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# Performance Analysis of Hedge Fonds

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Beitrag aus:

# Handbuch Hedge Funds

## Chancen, Risiken und Einsatz in der Asset Allocation

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# Performance Analysis of Hedge Funds

*by Jacqueline Henn/ Iwan Meier*

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# 1. Introduction

In 1990, Yale University became the first U.S. school to invest in hedge funds. Over the past fifteen years, the university increased the target for the absolute return portfolio from an astounding 15% in 1990 to 25%. At $11.0 billion in 2003, Yale is one of the largest university endowments.[1] A further milestone was when the California Public Employees' Retirement System (CalPERS) decided to allocate $1 billion to hedge funds in 2000. This announcement by the CalPERS state plan, if not before, made hedge funds an accepted asset class among large institutional investors. CalPERS, the largest pension plan in the U.S. with $182.9 billion under management at the end of 2004, provides retirement and health benefits to more than 1.4 million public employees, retirees and their families, and more than 2,500 employers. Today, they target an asset allocation to alternative investments of 7%.[2]

While investments of European institutional investors lag behind the U.S. experience, many large corporate pension plans have a track record of alternative investments. The Euro 3.8 billion Nestlé Fonds de Pensions, one of the biggest pension plans in Switzerland, started investing 1% in hedge funds in 1996. Meanwhile, the allocation has reached 18% of total assets.[3]

CalPERS' investments in hedge funds delivered a return of 8.9% in 2004. The pension fund also disclosed that they pay currently about $200 million a year to managers of 415 alternative investment firms to manage a total of $13.5 billion. This amounts to a management fee of approximately 1.5% of assets, not including performance fees.[4] Yale's investment in absolute return strategies over the past ten years yielded 12.2% per year, with essentially no correlation to U.S. stock and bond markets. How do these returns compare on a risk-adjusted basis?

FUNG/ HSIEH (1999) point out that the main common characteristic of hedge funds is rather their unregulated status than the fact that these funds pursue any common strategy. The lack of regulation also means that hedge funds are not required to submit semi-annual or annual reports to a supervisory institution like the U.S. Securities Exchange Commission (SEC). This makes it even more difficult for the investor to collect information on peer funds and compare their performance.

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1 The Yale Endowment, 2003 Update: www.yale.edu; Facts About Yale. Harvard University, at $25.4 billion, the largest U.S. university endowment has a 12% target for investments in absolute return strategies. See the Annual Financial Report of Harvard University, Fiscal Year 2003-2004: http://vpf-web.harvard.edu.

2 Asset Allocation: www.calpers.ca.gov; CalPERS Investments - CalPERS Assets.

3 James Mawson, April 2004, "Nestlé Puts 18% in Hedge Funds", Financial Times.

4 Marsh William, December 8, 2004. "CalPERS Tells What It Paid High-Risk Investment Funds", New York Times.

The goal of this chapter is twofold: First, we present an overview of the current research on hedge fund performance. Second, we provide new evidence for the European hedge fund industry. The empirical analysis scrutinizes the return patterns in the past and alerts investors to the potential failures of conventional performance measures. Major difficulties in evaluating the performance of hedge funds are the myriad of strategies and the large changes of statistical measures over time. Moreover, many strategies can be seriously hit by big losses (or gains) in the benchmark. Take merger arbitrage as an example. MITCHELL/ PULVINO (2001) show that this strategy resembles an uncovered short put on the market index, such that most of the times the strategy is uncorrelated with the market but large negative market returns can result in huge losses to the investor. Unfortunately, estimating the probability of the occurrence of such a catastrophic return is extremely hard and the characteristics of each event, like the near bankruptcy of Long Term Capital Management (LTCM) in 1998, are unique.

We start out our analysis with a discussion of the return and risk characteristics of European hedge funds. In particular, we analyze their return, volatility, and correlation pattern over time. Next, we investigate whether successful funds persistently outperform their peers. The chapter concludes with an outline of potential failures of commonly used performance measures.

## 2. Data Description

The empirical part of this chapter is based on the Eurekahedge European Hedge Fund Database.[5] All funds in this database either allocate at least 40% of their portfolio to Europe or have domicile in Europe. The database contains a total of 1,217 individual hedge funds (and CTAs) by the end of August 2004; 1,129 live funds and 88 dead funds (8%).[6] Eurekahedge is continuously adding new funds and collecting information on dead funds.

For 816 hedge funds we observe at least two monthly returns between January 1994 and August 2004. Figure 1 shows the number of funds for various lengths of the observation period. All our subsequent calculations restrict to the subsample of 352 funds with more than 36 months of data.

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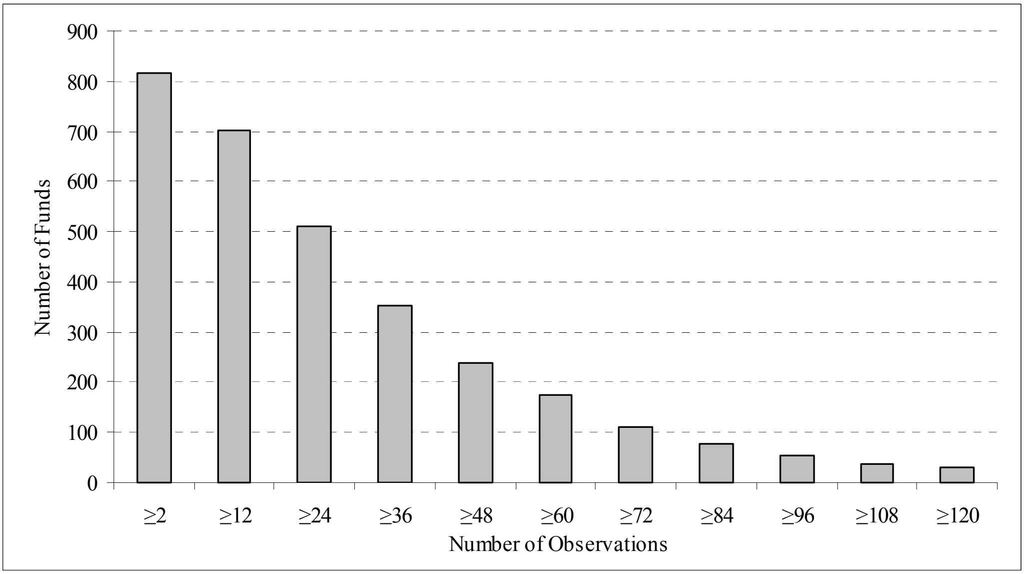
5 For details see www.eurekahedge.com. Eurekahedge was founded in 2001 and started distributing the European Hedge Fund Database in July 2003.

6 Agarwal/ Daniel/ Naik (2004) point out that the term “dead” funds is misleading in the hedge fund literature. They coined the term “missing-in-action” hedge funds. However, in the tradition of the mutual fund literature the term “dead” is also used in the hedge fund literature. The 88 funds in our sample are “missing-in-action” in July and August 2004.

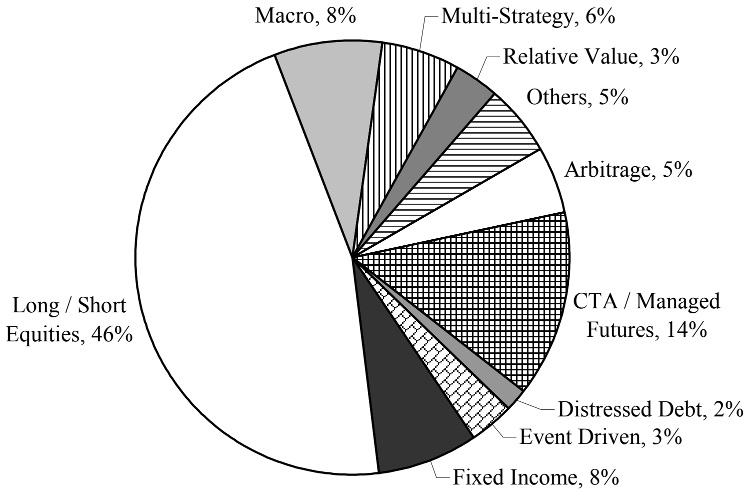



The exhibit shows the number of funds for which we observe more monthly returns than indicated on the horizontal axis. The sample period extends from January 1994 to August 2004. For our analysis, we exclude all funds with less than three years of data.

**Figure 1: Number of Observations per Fund**

Figure 2 reports the breakdown of the hedge funds by investment strategy. Eurekahedge distinguishes between ten strategies: Arbitrage, CTA/Managed Futures, Distressed Debt, Event Driven, Fixed Income, Long/Short Equities, Macro, Multi-Strategies, Relative Value, and Others. Almost half of the funds (46%) are classified as Long/Short Equities. The large fraction attributed to this investment style is consistent with other major hedge fund data providers. MALKIEL/ SAHA (2004) report 33% Long/Short Equity Hedge for the TASS database at the end of 2003. Once the 24% funds of funds in their study are excluded this translates into 43%.[7]

[7] 33% / (100% - 24%) = 43%.




The pie chart illustrates the breakdown of the total of 1,217 hedge funds by investment strategy at the end of the sample period in August 2004. All funds in the database invest at least 40% in Europe or are domiciled in Europe.

