RUSCOTM), which is consistent with Figure 2. Accordingly, the goodness-of-fit is lower than in any of the previous regression equations, but concerning performance, we find a positive α being significantly different from zero. Although the goodness-of-fit is low we conclude that on average Value funds employ dynamic trading strategies.

Finally, taking a look at the fifth portfolio, which is the P5: Market Neutral Arbitrage portfolio, Table IV reveals that again we identify two independent factors being significantly different from zero, which in this case is a bought deep-out-of-the-money put option with the MSCI World ex. US index as the underlying asset (MSCIWPDOTM) and the Fama and French Value-Growth factor (HML). Also the Market Neutral Arbitrage funds seem to employ dynamic trading strategies and this particular option is consistent to the findings presented in Figure 3. Moreover, we see that α is positive and statistically significant indicating superior performance.

As argued above the step-wise regression procedure may tend to overfit the factors in which case the αs will be downward biased. It is therefore useful to analyse the robustness of the portfolio results. To do so we will take a closer look at randomly selected individual funds. In fact we select 5 funds randomly from each of the five portfolios/strategies and perform the multi-factor step-wise regressions for each of these 25 individual funds.

For the P1: Opportunistic/Sector funds we find that for four of the five funds the fund excess return is significantly influenced by an option with the MSCI World ex. US index, and three of the five funds have a positive but statistically insignificant α. This evidence is very close to the portfolio evidence in Table IV.

Similarly, for the five random funds drawn from the P2: Event Driven portfolio we find that the fund excess return for all of these is significantly affected by a put option on the Lehman High Yield index and four of the five funds have a significantly positive α. Both results sustain the portfolio evidence in Table IV.

However, concerning the five P3: Global Macro funds we infer some differences to the portfolio evidence. In the portfolio no option strategies turned out to be significantly different from zero, but for four of the individual funds passive option strategies play a significant role. This lends further support to the argument that option strategies are important ingredients in the multi-factor style model. On the performance side there is, however, a clear similarity between the portfolio and the individual fund evidence in that three of the funds show insignificant performance. To validate the robustness of these results it is also worth mentioning that for each of the five individual funds a least one of the three market indices included in the portfolio in Table IV turn out to have a significant influence on the individual fund excess returns.

In the P4: Value portfolio in Table IV only a Russell call out-of-the-money option had a significant effect on the portfolio excess return, and this is confirmed for three of the five individual funds. Similarly, three of the five funds show a positive and significant α confirming the portfolio evidence.

Finally, we find that for four of the five funds in the P5: Market Neutral Arbitrage group, the fund excess return is influenced significantly by an option with the MSCI World ex. US index as was the case for the portfolio, but where the portfolio α is positively significant, only two of the five individual funds have a positive and significant α.

In summary, we believe that the results obtained from the 25 individual multi-factor models support the portfolio findings to a large extent. At this point it would therefore be relevant to sum up the similarities and differences across the five portfolio models.

Firstly, the relevance of including Trading Strategies in the multi-factor model has been documented. For four of the five portfolios, a dynamic option strategy turned out to have a significant influence on the portfolio excess returns. Accordingly, the goodness-of-fit is relatively high between 0.28 and 0.88, if we compare to e.g. Fung & Hsieh (1997), who find a goodness-of-fit of only 0.07 for a standard Sharpe style model including eight independent factors. If we compare the goodness-of-fit to Liang (1999), who finds a goodness-of-fit between 0.20 and 0.77, and to Agerwal & Naik (2000), who find a goodness-of-fit between 0.05 and 0.80, our goodness-of-fit is only marginally higher. However, compared to Fung & Hsieh (2002) who analysed the risk in fixed income hedge fund styles, the option strategies in our study are highly significant in explaining hedge fund returns, whereas in Fung & Hsieh the option strategies only play a marginal role.

Secondly, concerning performance we find that α is positive and statistically significant for three and almost four of the five portfolios. However, these αs have not been corrected for survivorship bias, as discussed in Section 2. Ackerman et al. (1999) find a survivorship bias of only 0.16% in a sample combined of the HFR and the MAR databases, and Edwards & Caglayan (2001a) find the survivorship bias in the MAR database to be 1.85% annually. Since our sample does not include defunct hedge funds, we are not able to estimate the actual survivorship bias in our data. However, our database is the former MAR database, and if we rely on the estimates found by Ackerman et al. (1999), we would conclude that survivorship biases probably are small, and therefore our conclusion that the hedge funds in our sample have obtained significantly positive αs should be valid[20]. On the other hand Edwards & Caglayan (2001a) find a bias of 1.85% in the MAR database, and it would therefore be appropriate to test the significance of the estimated αs if the data are corrected for a bias of 1.85%.

