HEDGE FUND PERFORMANCE 1990-2000

DO THE 'MONEY MACHINES' REALLY ADD VALUE?

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ABSTRACT

In this paper we investigate the claim that hedge funds offer investors a superior risk-return trade-off. We do so using a continuous time version of Dybvig's (1988a, 1988b) payoff distribution pricing model. The evaluation model, which does not require any assumptions with regard to the return distribution of the funds in question, is applied to the monthly returns of 77 hedge funds and 13 hedge fund indices over the period May 1990 – April 2000. The results show that as a stand-alone investment hedge funds do not offer a superior risk-return profile. We find 12 indices and 72 individual funds to be inefficient, with the average efficiency loss amounting to 2.76% per annum for indices and 6.42% for individual funds. Part of the inefficiency cost of individual funds can be diversified away. Funds of funds, however, are not the preferred vehicle for this as their performance appears to suffer badly from their double fee structure. Looking at hedge funds in a portfolio context results in a marked improvement in the evaluation outcomes. Seven of the 12 hedge fund indices and 58 of the 72 individual funds classified as inefficient on a stand-alone basis are capable of producing an efficient payoff profile when mixed with the S&P 500. The best results are obtained when 10-20% of the portfolio value is invested in hedge funds.

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I. INTRODUCTION

A hedge fund is typically defined as a pooled investment vehicle that is privately organised, administered by professional investment managers, and not widely available to the public[1]. Due to their private nature, hedge funds have less restrictions on the use of leverage, short-selling, and derivatives than more regulated vehicles such as mutual funds. This allows for investment strategies that differ significantly from traditional non-leveraged, long-only strategies.

Hedge funds have been around for over half a century. The first hedge fund is typically attributed to Albert W. Jones, who in 1949 started a fund that simultaneously took long and short positions in equity. Jones' fund did not inspire many imitators until in 1966 an article in *Fortune* described Jones' fund to have returns substantially higher than the best performing mutual funds.[2] This led to increased interest in hedge funds and many were formed in the two years that followed. After rapid expansion in 1967–1968, the hedge fund industry experienced a substantial setback during the bear markets of 1969–1970 and 1973–74, when many funds suffered losses and capital withdrawals. Hedge funds faded back into obscurity until 1986, when an article in *Institutional Investor* reported that during the first six years of its existence Julian Robertson's Tiger Fund had offered an annual return of 43%.[3] This lead to renewed interest and the formation of many new hedge funds. All this time the hedge fund industry remained somewhat of a mystery to the general investing public. This has changed over the last decade, however. Spectacular hedge fund activities, such as the attack on the British Pound led by George Soros and the near collapse of Long-Term Capital Management, have substantially increased public awareness.

Traditionally, high net worth individuals have been the largest investors in hedge funds. Lately, however, institutional investment into hedge funds has picked up as well. CalPERS for example, recently announced a $1 billion hedge fund program. Hedge funds are also popular amongst university endowments. It is well known that Harvard, Princeton and Yale for example have substantial allocations to hedge funds. It is generally believed that this vote of confidence combined with low interest rates and a declining stock market will give the industry a strong growth impetus in the next few years.

Due to its private nature, it is difficult to estimate the current size of the hedge fund industry. Van Hedge Fund Advisors[4] estimates that by the end of 1998 there were 5,830 hedge funds managing $311 billion in capital, with between $800 billion and $1 trillion in total assets. So far, hedge funds have primarily been an American phenomenon. About 90% of hedge fund managers are based in the US, 9% in Europe and 1% in Asia and elsewhere. Most funds have not been in existence for long. In the last five years the number of hedge funds has increased by at least 150%. Around 80% of hedge funds are smaller than $100 million and around 50% is smaller than $25 million, which reflects the high number of recent new entries.