**Figure 2: Investment Strategies**

In addition to monthly returns, the Eurekahedge European Hedge Fund Database supplies in depth fund profiles. Table 1 summarizes the main characteristics across all investment categories. Hedge funds typically charge a management fee of 1-2% of assets. This can be best seen from the two quantiles that are reported in the table: the 25% quantile is 1% and the 75% quantile 2%. When the fund realizes positive returns the investor pays an additional layer of fees in the form of performance fees. The industry standard for performance fees is 20% of the profits. For relatively few funds (16%) the performance fee becomes effective only once profits exceed a hurdle rate, which typically equals a short-term Treasury bill rate or LIBOR (occasionally LIBOR plus a spread). On the other hand, almost all funds (93%) in our sample provide high-water marks, which means that performance fees are paid only to the extent that the fund exceeds the high-water mark. A fund with a high-water mark provision has to recover first from previous losses before it can charge again performance fees. In practice, this threshold value is reset on a quarterly or annual basis.[8] Thirty-eight percent of the funds charge other fees like initial sales charges (front-load charges), custody fees, and similar fees for administrating the fund. The median of the minimum re-

8 Goetzmann/ Ingersoll/ Ross (2003) discuss the effects of high-water marks in detail.

quired investment is at Euro 100,000.[9] Just a relatively small percentage of hedge funds (10%) imposes a lockup period of three months to one year during which an investor initially cannot redeem her shares. The table provides a snapshot of the characteristics at the end of the sample period, however, fee arrangements of hedge funds are rarely revised.[10]

Fund size measured by assets under management varies considerably, with the largest hedge fund managing Euro 3.5 billion. The medium size in our database is $52 million. The boom of the hedge fund industry is very recent and furthermore the attrition rate is high. Figure 1 already indicates that individual fund histories are typically short. Table 1 confirms that the average lifespan is about three years. Eighty-tree percent, or 679 out of 816 funds, are open funds and the remaining 17% (137 funds) are closed funds.

| Characteristic | Mean | Median | Min. | 25% Quantile | 75% Quantile | Max. |
|---|---|---|---|---|---|---|
| **Management Fee** | 1.5 | 1.5 | 0.0 | 1.0 | 2.0 | 6.0 |
| **Performance Fee** | 19.8 | 20.0 | 0.0 | 20.0 | 20.0 | 50.0 |
| **Minimum Investment (Euro)** | 291,026 | 100,000 | 0 | 82,284 | 411,420 | 4,114,200 |
| **Fund Size (in million Euro)** | 145 | 52 | 1 | 19 | 63 | 3,513 |
| **Age (Years)** | 3.5 | 2.8 | 0.2 | 1.6 | 4.7 | 20.7 |

The table reports summary statistics of the fee structure and additional hedge fund characteristics. The statistics use the full sample of 816 funds in August 2004. Besides the mean and median, the distribution of each variable is described by the lower and upper quartile, plus the range (minimum and maximum).

**Table 1: Fee Structure and Fund Characteristics**

### Summary Statistics

Next, we analyze mean return, standard deviation, and higher moments of discrete, monthly hedge fund returns. A careful analysis of higher moments, like skewness and kurtosis, is crucial to understand the failures of conventional performance measures when applied to hedge funds. Table 2 reports the summary statistics for the subsample of 352 hedge funds with a time series that is at least three years long. The returns are measured net of management and performance fees. The mean return across all funds

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9 We convert numbers reported by funds with reference currency US$ into euros at the exchange rate of 0.8226 Euro/US$ (end of August 2004). This explains the odd numbers for the quantiles and the maximum of Euro 4,114,200, that actually corresponds to US$5 million.

10 Liang (2000) compares the changes in the fee structure between 1997 and 1998 and finds that about 1% of the hedge funds change their fees within one year.

is 0.94% per month and the standard deviation 3.69%. This corresponds to 11.28% and 12.78% on an annualized basis. The mean falls in the range that MALKIEL/ SAHA (2004) report for dead funds (6.05%) and live funds (13.45%) for U.S. data from 1996 to 2003. LIANG (2003) documents average monthly returns of 1.16% during the time period 1994 to 2001.

The strategies Relative Value, Long/Short Equities, and to a lesser extent Multi-Strategy and CTA/Managed Futures exhibit positive skewness. A positive skewness means that the observations are spread out more to the right and, hence, the mean of such a distribution is higher than the median. A skewness of zero indicates a symmetrical distribution. To the extent that a large number of funds in the Long/Short Equities category hedge their downside exposure to the stock market while maintaining the upside potential, such strategies would result in fewer large negative returns. Hence, the distribution becomes positively skewed.

| **Investment Style** | **Mean** | **STD** | **Skewness** | **Kurtosis** | **No. of Funds** | **Average No. of Obs.** |
|---|---|---|---|---|---|---|
| **Arbitrage** | 0.62 | 1.21 | -0.31 | 5.82 | 18 | 73 |
| **CTA/Managed Futures** | 1.12 | 4.87 | 0.28 | 3.78 | 57 | 74 |
| **Distressed Debt** | 1.72 | 4.41 | -0.65 | 10.55 | 10 | 73 |
| **Event Driven** | 0.82 | 1.78 | -0.37 | 6.61 | 10 | 51 |
| **Fixed Income** | 0.96 | 2.58 | -0.42 | 6.46 | 21 | 60 |
| **Long/Short Equities** | 0.93 | 3.75 | 0.68 | 6.61 | 163 | 63 |
| **Macro** | 0.81 | 3.49 | -0.05 | 4.69 | 24 | 70 |
| **Multi-Strategy** | 0.95 | 3.51 | 0.33 | 6.23 | 20 | 72 |
| **Relative Value** | 0.91 | 3.85 | 0.91 | 7.08 | 11 | 72 |
| **Others** | 0.65 | 4.14 | 0.16 | 4.82 | 18 | 61 |
| **All Funds** | 0.94 | 3.69 | 0.35 | 5.98 | 352 | 66 |
| **MSCI Europe (in Euro)** | 0.74 | 4.86 | -0.55 | 3.28 | | |
| **MSCI World (in Euro)** | 0.63 | 4.90 | -0.53 | 2.87 | | |
| **S&P 500** | 0.92 | 4.45 | -0.57 | 3.33 | | |

The table compares the average return characteristics of the ten hedge funds strategies and three benchmarks from January 1994 to August 2004. Mean and standard deviation (STD) are reported as percentages per month. The average number of observations in the last column describes the average length of the observation period for the funds within each style. The statistics are tabulated for the 352 funds with at least 36 returns.

**Table 2: Descriptive Statistics of Monthly Hedge Fund Returns**

A typical feature of hedge fund returns is a high kurtosis (leptokurtic) that exceeds the kurtosis of three for a normal distribution. BROOKS/ KAT (2002) document low skewness and high kurtosis for many hedge fund indices. In fact, the average kurtosis is higher within all ten strategies separately. Thus, the hedge fund returns in our sample have more returns centered around the mean and in the extremes. The concerns about the extreme left tail of the distribution, the catastrophic returns, are discussed in more detail below.

The fact that hedge funds do not necessarily report to a regulatory institution, like the SEC in the U.S., makes it more difficult to collect accurate data and construct a representative database. Our database does not cover dead funds systematically before 2003 and suffers from a number of measurement biases. Hedge funds drop out of the database for various reasons. The fund in question might cease to exist, either because it is liquidated or merges with another fund. A defunct fund may also be one that is delisted by the database provider or the fund stopped reporting voluntarily. A fund's decision to stop reporting in turn can be motivated by different reasons. The fund might be very successful and does no longer need to attract new investors, may simply want to operate in privacy, or prefers not to report low returns. This is called the self-selection bias. LIANG (2000) provides evidence that funds most likely disappear due to inferior performance and hence dissolve. He documents that returns decline significantly before exit.[11] MALKIEL/ SAHA (2004) point out that for such funds the last returns prior to liquidation are often not even reported.

A total of 88 (8%) funds in the Eurekahedge database drop out before August 2004. The empirical literature has primarily scrutinized U.S. data. LIANG (2000) documents an attrition rate for the TASS database (8.3%) that is three times higher than the attrition rate of the HFR database.[12] BROWN/ GOETZMANN/ IBBOTSON (1999) report an attrition rate of 20% for commodity trading advisors (CTAs), which is consistent with the 19% in FUNG/ HSIEH (1997b), and 14% for offshore hedge funds. Out of the 604 funds in 1996, less than 25% in the sample of MALKIEL/ SAHA (2004) survive until 2004.

The survivorship bias measures the difference between the returns for the sample with no dead funds compared to the universe of live and dead funds. On the basis of the reasons discussed above, it is not a priori given whether the survivorship bias distorts hedge fund returns positively or negatively. However, the consensus in the current literature seems to be that returns from major data providers are overstating the realized returns of the hedge fund industry by 2-4% per year due to the survivorship bias.[13] FUNG/ HSIEH (1997b) estimate the bias to be 3.4% for CTAs and BROWN/

[11] See Figure 1 in Liang (2000).

[12] Liang (2000) compares the time periods 1994-1997 in HFR and 1994-1998 in TASS.

[13] Ackermann/ McEnally/ Ravenscraft (1999) argue that the two effects cancel each other out. Liang (2000) provides evidence that their low estimate of a survivorship bias of only 0.16%, which is below the finding for mutual funds (e.g. Malkiel, 1995; Brown/ Goetzmann/ Ibbotson/ Ross, 1992; Carhart/ Carpenter/ Lynch/ Musto, 2002), is driven by the low number of dead funds in the HFR database and the use of data before 1994.

GOETZMANN/ IBBOTSON (1999) 3% for offshore funds. LIANG (2000) estimates a survivorship bias of over 2% per year, FUNG/ HSIEH (2000b) report 3%, and MALKIEL/ SAHA (2004) 3.7%.

Besides the survivorship bias and the self-selection bias, available returns are affected by the instant history bias (PARK (1995); FUNG/ HSIEH (2000b)). The instant history bias occurs when, after a few months in existence, a fund decides to be included in a database and its history is backfilled. When a fund decides to report to a database then it has likely a successful recent history and, therefore, you would expect the bias to be positive. This is a common problem of all existing databases. FUNG/ HSIEH (2000b) estimate that annual returns are biased upward by 1.4%. This is in contrast to the more recent finding of MALKIEL/ SAHA (2004) who estimate the backfilling bias as high as 5%. These magnitudes underscore that in the case of hedge funds the instant history bias needs to be taken seriously.