We will therefore re-estimate the portfolio regressions presented in Table IV after correcting the annual returns by 1.85%, which amounts to a monthly return bias of 0.1529%. Furthermore, Fung & Hsieh (2000) have found a survivorship bias of approximately 3.00% annually in the TASS database, and similarly Brown et al. (1999) find a survivorship bias of approximately 3.00% in a database of off-shore hedge funds. Based on these estimates of the survivorship bias, we will also correct our returns by an annual bias of 3.00%, which amounts to 0.2466% per month. We consider the 1.85% of Edwards & Caglayan (2001a) and the 3.00% of Fung & Hsieh (2000) and Brown et al. (1999) to represent valid estimates of the survivorship bias, which provide information of the robustness of the estimated αs in Table IV.

For the five portfolios, Table V summaries the estimated αs and their corresponding Newey-West corrected t-statistics for both the case before correcting for biases and the case, where returns have been reduced by 0.1529% and 0.2466%, respectively.

TABLE V here

In Table V the third and forth columns summarise the estimates before correcting for survivorship bias, the fifth and sixth columns are the equivalent estimates after reducing the returns by 0.1529% and columns seven and eight give the estimates when returns are reduced by 0.2466%[21]. We clearly see that correcting for a potential survivorship bias of 1.85% and 3.00% the conclusion concerning hedge fund performance is changed drastically, since in only one case (P5) the conclusion of out-performance holds, although all the αs are still positive. At best we can conclude that on average these 142 hedge funds have performed neutrally. The conclusion as to whether the hedge funds in our sample have obtained neutral or positive performance is therefore sensitive to the estimate of survivorship bias.

Finally, considering the econometric tests in Table IV we see that in most cases these are passed. For portfolio 3, 4 and 5 all the tests are passed, but for portfolio 1 the residuals do not fulfil the normality assumption, and for portfolio 2 there seems to be some serial correlation. However, standard errors being Newey-West corrected combined with the fact that almost all of the econometric tests are passed, we believe that our inferences are valid and our conclusions are credible.

6. Conclusion

The purpose of this analysis has been to provide further evidence on hedge fund styles and performance. Previous analyses do not agree whether hedge funds have obtained superior performance. Some analyses have found that hedge funds have performed better than market indices (the S&P 500) and/or mutual funds, whereas other studies find that for only a smaller percentage of the funds analysed (between 25% and 35%), significantly positive Jensen measures can be identified.

In this study we apply the CISDM database (the former MAR database), and we find that hedge funds have been able to obtain abnormal returns before correcting for survivorship bias. However, after correcting for an annual survivorship bias of 1.85% and 3.00%, hedge fund performance becomes neutral.

The methodology in this analysis is quantitative and although we apply different methods that have also been applied in other studies, no other studies have combined the quantitative classification method with a multi-factor model comprising dynamic trading strategies. Contrary to most other analyses, we use a Principal Component Analysis following Fung & Hsieh (1997, 2002) in order to be able to identify the minimum number of components necessary to describe the return on hedge funds. We find the optimal number of orthogonal components to be five and by comparing these to the qualitative classifications provided by the hedge funds themselves, we identify five different trading strategies which explain more than 60% of the hedge fund return variation. Also we set up a multi-factor model along the lines of Agerwal & Naik (2000), which comprises various market indices as well as a number of passive option strategies. We find that these passive option strategies play an important role in explaining hedge fund returns and in particular the goodness-of-fit is remarkably higher than in previous analyses that have not considered including option strategies.

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We want to thank Thomas Schneeweis at the Centre for International Securities and Derivatives Markets (CISDM) for supplying the data, and an anonymous referee for comments, although the usual disclaimer applies.

Footnotes

1. For a thorough description of hedge funds, their organisation, styles, differences to mutual funds, performance etc., we recommend Fung & Hsieh (1999) and Edwards & Caglayan (2001a).

2. However, in Fung & Hsieh (2002) they are able to explain up to nearly 80% of the return variation for fixed income hedge funds using only two principal components.

3. At present this database includes approximately 1,500 hedge funds.

4. Liang (2000) discusses differences and potential problems with these databases.

5. In Edwards & Liew (1999) the return difference between surviving funds and all funds in the MAR database is estimated to be 1.91%, but they argue that the actual survivorship bias is much smaller.