As management fees are based on assets under management, marketing is extremely important in asset management. Hedge fund marketing rests on two pillars: superior performance and diversification. Most hedge fund managers have substantial experience in capital markets, either as an investment manager, investment analyst or as a proprietary trader. This expertise is often presented to investors as a virtual guarantee for superior performance. A recent report by KPMG Consulting (1998, p. 3) for example boldly states that '…. the long-term average performance of hedge funds as a group can be estimated to be in the range of 17-20%, several percentage points higher than traditional equity returns'. Especially in today's market environment, many private as well as institutional investors are very sensitive to such arguments. The second marketing argument derives from the fact that many hedge funds follow strategies with low systematic exposure. As a result, hedge fund returns tend to exhibit only a weak relationship with the returns on other asset classes. The average correlation between the hedge funds studied in this paper and the S&P 500 for example is only 0.29. From a diversification point of view, this makes hedge funds an attractive portfolio component. Note, however, that this low correlation is typically the result of the general type of strategy followed and not special manager skills.

In this paper we investigate the claim that hedge funds offer investors a superior risk-return profile. We do so in two steps. First, we investigate whether hedge funds offer superior performance on a stand-alone basis. In other words, we study whether hedge funds offer good value for money to investors that invest in nothing else but the hedge fund(s) in question. Hedge fund managers may all be experts in their field, but the presence of certain special skills does not guarantee superior performance. The opportunity costs of potentially poor diversification across assets as well as through time, the transaction costs incurred and the management fee charged, all have to be borne by the investor. The question therefore is not whether hedge fund managers have special skills per se, but whether they have enough skill to compensate for all these costs, which can be very substantial. Only in that case can we speak of truly superior skill and performance. The next step is to look at hedge funds in a portfolio context. We do so by mixing hedge funds with equity to see whether this creates portfolios that offer a superior risk-return profile. These results are relevant for investors that, apart from hedge funds, also invest in equity.

Throughout we concentrate on the question whether in terms of risk and return hedge funds offer investors value for money. It is important to note from the outset that strictly speaking this is a different question than whether hedge funds should be included in an investment portfolio. The fact that an investment offers a superior risk-return profile does not automatically mean that investors should buy into it as the investment may not fit in with investors' preferences and/or the other available alternatives. An inefficient investment on the other hand might fit in well, despite its inefficiency.

We are not the first to study hedge fund performance. A number of authors have applied traditional performance measures such as Jensen's alpha, Sharpe ratios, asset class factor models and mean-variance analysis to hedge funds.[5] In general, the conclusion from this type of research is that hedge funds indeed generate superior results. There is a problem, however. All these methods explicitly or implicitly assume hedge fund returns to be normally distributed and to be linearly related amongst themselves and with other asset classes. As we will see in section IV, neither of these assumptions is correct. Due to the special nature of the investment strategies adopted by hedge fund managers, hedge fund returns may exhibit a high degree of non-normality as well as a non-linear relationship with the stock market. Since this makes the use of traditional performance measures questionable, in this paper we use a measure that does not require any assumptions about the distribution of hedge fund returns.

The paper is organized as follows. In the next section we briefly discuss the basic characteristics of hedge fund strategies and their typical classification. In section III we briefly discuss hedge fund data in general, while in section IV we study the monthly returns of 13 hedge fund indices and 77 individual funds over the period May 1990 – April 2000. In section V we apply traditional evaluation methods to these returns and discuss the limitations of these methods. In section VI we present the evaluation method to be used. In section VII we apply this method to mutual funds and buy-writes, while in section VIII we present the stand-alone hedge fund results. In section IX we study the impact of transaction costs. In section X we study hedge funds in a portfolio context, while in section XI we look at the sensitivity of our analysis for outliers and the reference index used. Section XII concludes.