Given these biases, comparisons across different databases should be performed with care. Moreover, the results also depend crucially on the particular time period that is being studied. In particular, earlier publications did not include the Russian crisis and the debacle of Long Term Capital Management (LTCM) in 1998.

### Non-Normality of Hedge Fund Returns

Many traditional performance measures are based on the assumption that underlying returns are normally distributed and, hence, can be accurately characterized using mean and standard deviation alone. The high values of kurtosis in Table 2 suggest that this assumption is violated. In this subsection, we apply the Jarque-Bera statistic (JARQUE/ BERA (1980)) to test whether we can reject the null hypothesis that monthly hedge fund returns are normally distributed. This test statistic draws on the skewness and kurtosis coefficients.[14] The results reported in Table 3 show that, overall, the normal distribution can be rejected in 57.4% of the cases (202 out of 352) at the 5% significance level and for 47.7% (168 out of 352) at the 1% significance level. The investment styles Event Driven, Relative Value, and Distressed Debt exhibit returns that are far from being normal. At the other end of the spectrum, the Jarque-Bera statistic rejects normality for one third of the hedge funds classified as CTA/Managed Futures. Under the assumption that the returns across different hedge funds were independent and a significance level of 5%, we would expect that the null hypothesis of a normal distribution would be rejected for approximately 5% of the funds. Our findings for European hedge funds are consistent with the evidence from the U.S. hedge fund in-

[14] The Jarque-Bera statistic is distributed Chi-square with two degrees of freedom:

$\frac{n}{6}\left[S^2+\frac{(K-3)^2}{4}\right]\sim\chi^2$, where $S$ measures skewness, $K$ kurtosis, and $n$ the sample size.

dustry. Using the TASS database, MALKIEL/ SAHA (2004) report the highest Jarque-Bera statistics for the arbitrage funds (Convertible Arbitrage and Fixed Income Arbitrage) and the lowest values for the strategy Managed Futures for which the authors cannot reject normality at the 5% significance level.

| Investment Style | 1% Level | | 5% Level | | No. of |
|---|---|---|---|---|---|
| | No. of Funds | Fraction | No. of Funds | Fraction | Funds |
| **Arbitrage** | 7 | 38.9% | 10 | 55.6% | 18 |
| **CTA/Managed Futures** | 13 | 22.8% | 19 | 33.3% | 57 |
| **Distressed Debt** | 6 | 60.0% | 7 | 70.0% | 10 |
| **Event Driven** | 7 | 70.0% | 8 | 80.0% | 10 |
| **Fixed Income** | 9 | 42.9% | 12 | 57.1% | 21 |
| **Long/Short Equities** | 90 | 55.2% | 105 | 64.4% | 163 |
| **Macro** | 10 | 41.7% | 11 | 45.8% | 24 |
| **Multi-Strategy** | 11 | 55.0% | 13 | 65.0% | 20 |
| **Relative Value** | 7 | 63.6% | 8 | 72.7% | 11 |
| **Others** | 8 | 44.4% | 9 | 50.0% | 18 |
| **Total** | 168 | 47.7% | 202 | 57.4% | 352 |

The table summarizes the number and fraction of funds for which the Jarque-Bera normality test is rejected at the 5% and 1% level, respectively. The Jarque-Bera statistic tests the joint null hypothesis that skewness and kurtosis take the values of a normal distribution (skewness = 0, kurtosis = 3) and is asymptotically Chi-square distributed with two degrees of freedom.

**Table 3: Jarque-Bera Test Results**

### Value-at-Risk

Independent of the exact distribution of returns, the investor will be particularly concerned about the extreme end of the left tail that contains the catastrophic losses. One way to quantify potential losses is to report the lower quantiles. Value-at-risk (VaR) at the 95% confidence level measures the cutoff value in the left tail of the distribution below which 5% of the worst losses fall.[15] In other words, the probability that the return will fall below this value is 5%. We calculate VaR from the historical distribution of returns. Thus, VaR can easily be computed by sorting the hedge fund returns and then picking the one value that corresponds to the, say, 5% quantile. Assuming we had 100 observations the fifth lowest value would correspond to the 5% quantile. We repeat this exercise for every fund individually and provide the average VaR values within each investment style category in Table 4.

[15] A classic reference for Value-at-Risk is the book by Jorion (2000).

The advantage of this non-parametric VaR approach is that we do not need to make any assumptions about the distribution of returns, which is convenient given that hedge fund returns often exhibit distributions that are far different from a normal distribution or any other familiar distribution. The main drawback of the method is its reliance on a short data window. To mitigate this issue we consider only funds with at least five years of data for this part of our analysis. However, LO (2002) demonstrates that one needs a much longer time series to allow any powerful inference.

Furthermore, the plain-vanilla VaR measure does only take into account the frequency of catastrophic events in the far left tail of the distribution but neglects their size. The expected shortfall reported in the last column of Table 4 attempts to incorporate this information and measures the expected value of the worst losses. To ensure that we have a reasonable number of observations in the left tail we report the expected shortfall for the 5% quantile only. In practice, the expected shortfall has become a widespread risk management tool. AGARWAL/ NAIK (2004) discuss the benefits of this measure in detail.[16] It is apparent that due to outliers the expected shortfall is, at times, much closer to the VaR(99%) than VaR(95%); the funds in the style category Macro are an example.

| Investment Style | VaR(95%) | VaR(99%) | Expected Shortfall |
|---|---|---|---|
| **Arbitrage** | -1.41 | -3.19 | -2.61 |
| **CTA/Managed Futures** | -6.21 | -10.44 | -8.75 |
| **Distressed Debt** | -4.64 | -16.34 | -10.69 |
| **Event Driven** | -1.40 | -3.19 | -2.52 |
| **Fixed Income** | -3.51 | -12.11 | -7.94 |
| **Long/Short Equities** | -5.68 | -11.24 | -9.13 |
| **Macro** | -5.54 | -9.40 | -9.04 |
| **Multi-Strategy** | -4.66 | -9.35 | -7.29 |
| **Relative Value** | -5.49 | -13.65 | -10.40 |
| **Others** | -8.24 | -15.80 | -11.92 |
| **MSCI Europe (Euro)** | -8.62 | -13.27 | -10.87 |
| **MSCI World (Euro)** | -8.29 | -11.66 | -10.69 |
| **S&P 500** | -7.12 | -10.87 | -9.70 |

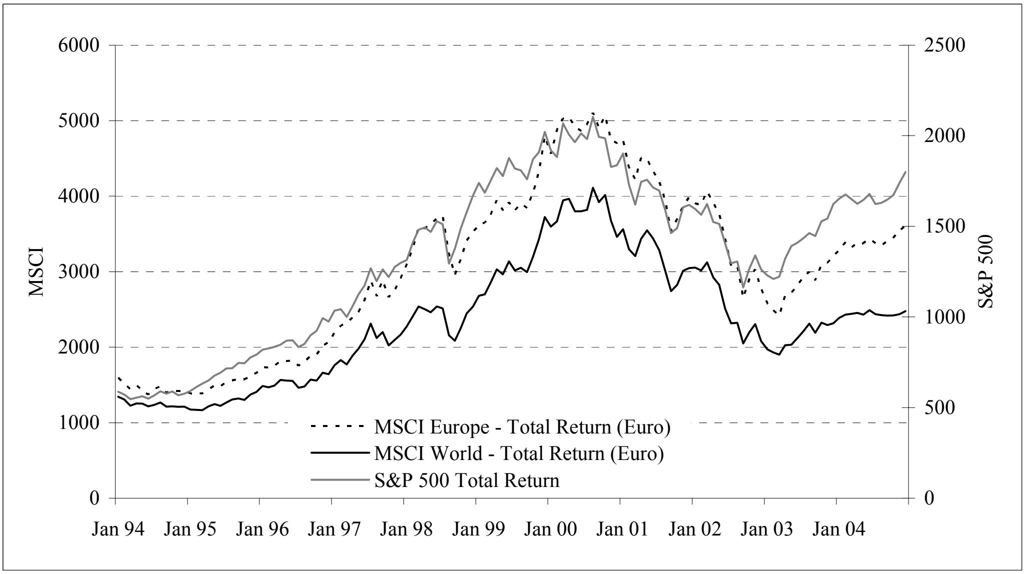
For each of the 173 funds with at least five years of data Value-at-Risk (VaR) is computed from the historical distribution of monthly returns. The table shows the average VaR with a 95% and 99% confidence interval by investment style. The expected shortfall measures the expected value of the losses in the 5% quantile. All numbers are expressed as percentages per month.

**Table 4: Value-at-Risk and Expected Shortfall**

16 Other names for this measure are tail conditional expectation, conditional loss, or tail loss.

## 3. Performance Persistence

In this section we study the performance pattern for the overall hedge fund industry and, at the fund level, whether past winners continue to outperform their peers. At first, we analyze the changes in volatility and correlation with the market index. The results provide insights on how major events interact with hedge fund performance. A further complication are the discrepancies that result from calculating these measures based on monthly or quarterly data.




The graph plots three major indices over the time period January 1994 to August 2004: the MSCI Europe, MSCI World, and S&P 500. The scale on the left applies to the two MSCI indices whereas the right scale shows the index value for the S&P 500. All indices are adjusted for dividends and splits.