6. In Ackermann et al. (1999) the instant history bias is termed a backfilling bias.

7. One exception is Ackermann et al. (1999).

8. The sample used by Capocci & Hubner (2003) included emerging market funds and they show that an emerging bond market index plays a significant role in explaining hedge fund returns.

9. Liang (2003) finds that due to the double-fee structure funds of funds tend to underperform hedge funds.

10. A recent study by Amin & Kat (2003) includes only 77 hedge funds and 13 hedge fund indices.

11. The special characteristics of funds of funds are analysed in Brown, Goetzmann and Liang (2002).

12. In the former MAR database 7 strategies were applied: event driven, global, global macro, market neutral, short sales, U.S. opportunistic and fund of funds. The HFR database specifies 16 different strategies, see Liang (1999) for an overview. Brown and Goetzmann (2003) identify at least 8 distinct styles and find that style affiliation turns out to be important for the hedge fund risk exposure.

13. It should be noted that five components do not comprise the full information required to explain the return variance.

14. The reason that all of the strategies load on the first principal component is probably because the first principal component mimics an equally-weighted portfolio.

15. Edwards & Caglayan (2001b) find that hedge fund returns have a higher correlation with stock market returns in bear markets than in bull markets.

16. Dybvig & Ross (1985) argue that if the portfolio weights change over time, linear performance models will not be able to measure performance correctly, and in their model they show that if a manager possesses private information, we may conclude in favour of both under performance and out-performance.

17. Since our sample contains only 37 observations, the states are sensitive to extreme observations.

18. Mitchell & Pulvino (2001) show that performance is affected only marginally using theoretical prices rather than market prices.

19. Excess returns are determined by subtracting the 1 month Treasury Bill rate.

20. Liang (2000) argues that the Ackerman et al. (1999) estimate of only 0.16% is below the range of 0.5-1.4% bias for mutual funds, which is inconsistent with the fact that usually hedge funds are considered to be more risky than mutual funds.

21. Just subtracting the bias from the returns may not be appropriate, see Carhart et al. (2002), but at least this procedure gives some indication of how performance is affected by survivorship biases.

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TABLE I

Industry classification of hedge funds

Classification	No. of funds	Mean return	Median return	Std. Dev.
Total	185	12.18	6.69	15.21
Sector fund (S)	20	12.16	6.26	19.07
Event driven distressed (ED)	15	11.01	6.44	13.37
Event driven risk arbitrage (ER)	24	14.69	8.80	13.71
Global macro (GM)	14	11.84	4.90	17.74
Global established (GE)	55	9.95	9.97	11.09
Global international (GI)	8	15.04	4.01	17.64
Market neutral long/short (MI)	21	16.74	12.64	19.30
Market neutral arbitrage (MA)	26	9.31	4.24	17.05
Market neutral mortgage-backed (MM)	2	8.86	3.96	7.93

Note: The 185 hedge funds are classified into 9 different strategies, and the Table presents annual mean and median returns as well as the annual standard deviation.

TABLE II

Identified components

	No. of funds	Average factor loading	Max. factor loading	Min. factor loading
Component 1	58	0.722	0.938	0.417
Component 2	29	0.694	0.861	0.386
Component 3	30	0.597	0.856	0.409
Component 4	16	0.624	0.805	0.405
Component 5	9	0.631	0.842	0.508
Total	142	0.654	0.938	0.386

Note: The PCA identifies 5 independent components, and the Table presents the average, the maximum and the minimum factor loadings obtained from the PCA.

TABLE III

Summary statistics for portfolios

	No. of funds	Mean return	Median return	Std. Dev.	Jacque-Bera
P1: Opportunistic/Sector	58	17.76	4.68	15.35	64.28
P2: Event Driven	29	8.40	9.48	3.39	17.55
P3: Global Macro	30	7.08	3.12	11.81	0.04
P4: Value	16	12.60	8.52	9.28	5.34
P5: Market Neutral Arbitrage	9	11.64	9.84	3.29	8.55
S&P 500		-8.88	-14.28	17.08	1.03

Note: For each of the 5 components obtained from the PCA, 5 strategies are determined, and the Table presents for each strategy and for the S&P 500 index annual mean and median returns, the annual standard deviation and the Jacque-Bera statistic for normality, which has a 5% critical significance value of $\chi^2(2) = 5.99$.