II. TYPES OF HEDGE FUNDS

Hedge fund investment strategies tend to be quite different from the strategies followed by traditional money managers. Moreover, in principle every fund follows its own proprietary strategy. This means that hedge funds are a very heterogeneous group. There are, however, a number of 'ideal types' to be distinguished.[6] MAR/Hedge, which is the source of the data we will use, uses the following main- and subcategories:

Global: International

Funds that concentrate on economic change around the world and pick stocks in favoured markets. Make less use of derivatives than macro funds (see below).

Global: Emerging

Funds that focus on emerging markets. Because in many emerging markets short selling is not permitted and without the presence of futures markets, these funds tend to be long only.

Global: Established

Funds that look for opportunities in established markets.

Global: Macro

These funds tend to go wherever there is a perceived profit opportunity and make extensive use of leverage and derivatives. These are the funds that are responsible for most media attention.

Event Driven: Distressed Securities

Funds that trade the securities of companies in reorganization and/or bankruptcy, ranging from senior secured debt to common stock.

Event Driven: Risk Arbitrage

Funds that trade the securities of companies involved in a merger or acquisition, typically buying the stocks of the company being acquired while shorting the stocks of its acquirer.

Market Neutral: Long/Short Equity

This category makes up the majority of hedge funds. Exposure to market risk is reduced by simultaneously entering into long as well as short positions.

Market Neutral: Convertible arbitrage

Funds that buy undervalued convertible securities, while hedging all intrinsic risks.

Market Neutral: Stock Arbitrage

Funds that simultaneously take long and short positions of the same size within the same market, i.e. portfolios are designed to have zero market risk.

Market Neutral: Fixed Income Arbitrage

Funds that exploit pricing anomalies in the global fixed income (derivatives) market.

Fund of Funds: Diversified

Funds that allocate capital to a variety of hedge funds.

Fund of Funds: Niche

Funds that only invest in a specific type of hedge funds.

Another important distinction concerns the location of the fund. The latter depends heavily on the residence of the investors that a fund wants to attract. Apart from tax exempt pension plans, US based investors will typically prefer to invest in a US based fund, often a Delaware limited partnership (LP) or limited liability company (LLC). Non-US based and US tax exempt investors on the other hand will prefer to invest in a non-US corporate fund domiciled in a tax haven such as Bermuda, Cayman Islands, British Virgin Islands, Dublin or Luxembourg.

Because many investors see hedge fund managers as true 'investment wizards', the latter have no problem charging hefty fees. Most hedge funds charge a fixed annual management fee of 1-2% plus an incentive fee of 15-25% of the annual fund return. The incentive fee is generally paid only after a particular hurdle rate is achieved. This hurdle rate can be an absolute figure or a reference rate like the T-bill rate plus or minus a spread. For the majority of funds the incentive fee is generally also subject to a so-called high water mark provision. Under such a provision the hedge fund manager has to make up any past losses before the incentive fee is paid.[7]

Funds of funds are in a league of their own. Apart from issues such as transparency, diversification and liquidity, the most important marketing argument used by funds of funds is that they employ experienced managers to select funds, carry out due diligence and continuously monitor the portfolio. This is the usual superior skills argument. Of course, funds of funds charge investors for their services. Very similar to other hedge funds, the average fund of funds charges an annual management fee of 1.4% plus an incentive fee of around 10%. Although funds of funds will generally obtain rebates from the managers they invest in, this extra layer of fees substantially increases the pressure on these funds' performance.

III. HEDGE FUND DATA

With the industry still in its infancy and hedge funds under no formal obligation to disclose their results, gaining insight in the performance characteristics of hedge funds is not straightforward. Fortunately, many hedge funds release monthly return information to attract new and accomodate existing investors. These data are collected by a number of parties, some of which make them available (either or not at a fee) to the (qualifying) public. The most noteworthy databases are those maintained by HFR (1400 funds),[8] TASS (2200 funds) and MAR/Hedge (1500 funds).[9] Apart from performance data, these data vendors also collect many other useful pieces of information such as type of strategy followed, assets under management, management and incentive fees, formal structure, manager details, etc. In addition, these databases are used to calculate a number of hedge fund indices. Although most academic and commercial studies of hedge fund performance use data from the above databases, there are strong reasons to believe that these data are not representative for the entire (unobservable) hedge fund universe.