**Figure 3: Evolution of Stock Market Indices**

Before inspecting the robustness of basic measures, it is worthwhile to review the recent history of international stock markets. Figure 3 displays three major indices during our sample period from January 1994 to August 2004. This time period is marked by a number of major events: The Mexican Peso crisis (December 1994 – March 1995), the Asian financial crisis (May – December 1997) that culminated in the devaluation of the Thai baht in July 1997, the Russian crisis and the subsequent collapse of the Long Term Capital Management (LTCM) group (May – November 1998), the Brazil crisis (January – March 1999), and the downturn of the stock market in 2000. The demise of LTCM may have been even the first time that hedge funds hit the headlines worldwide. The turmoil began when the Russian government announced the devaluation of the rouble, suspended the trading of short-term Treasury bills, and imposed a 90-day moratorium on international debt repayments. In the aftermath of the announcement a crisis unsettled international financial markets.[17]

### Risk and Return over Time

Table 5 reports each year the mean and standard deviation for the two largest investment categories, Long/Short Equities and CTA/Managed Futures, and all funds together, using discrete, monthly net-of-fee returns. The results are compared with annual returns and standard deviations for the two benchmark indices MSCI Europe and MSCI World. A number of patterns stand out for Long/Short Equities: First, it is evident that the LTCM debacle during the fall of 1998 affected hedge fund returns much more than the MSCI Europe or MSCI World index. Second, to some degree hedge funds offer indeed an insurance against declining stock market prices and, on aggregate, the funds in our sample delivered positive returns after 2000. Finally, it is important to note that the standard deviation of all funds pooled together, and the Long/Short Equities in particular, is much lower after 2000. CTA/Managed Futures fared well in 1998 and 2000. FUNG/ HSIEH (2001) describe the risk-return pattern of CTAs as a long volatility position. The beta of CTAs is high in up markets and low in down markets. However, we do not see the big gains in up markets in our sample. In general, we observe considerable variation over time and, thus, any measure that compares past return and risk will crucially depend on the chosen time window.

[17] Fung/ Hsieh (2000a) study the role of hedge funds in major financial crises. Brown/ Goetzmann/ Park (2000) discuss specifically the Asian currency crisis.

| Year | Long/Short Equities | | CTA/Managed Futures | | All Funds | | MSCI Europe (Euro) | | MSCI World (Euro) | |
|---|---|---|---|---|---|---|---|---|---|---|
| | Return | STD | Return | STD | Return | STD | Return | STD | Return | STD |
| **1994** | -0.01 | 3.31 | -0.07 | 4.03 | 0.34 | 3.83 | -0.50 | 4.10 | -0.29 | 3.45 |
| **1995** | 1.92 | 3.25 | 1.92 | 5.60 | 1.73 | 4.12 | 1.33 | 2.07 | 1.29 | 2.67 |
| **1996** | 2.89 | 4.45 | 1.91 | 4.95 | 2.36 | 3.59 | 1.87 | 2.62 | 1.36 | 3.80 |
| **1997** | 3.23 | 5.80 | 1.64 | 4.36 | 1.86 | 4.65 | 3.05 | 5.45 | 2.51 | 5.89 |
| **1998** | -0.09 | 6.49 | 2.42 | 4.68 | 0.41 | 6.10 | 1.81 | 6.76 | 1.50 | 6.29 |
| **1999** | 4.23 | 6.25 | 0.96 | 3.86 | 2.79 | 5.27 | 2.68 | 4.11 | 3.34 | 4.29 |
| **2000** | 1.13 | 5.03 | 1.78 | 4.47 | 1.27 | 4.61 | -0.09 | 3.92 | -0.49 | 5.04 |
| **2001** | 0.78 | 2.72 | 1.17 | 4.93 | 0.84 | 3.25 | -1.24 | 5.38 | -0.91 | 5.69 |
| **2002** | 0.29 | 2.70 | 1.38 | 5.16 | 0.57 | 3.08 | -2.76 | 6.88 | -2.94 | 6.43 |
| **2003** | 1.25 | 2.49 | 0.88 | 4.87 | 1.23 | 2.71 | 1.34 | 5.01 | 0.97 | 4.15 |
| **2004** | 0.26 | | -0.59 | | 0.11 | | 0.56 | | 0.59 | |

The table reports the average monthly net-of-fee return and standard deviation (STD) for each year from 1994 to 2004. The two investment strategies with the largest number of funds, Long/Short Equities and CTA/Managed Futures, are shown separately. Standard deviations are calculated based on funds that are observed over the full year; hence, no standard deviation is reported for 2004 as the sample ends in August. All numbers are in percentage per month.

**Table 5: Monthly Hedge Fund Returns and Volatilities Over Time**

### Monthly vs. Quarterly Returns

ASNESS/ KRAIL/ LIEW (2001) argue that for illiquid, exchange-traded securities the last observed price does often not reflect current market conditions; known in the literature as stale prices. Moreover, many hedge funds hold sophisticated and exotic over-the-country (OTC) products that are difficult to price. Most importantly, the authors point out that a hedge fund manager has an incentive to deliver a low volatility and correlation with the market and may therefore be tempted to smooth out reported monthly returns. For these reasons we are likely to be confronted with non-synchronous observations when comparing hedge fund returns with a benchmark index.

Table 6 shows means and standard deviations using monthly and quarterly data, as well as the average correlation of the Long/Short Equities investment style with the MSCI Europe index. The previous table demonstrates that this hedge fund strategy behaves differently in up- and down-markets. Therefore, besides reporting the statistics for the full sample we split the dataset into two subperiods; prior to 2000 and after. As we need long enough data periods to calculate correlations, we focus on the largest investment category only and exclude funds with less than two years of data over the corresponding subperiod. The comparison of the annualized monthly and quarterly standard deviations indicates that monthly returns may indeed suffer from the impact of non-synchronous data.[18] As in ASNESS/ KRAIL/ LIEW (2001) we find that quarterly standard deviations and correlation coefficients with the market are higher, independent of the subperiod. The results also illustrate the decline of the correlation coefficient after the year 2000. The lesson to learn from this is that not only the time window but also the frequency matters when assessing the risk-return tradeoff and correlation properties of hedge funds.

| Time Period | Monthly Annualized Returns | Monthly Annualized STD | Quarterly Annualized STD | Monthly Correlation with MSCI Europe (Euro) | Quarterly Correlation with MSCI Europe (Euro) |
|---|---|---|---|---|---|
| **01/1994 – 09/2000** | 26.5 | 21.8 | 26.1 | 0.40 | 0.49 |
| **10/2000 – 08/2004** | 7.7 | 9.7 | 11.6 | 0.21 | 0.24 |
| **01/1994 – 08/2004** | 11.2 | 13.0 | 15.7 | 0.27 | 0.32 |

The table reports mean, standard deviation (STD), and correlation with the market, measured by the MSCI Europe, using monthly and non-overlapping quarterly data. The full time period from January 1994 to August 2004 covers 163 Long/Short Equities hedge funds with at least three years of data. For the two subperiods January 1994 to September 2000 and October 2000 to August 2004, we exclude funds with less than two years of data over the respective time period. Mean and standard deviation are expressed in percentages and annualized.

**Table 6: Monthly vs. Quarterly Returns for Category Long/Short Equities**

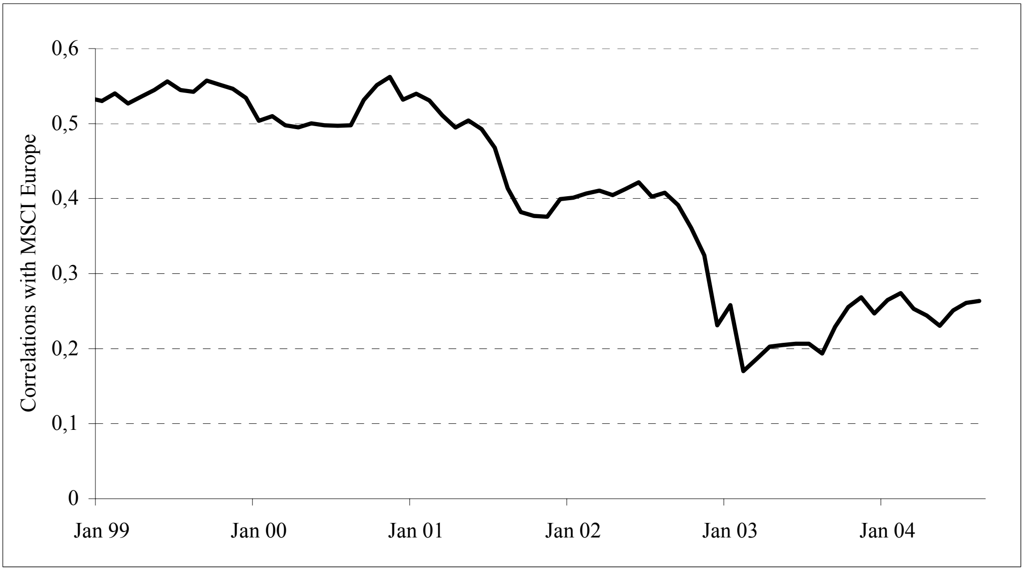
### Correlations

The finding that correlations differ substantially across subsamples deserves closer attention. We apply a 36-months rolling window to calculate the change of the correlation coefficient over time. Thus, the correlation coefficient reported on January 1999 is calculated using the past 36 monthly returns from February 1996 to January 1999. Next, the observation window is rolled forward by one month and, consequently, the February 1999 value is based on the period from March 1996 to February 1999. Due to the few available observations prior to 1996 we begin this analysis in 1999.

Figure 4 shows the apparent drop in the correlation between the Long/Short Equities hedge funds and the MSCI Europe. A comparison with the overall market movements that are plotted in Figure 3 is illuminating. In August 1998, the Russian crisis coupled with the near bankruptcy of LTCM, made stock markets crash. As we have seen in Table 5, monthly returns of Long/Short Equities were heavily affected by this market event. These large parallel down movements of the market and the hedge fund strategy contribute positively to the correlation coefficient. In August 2001, these observations drop out of the three-year rolling window, which explains the sharp drop in the correlation coefficient from 0.5 to a value below 0.4. The second major decrease may be

[18] We drop the months July and August 2004 when calculating the statistics for quarterly data.

explained by the last bull market months of 1999 (with relatively high correlations) being replaced by the first months of the recovery of stock markets in 2003. After a stretch of two years with crumbling stock market prices, Long/Short Equities funds may have been still heavily invested in short positions at the end of 2002 and, on average, adapted to the resurging markets with a delay. Thus, their portfolio values would exhibit low correlation with the market during these months. These findings underscore how sensitive historic correlation coefficients may be for some hedge fund strategies.