TABLE IV

Regression results

Portfolio	Equation	R^2-adj	SE	Q(12)	Q^2(12)	ARCH(12)	J-B
P1	$R_{1t} = 0.009 + 0.016 \cdot MSCIWCATM_t + 0.308 \cdot SMB_t$	0.38	0.035	7.26	9.61	17.51	15.02
	(1.24) (2.28) (2.19)			(0.84)	(0.65)	(0.13)	(0.00)
P2	$R_{2t} = 0.003 - 0.002 \cdot LEHPOTM_t + 0.038 \cdot GSC_t$	0.51	0.006	27.70	10.00	13.01	2.50
	(2.40) (-5.47) (2.19)			(0.01)	(0.62)	(0.37)	(0.29)
P3	$R_{3t} = 0.004 + 0.392 \cdot RUS_t + 0.347 \cdot LEH_t + 0.212 \cdot SMB_t$	0.88	0.012	9.74	5.08	14.57	1.03
	(1.96) (8.08) (3.98) (5.59)			(0.64)	(0.96)	(0.27)	(0.60)
P4	$R_{4t} = 0.009 + 0.009 \cdot RUSCOTM_t$	0.28	0.023	13.93	15.99	11.95	4.39
	(2.42) (3.09)			(0.31)	(0.19)	(0.45)	(0.11)
P5	$R_{5t} = 0.004 + 0.001 \cdot MSCIWPDOTM_t + 0.073 \cdot HML_t$	0.44	0.007	12.46	10.57	14.14	4.43
	(4.01) (4.52) (3.62)			(0.41)	(0.57)	(0.29)	(0.11)

Note: Figures in parentheses are Newey-West corrected t-statistics, the R^2-adj gives the adjusted goodness-of-fit, SE is the standard error of the regression, Q(12) and Q^2(12) are the Ljung-Box Q-statistics for 12th order serial correlation in the residual levels and squares, respectively, ARCH(12) is an LM-test for 12th order conditional heteroskedasticity, and J-B is the Jacque-Bera statistic testing for normality. Figures in parentheses below test statistics are probability values.

TABLE V

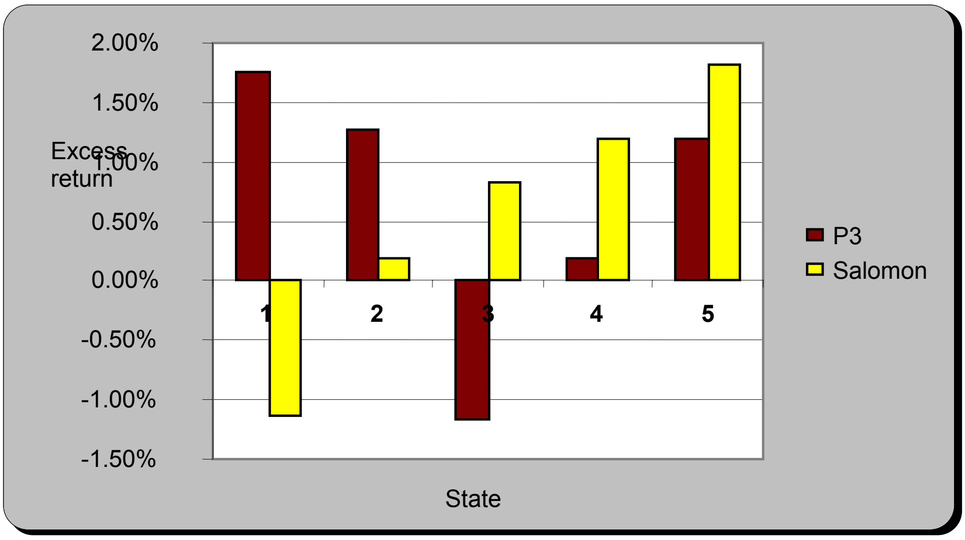
Estimated annual α's before and after correcting for a survivorship bias of 1.85% and 3.00% annually

	No. of funds	α	t-stat	$\alpha_{1,85}$	t-stat	$\alpha_{3,00}$	t-stat
P1: Opportunistic/Sector	58	11.09	1.24	9.26	1.03	8.13	0.91
P2: Event Driven	29	4.10*	2.40	2.26	1.32	1.14	0.67
P3: Global Macro	30	4.44	1.96	2.61	1.15	1.48	0.65
P4: Value	16	10.92*	2.42	9.08	2.01	7.96	1.78
P5: Market Neutral Arbitrage	9	4.37*	4.01	2.54*	2.33	1.41	0.96

Note: For each of the 5 strategies the Table presents the estimated annual αs and their Newey-West corrected t-statistics before correcting for survivorship bias, after correcting for a bias of 1.85% annually, and after correcting for a bias of 3.00% annually, respectively. A * indicates that the estimated α's are significantly different from zero at the 5% level.