One reason why a database may be biased is that, based on the argument that subscribers are only interested in funds in which they can actually invest, the data vendor deletes funds as soon as they become defunct. When the emphasis is on survivors, average returns will be overestimated and volatility will be underestimated. Although this is not the case with the HFR, TASS and MAR/Hedge databases, all three data vendors do tend to backfill a fund's performance history when it is added to the database. This allows a data vendor to provide data that go back beyond the start date of the database itself. The downside, however, is that the database will not contain any funds that ceased operation before the start of the database itself. Since most hedge fund databases started around 1994, this means that even databases that normally do not eliminate defunct funds suffer from survivorship bias for the years before 1995.

Several authors have estimated the potential for survivorship bias by comparing the performance of all surviving funds with that of all the funds in a particular database.[10] Based on hand-collected data from the US Offshore Funds Directory, Brown, Goetzmann and Ibbotson (1999) estimated survivorship bias at 3% per annum. A similar estimate can be found in Fung and Hsieh (2000) and Liang (2001), based on analysis of the TASS database. The HFR database is known to contain a relatively low proportion of defunct funds and can therefore be expected to produce a much lower estimate. Liang (2000) reports a survivorship bias estimate from the HFR database of only 0.39% per annum. The consensus in the industry appears to be that the TASS and MAR/Hedge databases better reflect the (unobservable) hedge fund universe than the HFR database. If so, we should reckon with a potential survivorship bias of around 3%. This is quite a high number, especially when compared to the 0.8–1.5% reported by Malkiel (1995) and Brown and Goetzmann (1995) for US mutual funds.

There are some other reasons why the available hedge fund data may be biased. First, database vendors have certain criteria that need to be satisfied before a fund is included in a database. Second, since hedge funds are not allowed to advertise, hedge funds see inclusion in a database primarily as a marketing tool. Funds with a good history are therefore more likely to apply for inclusion than funds with a less satisfactory performance history. Since after inclusion a fund's performance history is backfilled, this may cause a significant upward bias. Using the TASS database, Fung and Hsieh (2000) estimated this 'instant history bias' to be responsible for an extra average return of 1.4% per annum. Third, poorly performing hedge funds may stop reporting before they actually close shop. Ackermann, McEnally and Ravenscroft (1999) report an average delay in redemption of 18 days and an accompanying upward bias of 0.7%. Fourth, some hedge funds invest in relatively illiquid securities for which there is often no recent market price available. To produce a monthly return figure, these funds will typically use either the last available price or their own estimate of the market price. Although this will not affect the average return, it may lead one to underestimate true return variance and correlation with other assets.

The above biases may easily lead one to overestimate hedge fund performance and underestimate risk and should therefore be properly discounted for whenever possible. At times, however, this is not at all straightforward. In those cases one can do little more than rely on some 'mental accounting'.

IV. HEDGE FUND RETURNS

The data used in this study were obtained from the MAR/Hedge database. Managed Accounts Reports (MAR) is one of the oldest sources of global managed futures information. In 1994 its sister publication MAR/Hedge started publishing similar information on hedge funds. Per April 2000, the database contained monthly return data on 1476 hedge funds, net of all fees. For reasons that will become clear later, in this study we concentrate on the 77 funds for which at least ten years of consecutive monthly return data is available, from May 1990 until April 2000. Obviously, this introduces survivorship bias, i.e. our conclusions will be too optimistic. There is no simple way to mitigate this problem though. Note that our sample includes the period 1997-1998. With crises in Asia and Russia and the subsequent collapse of LTCM, this was an especially difficult time for hedge funds. A further classification of the 77 funds we will use in this study can be found in table 1.