The graph plots the change in correlation of the strategy Long/Short Equities with the MSCI Europe from January 1999 to August 2004. Each month, the correlation coefficients for the individual funds are calculated based on the preceding 36 monthly returns. The graph shows the evolution of the equally-weighted average correlation coefficient.

**Figure 4: Change in Correlation Using 36-Months Rolling Window**

## Do Winners and Losers Repeat?

We conclude this section with an in depth analysis of performance persistence among European hedge funds. In particular, we investigate whether past winners consistently outperform and/or losers underperform their peers within the Long/Short Equities investment style. Following BROWN/ GOETZMANN/ IBBOTSON (1999), we rely on two-way winner-loser contingency tables and examine whether winners (losers) tend to be winners (losers) in two consecutive periods using months, quarters, or years between 1998 and 2004. We apply a non-parametric test to distinguish whether, on average, superior fund performance is due to luck or manager ability.

**Panel A: Monthly Data**

| Holding Periods | WW | WL | LW | LL | CPR | Z-statistic |
|---|---|---|---|---|---|---|
| **09/1998-08/1999** | 178 | 142 | 141 | 178 | 1.58*** | 2.88 |
| **09/1999-08/2000** | 301 | 212 | 216 | 294 | 1.93*** | 5.19 |
| **09/2000-08/2001** | 386 | 364 | 358 | 394 | 1.17 | 1.50 |
| **09/2001-08/2002** | 564 | 404 | 401 | 561 | 1.95*** | 7.25 |
| **09/2002-08/2003** | 553 | 411 | 409 | 552 | 1.82*** | 6.47 |
| **09/2003-08/2004** | 488 | 449 | 451 | 487 | 1.17** | 1.73 |
| **09/1998-08/2004** | 2470 | 1982 | 1976 | 2466 | 1.56*** | 10.34 |

**Panel B: Quarterly Data**

| Holding Periods | WW | WL | LW | LL | CPR | Z-statistic |
|---|---|---|---|---|---|---|
| **09/1998-08/1999** | 55 | 37 | 34 | 58 | 2.54*** | 3.07 |
| **09/1999-08/2000** | 81 | 71 | 73 | 82 | 1.28 | 1.08 |
| **09/2000-08/2001** | 121 | 99 | 97 | 122 | 1.54** | 2.24 |
| **09/2001-08/2002** | 175 | 140 | 141 | 174 | 1.54*** | 2.70 |
| **09/2002-08/2003** | 171 | 147 | 150 | 172 | 1.33* | 1.82 |
| **09/2003-08/2004** | 184 | 128 | 128 | 184 | 2.07*** | 4.46 |
| **Fourth Quarter 2000** | 22 | 28 | 23 | 26 | 0.89 | -0.29 |
| **09/1998-08/2004** | 828 | 708 | 691 | 840 | 1.42*** | 4.85 |

**Panel C: Annual Data**

| Holding Period | WW | WL | LW | LL | CPR | Z-statistic |
|---|---|---|---|---|---|---|
| **09/1998-08/1999** | 7 | 7 | 7 | 7 | 1.00 | 0.00 |
| **09/1999-08/2000** | 11 | 11 | 8 | 14 | 1.75 | 0.91 |
| **09/2000-08/2001** | 10 | 25 | 20 | 16 | 0.32** | -2.27 |
| **09/2001-08/2002** | 29 | 21 | 22 | 27 | 1.69 | 1.30 |
| **09/2002-08/2003** | 46 | 34 | 33 | 46 | 1.89** | 1.97 |
| **09/2003-08/2004** | 49 | 30 | 27 | 47 | 2.84*** | 3.12 |
| **09/1998-08/2004** | 152 | 128 | 117 | 157 | 1.59*** | 2.71 |

A winner (loser) is defined as a fund with a higher (lower) than median return. WW (LL) denotes winners (losers) in two consecutive periods, WL (LW) denotes winners (losers) in the first period and losers (winners) in the second period. The cross product ratio (CPR) is defined as (WW × LL) / (WL × LW). The Z-statistic tests whether the CPR is statistically different from one. ***/**/* denotes significance at the 1% / 5% / 10% level. The results for monthly and quarterly data are aggregated over annual time periods. The first period 09/1998-08/1999 in Panel A, e.g., counts a total of 178 repeated winners from one month to the next (column WW) for the twelve monthly holding periods over this time period.

**Table 7: Winner-Loser Contingency Tables for Strategy Long/Short Equities**

Table 7, Panel A, shows the contingency table for the persistence from one month to the next. The contingency tables are constructed as follows: Over the formation period funds are classified as winners (losers) if their return is above (below) the median return. Then, over the subsequent holding period we count the number of winners (losers) that remain among the top (bottom) 50% performers or switch to losers (winners). Thus, for monthly data the result for the first holding period, September 1998, is based on the rankings over the previous month, August 1998 (the formation period). To reduce the size of the table, Panel A aggregates the results for one month formation and holding periods over annual intervals. WW (LL) denotes winners (losers) in two successive periods, WL (LW) denotes winners (losers) in the first period and losers (winners) in the second period. The cross product ratio (CPR), defined as (WW × LL) / (WL × LW) is used to test for performance persistence. The test is based on the null hypothesis that the performance in the two periods is unrelated. In other words, the probability of a repeated winner (WW) has equal probability compared to a winner switching to a loser (WL); and similarly for a loser. Therefore, under the null hypothesis the numerator (WW × LL) and denominator (WL × LW) are equal and the CPR becomes one.[19]

For the full data period from September 1998 to August 2004, the null hypothesis of no persistence can be rejected at the 1% level. Given our earlier results that monthly returns are likely smoothed out, either due to holding illiquid securities or "managed returns", the persistence in monthly returns is no surprise.[20] One important finding emerges when the test statistics are evaluated for each year separately. In 2000, when stock markets start plummeting, the persistence for Long/Short Equities fades away. The turnaround of the stock market was bad news for hedge funds with a levered, long position and these may have been exactly the funds that fared well in the previous up months and, hence, ranked above the median. BROWN/ GOETZMANN/ IBBOTSON (1999) find that over their sample period from 1989 to 1995, a period of a strong bull market, dedicated short sellers did poorly, and sector funds performed relatively well.

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[19] To test for statistical significance we use the Z-statistic which is defined as the logarithm of the CPR divided by its standard error. In large samples the standard error of the natural logarithm of the CPR is given by $(1/WW + 1/WL + 1/LW + 1/LL)^{0.5}$. The Z-statistic is asymptotically, normally distributed $N(0,1)$.

[20] Agarwal/ Naik (2000b) point out that monthly returns may produce spurious results due to their high volatility.

| Author | Database | Methodology | Time | Time Horizon | Result |
|---|---|---|---|---|---|
| **Agarwal/ Naik (2000a)** | HFR | Multi-period framework. Parametric (regression) and non-parametric (contingency table) methods. Test by individual HF strategy using alpha and appraisal ratio. | 1982-1998 | Quarterly/ semi-annual/ annual | Maximum persistence for quarterly returns. Multi-period persistence lower than for only 2 periods. Nearly no persistence for yearly returns in multi-period analysis. |
| **Agarwal/ Naik (2000b)** | HFR | Analysis within individual hedge fund strategies. Use alpha and appraisal ratio for parametric (regression) and non-parametric (contingency table) methods.[21] | 1995-1998 | Quarterly | Depending on the method they find persistence in 6 to 8 out of 13 performance periods. Losers seem to be more persistent than winners. |
| **Bares/ Gibson/ Gyger (2003)** | FRM | 1. Non-parametric test: Look at performance (winners and losers) for different periods and HF strategies.<br>2. Consider top and bottom ranked funds separately. Analyze momentum/reversal pattern.<br>3. Use Arbitrage Pricing Theory (APT) to test long-term, risk-adjusted performance persistence. | 1992-2000 | 4 time horizons | 1. The strategies Specialist Credit and Relative Value are the "most persistent"; no higher risk for managers that perform above the median.<br>2. Document short-term, but no long-term persistence.<br>3. Directional strategies tend to overreact. Alphas of HF portfolios unstable over time. |
| **Brown/ Goetzmann/ Ibbotson (1999)** | U.S. Off-shore Funds Directory | Use contingency table to test persistence in raw and style-adjusted returns. | 1989-1995 | Annual | No evidence of performance persistence. Size is unrelated to superior relative performance. |
| **Capocci/ Hübner (2004)** | HFR, MAR | Ten-factor composite performance model. Build 10 equally-weighted portfolios based on the ranking of the HFs returns over the previous year. | 1994-2000 | | No persistence for best and worst performing funds, but limited evidence for persistence among middle decile funds; negative persistence among past losers. |
| **Edwards/ Caglayan (2001)** | MAR | Contingency table and regression analysis. | 1990-1998 | 1- and 2-year horizon | Find persistence for winners and losers, especially top and worst performers. Higher incentive fees lead to higher excess returns. |
| **Kosowski/ Naik/ Teo (2004)** | CISDM, HFR, MSCI, TASS | Bootstrap and Bayesian techniques. | 1991-2002 | | HF alphas persist. However, top HFs often small and closed. |
| **Malkiel/ Saha (2004)** | TASS | Contingency table. | 1996-2003 | Annual | Probability of repeated winners is 50%. |

**Table 8: Literature Overview on Performance Persistence**

[21] Alpha is defined as the difference of the return of a fund manager and the average return for all fund managers following the same strategy.