FIGURE 1

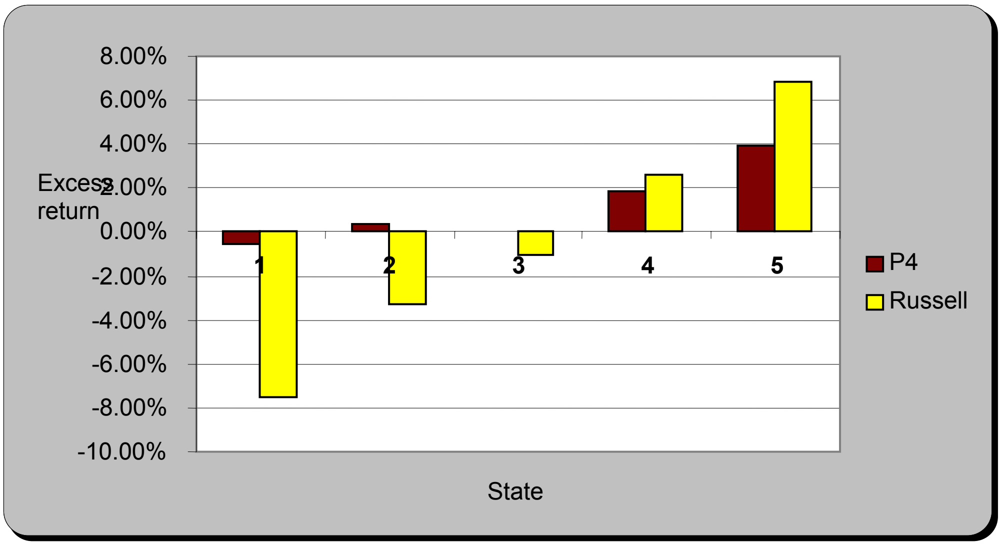
Monthly return on portfolio 3 and the Salomon Brothers Government and Corporate Bond index



Note: The return on portfolio 3 is sorted and divided into 5 equal groups, where the first group contains the 20% lowest returns and group 5 contains the 20% highest returns. These returns are compared to the return on the Salomon Brothers Government and Corporate Bond index.

FIGURE 2

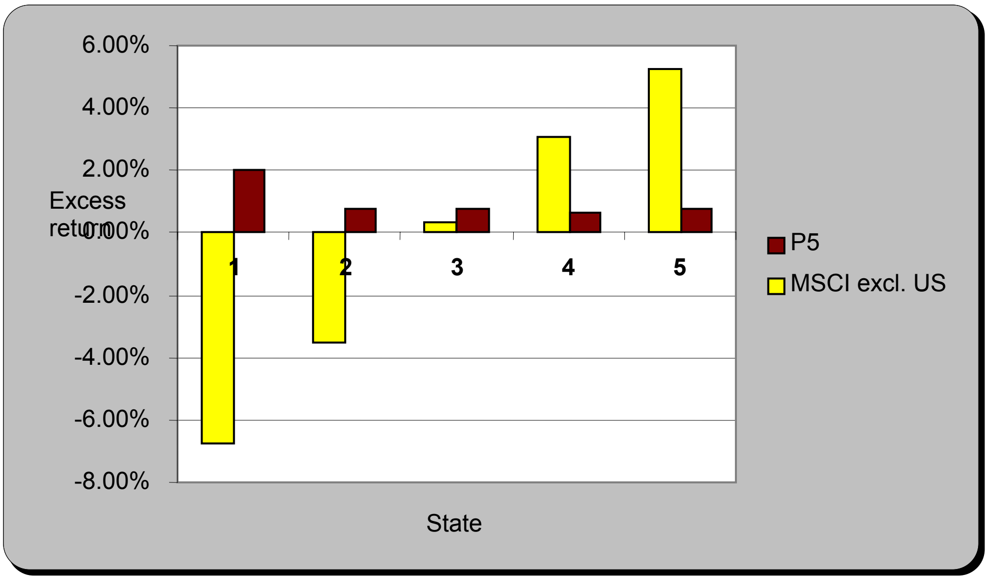
Monthly return on portfolio 4 and the Russell 3000 index



Note: The return on portfolio 4 is sorted and divided into 5 equal groups, where the first group contains the 20% lowest returns and group 5 contains the 20% highest returns. These returns are compared to the return on the Russell 3000 index.

FIGURE 3

Monthly return on portfolio 5 and the MSCI World ex. US index



Note: The return on portfolio 5 is sorted and divided into 5 equal groups, where the first group contains the 20% lowest returns and group 5 contains the 20% highest returns. These returns are compared to the return on the Morgan Stanley Capital Market ex. US index.