<< Insert Table 1 >>

Apart from individual funds, we also study the monthly returns on 13 different hedge fund indices calculated by MAR/Hedge over the same sample period. All 13 indices are equally-weighted and correspond with the classification discussed earlier. The 13 indices considered are listed below with the number of funds included as of April 2000 between brackets: Event Driven (106), Event Driven: Distressed (45), Event Driven: Risk Arbitrage (61), Fund Of Funds (265), Fund Of Funds: Niche (232), Fund Of Funds: Diversified (33), Global: Emerging (85), Global: Established (245), Global: International (34), Global: Macro (58), Market Neutral (231), Market Neutral: Long/Short (109), and Market Neutral: Arbitrage (122). Note that the Event Driven, Fund of Funds and Market Neutral indices are simply baskets of the relevant sub-indices.

<< Insert Table 2 and 3 >>

Table 2 and 3 provide information on the monthly return characteristics of the S&P 500 index, the 13 hedge fund indices and the 77 individual funds over the ten-year period studied. The S&P 500 return is a total return, i.e. it includes dividends. All returns use continuous compounding. We decided it would be inappropriate to name the individual funds by name. Instead, we numbered the funds in each class of funds arbitrarily and refer to them only by number. We do, however, provide information on the type of fund. The capitals denote whether a fund is classified as global (G), event driven (E), market neutral (M) or as a fund of funds (F). The lowercase letters denote whether the fund is US based (u) or not (n).

Starting with table 2, we see some marked differences between the various hedge fund indices. Ignoring the MKT NEUTRAL, EVENT-DRIV and the three fund of funds indices, we can classify the remaining 8 'pure' indices in four distinct risk groups, based on their return standard deviations. With 0.50% the Market Neutral: Long/Short index has by far the lowest standard deviation, followed by the Event Driven: Risk Arbitrage index with a standard deviation of 1.34%. The third group is made up of the Event Driven: Distressed, Global: International, Global: Macro, and Market Neutral: Arbitrage indices with an average standard deviation of 2.13%. The fourth group contains the Global: Established (2.68%) and the Global: Emerging (4.97%) indices which show a standard deviation which (far) exceeds that of the other indices. The means reflect the differences in standard deviation. The return distribution of most hedge fund indices appears to be highly skewed. The last column in table 2 shows the results of the Jarque-Bera (1987) test for normality,[11] which confirms that for none of the index return distributions normality is a satisfactory approximation.

The individual fund results in table 3 tell very much the same story. Although there are substantial differences between funds, on average market neutral funds tend to show a lower standard deviation (2.49%) than event driven funds (2.83%) and especially global funds (4.82%). The average mean returns are again in line with the average standard deviations. Many funds' return distributions exhibit substantial skewness. The Jarque-Bera (1987) test results in the last column of table 3 show that at a 5% significance level only 14.1% of the individual hedge funds return distributions can be considered normal.

Comparing individual fund results with the corresponding index results, we see strong diversification effects. The standard deviation of the MKT NEUTRAL index is 2.06% lower than that of the average market neutral fund. Likewise, the standard deviation of the EVENT-DRIV index is 1.58% lower than that of the average event driven fund. The standard deviations of the latter indices are also substantially lower than those of the component sub-indices, suggesting that combining different sub-types of funds yields additional risk reduction.

Given that funds of funds are nothing more than baskets of other hedge funds, it is not surprising that the three fund of funds indices exhibit similar return characteristics with an average standard deviation (1.47%) which places them in between risk group 2 and 3. With 0.92% the fund of funds indices' average mean return, however, is significantly lower than what one would expect from a basket of hedge funds. A similar phenomenon is observed for individual funds of funds. Due to diversification effects, the average fund of funds standard deviation is quite low (2.44%). The same, however, is true for the average mean return (0.88%). Of course, the results on individual non-funds of funds suffer from survivorship bias, which may explain the individual funds results. However, since (with the exception of the early years) the hedge fund indices do take failures into account, this is not true for the index results. This strongly suggests that the average fund of funds manager is unable to make up for the fees he charges. Although smaller investors have little choice, larger-sized investors should therefore think twice before externalising their hedge fund portfolio management.