Next, we consider the results for quarterly (Table 7, Panel B) and annual data (Panel C). Looking at the figures for quarterly returns, we find some evidence for persistence at the 1% significance level. However, as the fourth quarter of 2000 shows, persistence vanishes quickly when stock markets crash. Similar to BARES/ GIBSON/ GYGER (2003) the significance tends to decrease with longer time horizons. In contrast to AGARWAL/ NAIK (2000b), who analyze quarterly returns from April 1995 to September 1998, we do not find that losers are more persistent than winners for our particular hedge fund style. Overall, it appears that the ranking of Long/Short Equities funds is perturbed when stock markets change direction.

Table 8 provides a summary of the major contributions to the literature on performance persistence of hedge funds. In addition to the results already mentioned above, EDWARDS/ CAGLAYAN (2001) find supporting evidence for persistence during the period 1990-1998. CAPOCCI/ HÜBNER (2004) use deciles instead of just two broad categories, above and below median. They document limited evidence of persistence for middle decile funds in their large sample of 2,894 funds from 1994-2002, but attribute the realized returns of the best and worst performing funds mostly to luck. Typically, the top and bottom performers exhibit high volatility and, hence, are more likely to show up in the top or bottom decile purely due to luck – or bad luck. MALKIEL/ SAHA (2004) observe that the frequency for repeat winners and winners switching to losers is basically the same over the period from 1996 to 2003 and argue that previous evidence in support of persistence may be driven by data biases. This is consistent with the earlier results of BROWN/ GOETZMANN/ IBBOTSON (1999) for offshore hedge funds. Recapitulating, the empirical evidence on performance persistence is mixed and subject to future research. Our results suggest that significant changes in stock markets have a major impact on the persistence of directional strategies.

## 4. Risk-Adjusted Performance Measures

One way to evaluate hedge fund returns is peer-group comparison. However, comparing the returns of hedge funds within the same investment style crucially depends on the classification system. It turns out that even for mutual funds it is difficult to group funds into coherent style categories and for hedge funds this task is far more complex. Take as an example a manager in the category Long/Short Equities. Even if the manager would only be allowed to take long positions we need to differentiate between the type of stocks the manager invests in. Morningstar, a major provider of mutual fund data in the U.S., breaks down mutual funds into nine style categories along the dimensions large/small and value/growth stocks. Given that hedge funds are allowed to take short positions with all levels of leverage introduces another dimension and renders peer group comparisons even more difficult. Once we take into consideration the possibility to invest in derivatives, the soaring number of exchange-traded structured products, or sophisticated, tailored over-the-counter contracts, the number of possible investment styles becomes unmanageable. Moreover, the investor would like to compare funds that operate in different style categories.

For these reasons, investors often turn to risk-adjusted performance measures. As the hedge fund industry is to a large extent very young, it is common practice to adopt performance measures that have been proven successful in the case of mutual funds. We devote the rest of the chapter to a critical analysis of these measures and their application to hedge funds.[22]

## Sharpe Ratio

The Sharpe ratio, introduced by SHARPE (1966), was originally designed to evaluate mutual fund managers.[23] Since then, it has also become the most widespread measure in the hedge fund industry. It is defined as the quotient of the average excess returns over the risk-free rate, $(\overline{r}_P - \overline{r}_f)$, divided by the standard deviation of the fund returns, $\sigma_P$.

$$\text{(1)} \qquad \text{Sharpe Ratio} = (\overline{r}_P - \overline{r}_f) / \sigma_P$$

The higher the ratio, the more desirable are the returns relative to the risk of the investment. The popularity of the Sharpe measure can be explained to some extent by the fact that risk is measured by standard deviation. Thus, there is no need to decide on an appropriate benchmark and the difficulties associated with estimating the sensitivity of the fund returns relative to this benchmark can be avoided. In addition, this facilitates comparisons across different strategies.

There are at least three caveats to keep in mind when using the Sharpe ratio. (i) It is common practice to infer the Sharpe ratio from past monthly returns. In this sense, it is backward-looking and can be deceptive for investments in assets that rely on markets with changing volatility. As the analysis in the previous sections has shown, the main ingredients for the measure change over time and the estimation of the standard deviation critically depends on the choice of the past time horizon and the frequency at which returns are observed. (ii) The main purpose of the ratio is to rank portfolios and there is no straightforward interpretation of the number. GRAHAM/ HARVEY (1997) suggest a variant of the Sharpe ratio that has an easy interpretation. Due to the article

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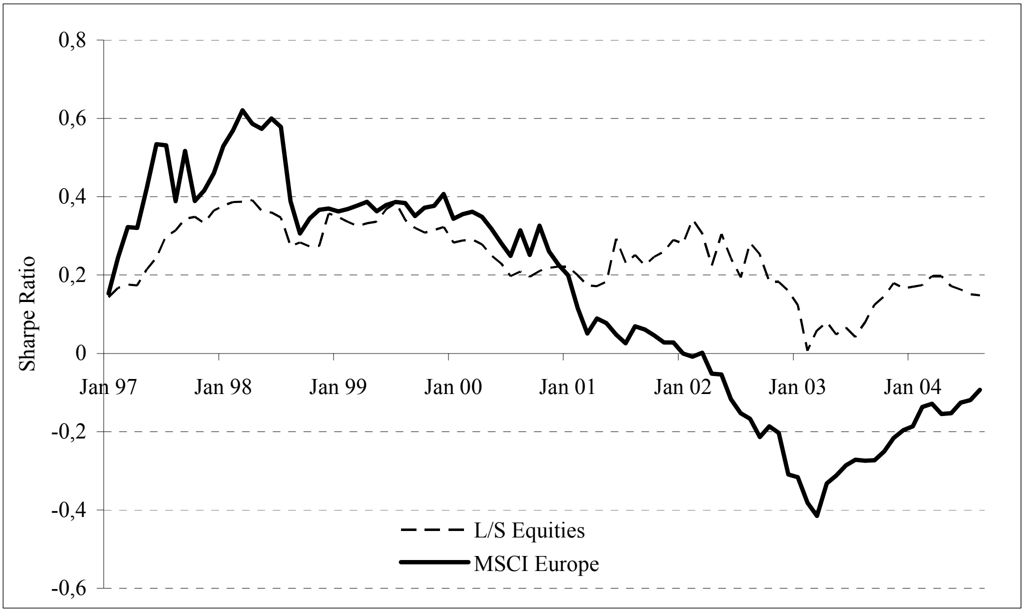
[22] An alternative route is to apply return-based style analysis introduced by Sharpe (1992). This method attempts to identify the major exposures of a given strategy to a set of benchmarks and no longer relies on the self-declared investment style of a hedge fund. Among others, Fung/ Hsieh (1997a), Agarwal/ Naik (2000a), and Ben Dor/ Jagannathan/ Meier (2003) implement this methodology for hedge funds.

[23] As Sharpe (1994) points out, he initially suggested the term risk-to-reward ratio. The term Sharpe ratio was coined later.

published by MODIGLIANI/ MODIGLIANI (1997), this measure became generally known as the $M^2$ measure (for Modigliani square). To compute the $M^2$ measure a portfolio consisting of a levered position in the fund and an investment at the risk-free rate is constructed such that its standard deviation equals the standard deviation of the benchmark. (iii) The denominator is defined as the standard deviation of the fund returns. This is a measure of total risk and we discuss this point in further detail later in the text.




Each month, the Sharpe ratio is calculated for all individual funds in the category Long/Short Equities using monthly observations over the previous 36-months period. The graph plots the average Sharpe ratio for this investment style and the MSCI Europe index over time during the period from January 1997 to August 2004.

**Figure 5: Sharpe Ratio for Long/Short Equities, 36-Months Rolling Window**

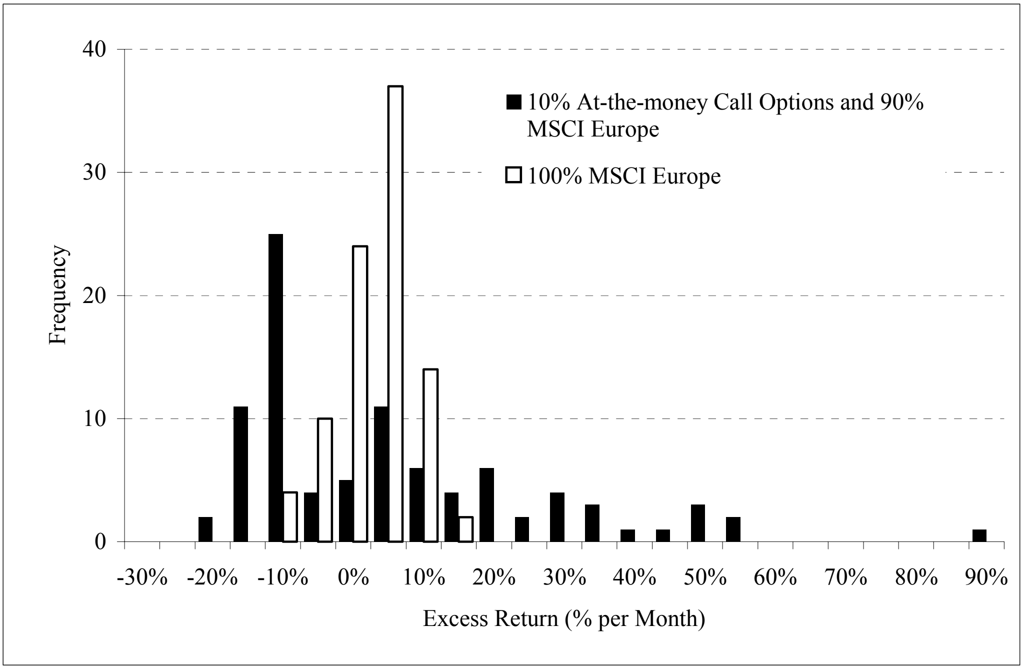
Figure 5 illustrates the time dependency of the Sharpe ratio. Each month, we take the average of the individual Sharpe ratios of all funds in the investment style Long/Short Equities. To account for the period before and after the launch of the Economic and Monetary Union (EMU) in 1999, when the Euro was established as the official currency, we take the London middle rate for Ecu 3-months deposits as the risk-free rate. The Sharpe measure is calculated using a 36-months window and funds with fewer than twelve months are excluded from the calculations for any given month. We contrast this average Sharpe ratio with the ratio for the MSCI Europe index. The graph confirms an earlier finding: The strategy Long/Short Equities provides, to some degree, a hedge against the market. During the slump 2000-2002, when the measure declines for the MSCI Europe, the Long/Short Equities funds on average deliver positive values. Overall, the Sharpe measure is subject to large fluctuations and the length of the chosen time window has a major impact on the exact number.

The third caveat we listed above is the use of total risk. Many institutional investors target to increase their share in alternative vehicles primarily for their low correlations with bond and stock markets and the corresponding diversification effects these investments promise. What matters, once we consider adding a hedge fund to an existing portfolio, is the contribution to the systematic risk (see e.g. BODIE/ KANE/ MARCUS, 2004). This is the motivation for the Treynor measure (TREYNOR (1966)) that divides the fund's excess returns by systematic risk instead of total risk. Unfortunately, the Treynor measure is not well suited for hedge funds. Consider a market neutral strategy that, by definition, aims at providing zero correlation with the market. Hence, systematic risk in the denominator of the Treynor measure will be close to zero and the measure itself goes to infinity. Moreover, using the beta coefficient requires a properly defined benchmark and a reliable beta estimate. While these obstacles may not be unsurmountable for most traditional mutual funds they may explain its rare use in the hedge fund industry.

However, the conceptual problems when applying the Sharpe ratio to hedge fund data are more fundamental. The first problem is related to the common practice of using monthly data and then annualizing the Sharpe ratio by multiplying with $\sqrt{12}$. LO (2002) demonstrates that when monthly returns are positively, serially correlated, and this is likely true for many hedge funds as we have seen in the previous section, the annualized figures can massively overstate the true values. He provides an example of a mortgage-backed securities fund for which the annualized Sharpe ratio overstates the true value by 65%.

Furthermore, the Sharpe ratio emanates from a mean-variance framework and if higher moments matter the rankings may become questionable. FUNG/ HSIEH (1997a) and MITCHELL/ PULVINO (2001) empirically demonstrate the option-like return patterns generated by trend followers and merger arbitrage, two common hedge fund strategies. We illustrate this point by considering the following two managers who have no skill and blindly pursue predetermined strategies. Manager A holds 10% of his portfolio in at-the-money call options on the MSCI Europe index and the other 90% in the index. He rebalances his portfolio at the beginning of each month when he buys new call contracts with one month time-to-maturity. We assume that fairly priced Black-Scholes option prices are available and that the volatility of the underlying index can be accurately inferred using the past three years of data. Manager B invests 100% in the index. If one compares the Sharpe ratio for these two managers from January 1997 to August 2004, manager A (Sharpe ratio of 0.562) clearly outperforms manager B (0.206) even though both managers stick to a predetermined strategy that requires no skill.[24]

The histograms in Figure 6 help to understand the reasons for these differences in the Sharpe ratio. Whereas the 100% index portfolio has a more or less symmetric distribution the portfolio mixed with call options generates an asymmetric, heavily right-skewed distribution. What drives our example are the few observations in the far right tail that increase the mean excess return by so much that even the increased standard deviation cannot equilibrate the mean-variance ratio. In our example, manager B would need to outperform the index each month by 0.56% in order to achieve the same Sharpe ratio as manager A. This corresponds to 6.70% p.a. and would truly reflect superior management talent.




The graph shows the combined histogram of monthly returns for the two strategies 10% at-the-money call options on the MSCI Europe index and 90% in the index itself, and 100% in the MSCI Europe index. The horizontal axis measures the excess return over 3-months Ecu deposits; for example, 90% labels the bin containing all observations with an excess return between 85 and 90%. The observation period is from January 1997 to August 2004.

**Figure 6: Histogram for Index and Index Plus Call Portfolios**

24 At most, one could argue that manager A made a successful bet on sharp up-moves of the market.

GOETZMANN/ INGERSOLL/ SPIEGEL/ WELCH (2002) demonstrate that managers can manipulate the Sharpe ratio, at least in expected terms, by employing strategies with non-normal distributions. The authors provide a closed-form solution as to how select skewness and kurtosis in order to maximize the Sharpe ratio. Their results show that strategies with a negative skewness and a truncated right tail perform best. This payoff pattern can be achieved by investing long in the market and selling short an out-of-the-money call option, which is actually the opposite position of what works for the specific time period we consider in the above example.

MADHAVI (2004) proposes an adjusted Sharpe ratio to account for the distortions caused by non-normal distributions. His method transforms the original distribution of the hedge fund returns in question such that it looks alike the benchmark. The disadvantage of all such modifications is the loss of the main appeal of the original Sharpe ratio; its simplicity and ease to communicate to investors.

### Sortino Ratio

The Sortino ratio (SORTINO/ PRICE (1994)) has been advocated to better account for the asymmetry of hedge fund return distributions. It is similar to the Sharpe ratio, replacing the standard deviation with the downside deviation. The downside deviation in turn differs from the standard deviation by considering only those returns that fall below a minimum acceptable return (MAR).[25]

(2) $$\text{Downside Deviation} = \sqrt{\frac{1}{n} \sum_{r_P < MAR} \left(r_P - MAR\right)^2} \, .$$

MAR is often defined as a long-term Treasury bond, short-term Treasury bill, or zero, but can in principle be set to any desired target level.

Table 9 compares standard deviation and downside deviation for the ten hedge fund styles in our database. The next two columns contain the associated Sharpe and Sortino ratios. The numbers in the table are based on a Sortino ratio that takes the 3-month risk-free rate as the MAR. A comparison with the average skewness of each strategy (these numbers can be found in Table 2) sheds some light on the source of the differences in the rankings that result when using either of the two measures. With the exception of Distressed Debt – this strategy excels all others with its return of 20.6% p.a. – and Event Driven, investment styles that exhibit a large negative skewness move down in the ranking when the Sortino ratio is considered, and the ones with large positive skewness move up. To further quantify the change in the rankings of the 352 indi-

[25] Note that the sum of squared deviations is divided by the number of observations (and not by $n$ - 1) since we do not need to estimate the mean from past returns as is the case for the standard deviation.

vidual funds we calculate the Spearman rank order correlation.[26] The rank order correlation is very high at 0.965, which means that most of the times the order does not change much.

| Investment Style | Standard Deviation | Downside Deviation | Sharpe Ratio | Rank (Sharpe) | Sortino Ratio | Rank (Sortino) | No. of Funds |
|---|---|---|---|---|---|---|---|
| **Arbitrage** | 1.21 | 1.06 | 0.24 | 3 | 0.32 | 6 | 18 |
| **CTA/Managed Fut.** | 4.87 | 4.28 | 0.18 | 7 | 0.25 | 8 | 57 |
| **Distressed Debt** | 4.41 | 4.89 | 0.39 | 1 | 0.55 | 1 | 10 |
| **Event Driven** | 1.78 | 1.45 | 0.24 | 3 | 0.45 | 3 | 10 |
| **Fixed Income** | 2.58 | 2.66 | 0.34 | 2 | 0.35 | 5 | 21 |
| **Long/ Short Equities** | 3.75 | 3.10 | 0.17 | 8 | 0.29 | 7 | 163 |
| **Macro** | 3.49 | 3.45 | 0.15 | 9 | 0.17 | 9 | 24 |
| **Multi-Strategy** | 3.51 | 2.96 | 0.21 | 6 | 0.37 | 4 | 20 |
| **Relative Value** | 3.85 | 3.27 | 0.23 | 5 | 0.50 | 2 | 11 |
| **Others** | 4.14 | 3.85 | 0.13 | 10 | 0.16 | 10 | 18 |
| **All Funds** | 3.69 | 3.22 | 0.20 | | 0.30 | | 352 |

The downside deviation is defined in equation (2) in the text. The Sharpe ratio measures the average excess return of the hedge fund over the risk-free rate divided by the standard deviation of the fund returns. The Sortino ratio uses the downside deviation in the denominator with the minimum acceptable rate (MAR) set equal to the risk-free rate, for which we use the rate on 3-months Ecu deposits. The statistics are shown by investment style for all 352 funds with at least 36 observations from January 1994 to August 2004.

**Table 9: Sharpe vs. Sortino Ratio**

## Jensen's Alpha and Appraisal Ratio

Jensen's alpha (JENSEN (1968; 1969)) is a risk-adjusted performance measure that represents the average return on a portfolio over and above that predicted by the Capital Asset Pricing Model (CAPM). In the CAPM only market risk, which is measured by the beta coefficient, is rewarded. Formally, Jensen's alpha is defined as

$$\text{(3)} \qquad \text{Jensen's Alpha} = (r_P - r_f) - \beta_P (r_M - r_f)\,,$$

where $r_P$ is the hedge fund return, $r_M$ the return on the market, and $r_f$ the risk-free rate.

[26] The Spearman rank-order correlation is a non-parametric (distribution-free) rank statistic proposed by Spearman in 1904 as a measure of the strength of the associations between two variables. It is calculated on the ranks instead of the scores and thus more robust to extreme values than the linear correlation coefficient.

In many situations estimating beta coefficients becomes a quite challenging task. Beta is inferred from a regression of the fund's excess returns on the excess returns of the market.[27] Often, the coefficient of determination, $R^2$, that indicates the explanatory power of the regression, is low. In addition, ASNESS/ KRAIL/ LIEW (2001) and MALKIEL/ SAHA (2004) recognize that serially correlated hedge fund returns lead to underestimation of beta coefficients. In the presence of serial correlation SCHOLES/ WILLIAMS (1977) and DIMSON (1979) propose to include lagged benchmark returns in the regression and then using the sum of the coefficients for the contemporaneous and the lagged benchmark returns. Table 10 details the differences between beta estimates using only the contemporaneous excess returns of the benchmark (MSCI Europe) as the explanatory variable, and those when three lagged terms are included. The sum beta for the strategy Long/Short Equities increases by 0.12 relative to the regular beta (from 0.23 to 0.35), an increase by 52%. For all strategies with positive betas the sum betas are considerably larger, and for CTA/Managed Futures the negative sensitivity becomes more pronounced as well. We then calculate Jensen's alpha for both beta estimates. Interestingly, the values for the average Jensen alphas within each investment style are very similar. MALKIEL/ SAHA (2004) find that the average beta across their hedge fund universe is 0.231 and increases to 0.393 when applying sum betas. ASNESS/ KRAIL/ LIEW (2001) conjecture that sum betas are considerably above regular betas in down markets, what they interpret as circumstantial evidence that managers attempt to smooth returns primarily in down markets.

Also the Jensen's alpha is known to suffer form deficiencies. JAGANNATHAN/ KORAJCZYK (1986) show that a manager selling call options on a standard benchmark will appear to be falsely classified as a superior performer. Another critique of Jensen's alpha, which becomes especially acute for many hedge fund strategies, is that the measure does not take into account the scale effect if a fund takes levered positions and, therefore, increases the volatility of returns. The appraisal ratio (or information ratio) attempts to correct for this effect and divides Jensen's alpha by the standard deviation of non-systematic risk, $\sigma(e_P)$. In this sense the appraisal ratio imposes a penalty on those funds that are subject to substantial diversifiable risk. It is apparent from Table 9 that especially the strategy CTA/Managed Futures gets penalized heavily by the appraisal ratio.

[27] Practitioners and most services (e.g. Bloomberg, Value Line) use total returns rather than excess returns.

| Investment Style | Beta | Sum Beta | Jensen's Alpha Using Beta | Jensen's Alpha Using Sum Beta | Appraisal Ratio |
|---|---|---|---|---|---|
| **Arbitrage** | 0.04 | 0.06 | 0.32 | 0.28 | 0.21 |
| **CTA/ Managed Futures** | -0.16 | -0.18 | 0.79 | 0.79 | 0.17 |
| **Distressed Debt** | 0.31 | 0.36 | 1.44 | 1.51 | 0.43 |
| **Event Driven** | 0.08 | 0.15 | 0.61 | 0.65 | 0.28 |
| **Fixed Income** | 0.09 | 0.13 | 0.71 | 0.73 | 0.37 |
| **Long/Short Equities** | 0.23 | 0.35 | 0.70 | 0.72 | 0.20 |
| **Macro** | 0.11 | 0.12 | 0.51 | 0.50 | 0.15 |
| **Multi-Strategy** | 0.15 | 0.21 | 0.72 | 0.73 | 0.23 |
| **Relative Value** | 0.20 | 0.25 | 0.60 | 0.57 | 0.23 |
| **Others** | 0.17 | 0.25 | 0.38 | 0.38 | 0.13 |
| **All Funds** | 0.13 | 0.20 | 0.68 | 0.70 | 0.21 |

Beta is inferred from the regression of individual, monthly excess fund returns on the excess returns of the MSCI Europe index. The sum beta adds the coefficients from a similar regression which uses the contemporaneous excess returns of the MSCI Europe and three lags. Jensen's alpha is defined in equation (3) in the text. The appraisal ratio divides Jensen's alpha by the standard deviation of diversifiable risk (we report the appraisal ratio using Jensen's alpha based on the sum beta). The results are tabulated as averages by investment style for the 352 funds with at least 36 observations from January 1994 to August 2004.

**Table 10: Jensen's Alpha and Appraisal Ratio**

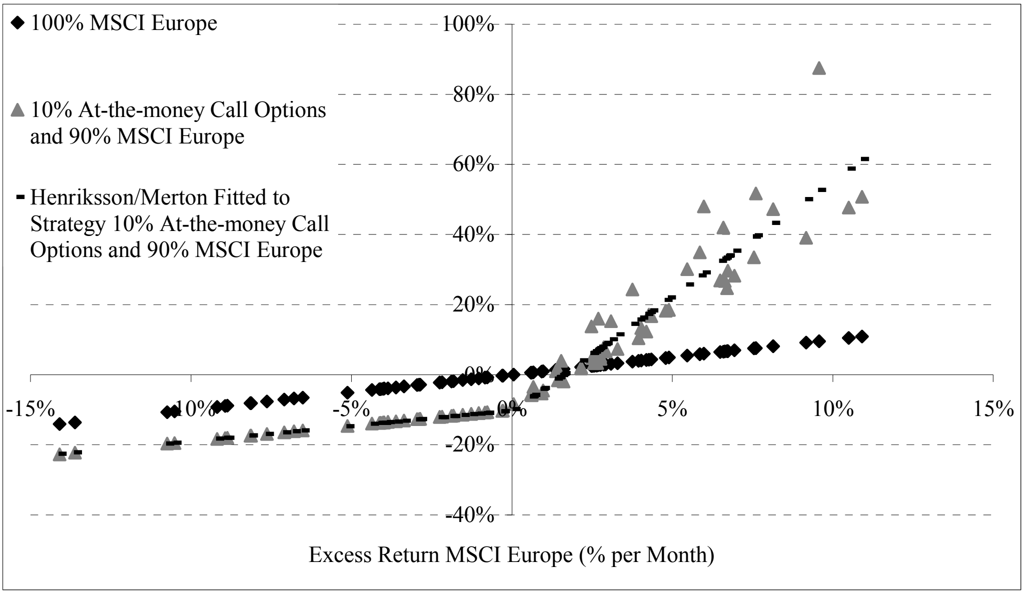
### Measures for Market Timing

While Jensen's alpha captures the selection ability of a manager, HENRIKSSON/ MERTON (1981) propose a model to assess the timing ability. For directional hedge fund strategies the investor expects the manager to successfully predict the future direction of markets and adapt his portfolio correspondingly. The HENRIKSSON/ MERTON model is defined as

$$r_P - r_f = \alpha + \beta_0 (r_M - r_f) + \beta_1 (r_M - r_f) \text{Max}[0, r_M - r_f] + e_P, \quad (4)$$

where $\text{Max}[0, r_M - r_f]$ is the option component and $e_P$ the residual. Whenever the market is above the risk-free rate the second term becomes relevant.[28] If a manager indeed delivers market timing ability the coefficient $\beta_1$ is positive. Similar to Jensen's alpha, the intercept of this regression model can be interpreted as the manager's selection ability.

[28] An alternative model, suggested earlier by Treynor/ Mazuy (1966), fits the fund returns to a quadratic function instead of the kinked line. Here, a positive coefficient for the quadratic term indicates that the relation with the market returns is convex and the manager has market timing ability.
$r_P - r_f = \alpha + \beta_0 (r_M - r_f) + \beta_1 (r_M - r_f)^2 + e_P$




The scatter plot shows the payoffs of the two predetermined strategies from before versus the excess return of the MSCI Europe. Consequently, the monthly excess returns of a 100% MSCI Europe investment form a straight 45 degree line (the line appears flatter due to the larger vertical scale). The gray triangles indicate the observations for the strategy 10% at-the-money options on the MSCI Europe and 90% in the index with monthly rebalancing. The black bars are the fitted values from the HENRIKSSON/ MERTON (1981) regression that is described by equation (4) in the text.

**Figure 7: Fitting the Henriksson/ Merton Model to Option-Like Strategies**

Figure 7 exemplifies the point put forward by JAGANNATHAN/ KORAJCZYK (1986): The predetermined strategy from above, investing at the beginning of each month 10% in at-the-money call options on the MSCI Europe and the remainder in the index itself, generates the typical payoff pattern for a call option. Running the HENRIKSSON/ MERTON regression then results in a negative selection coefficient $\alpha$ but a positive coefficient $\beta_1$ that indicates market timing. Thus, our manager A with no skill gets falsely classified as a superior market timer. In addition, given that hedge funds are allowed to take short positions, we might not only expect a flat payoff structure below an excess return of zero, but rather a V-shaped straddle.[29] This example illustrates that for the case of hedge funds it is extremely difficult to separate selection from timing ability.

[29] Applying multifactor versions of the Treynor/ Mazuy (1966) and Henriksson/ Merton (1981) model to hedge fund data Chen (2004) finds some evidence for selection and timing ability.

## 5. Concluding Remarks

One of Winston Churchill's most famous quotes is "democracy is the worst form of government except for all those others that have been tried". The same applies to the Sharpe ratio that continues to be a standard risk-adjusted performance measure in the hedge fund industry. The goal of any performance measures is to summarize the information contained in realized hedge fund returns in one number to render communication easy and to allow investors to make comparisons across different investment styles. However, this abstraction will inevitably lead to a loss of information and situations where the performance measure fails. The key for the investor is to understand the advantages and potential failures of common performance measures. The goal of this chapter is to alert the reader under which circumstances commonly used risk-adjusted performance measures may become misleading. We show the difficulties the investor may encounter when estimating return, risk, and correlation using historic data. Moreover, we illustrate the potential failures through numerous examples, provide new empirical evidence for the European market, and relate our results to the recent academic literature in the field.

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