<< Insert Figure 1 >>

Figure 1 shows normality plots for four hedge fund indices and two arbitrary individual hedge funds. In these plots the straight line is the normal line and any deviation from it indicates non-normality. Although index returns and individual fund returns both show clear evidence of non-normality, due to diversification effects the indices do not show the same high level of non-normality as the individual funds.

Another important question concerns the relationship between hedge fund returns and the returns on other asset classes. Several authors have suggested this relationship to be non-linear.[12] To test for non-linearity in our data, we estimated the following piecewise linear CAPM-type model for every one of the 13 hedge fund indices and 77 individual hedge funds in our sample

$$(R_h - R_f) = (1-\delta)\{\alpha_L + \beta_L(R_{S\&p} - R_f) + e_h\} + (\delta)\{\alpha_H + \beta_H(R_{S\&P} - R_f) + e_h\}. \qquad (1)$$

In the above expression, R_h and $R_{S\&P}$ denote the hedge fund (index) return and the S&P 500 return respectively, R_f denotes the short term USD interest rate in the form of 3-month USD LIBOR, and δ is a dummy variable which is 1 if ($R_{S\&P}$ - R_f) is above 1.3% and 0 otherwise. The threshold level of 1.3% was chosen because it divides the available data set in two equal parts of 60 observations each. For comparison, we also estimated the standard linear CAPM model given by

$$(R_h - R_f) = \alpha + \beta(R_{S\&P} - R_f) + e_h . \qquad (2)$$

The estimation results can be found in table 4 and 5. In both tables, columns 2-5 report on equation (1), and columns 6-8 on equation (2). Comparing the R^2 of both models we see that for all indices and funds the piecewise linear model provides a better fit than the linear model. In addition, both the betas of model (1) show large differences, which all test significant at a 1% significance level. This strongly suggests the presence of a non-linear relationship between hedge fund returns and S&P 500 returns.

<< Insert Table 4 and 5 >>

Because traditional performance measures are implicitly or explicitly based on the assumption of normally distributed fund returns which are linearly related to the reference index, normality and linearity are very important issues when it comes to investment performance evaluation. The above results indicate that many hedge funds generate non-normal returns that are non-linearly related to equity returns. Correct evaluation of hedge fund performance requires a performance measure that takes this into consideration. We will discuss such a measure in section VI. First, however, we take a look at the results that one would obtain if one used the most popular traditional performance measures to detect superior performance.

V. TRADITIONAL PERFORMANCE MEASURES

Although over the years much work has been done in this area,[13] practitioners typically use of either one of two performance measures: the Sharpe ratio and Jensen's alpha. The first measure was introduced in Sharpe (1966) and is calculated as the ratio of the average excess return and the return standard deviation of the fund in question. As such it measures the excess return per unit of risk. The benchmark value is the Sharpe ratio produced by the relevant market index. Theoretically, the Sharpe ratio derives directly from the CAPM. Assuming all asset returns to be normally distributed (or, less plausible, that investors have mean-variance preferences), the CAPM tells us that in equilibrium the highest attainable Sharpe ratio is that of the market index. A ratio higher than that therefore indicates superior performance. The alpha measure was introduced in Jensen (1968) and equals the intercept of the regression given by.

$$\left(R_h - R_f\right) = \alpha + \beta\left(R_i - R_f\right) + e_h , \qquad (3)$$

where R_h is the fund return, R_f is the risk free rate and R_i is the total return on the market index. Alpha measures the excess return that cannot be explained by a fund's beta. An alpha higher than zero indicates superior performance. Like the Sharpe ratio, Jensen's alpha is deeply rooted in the CAPM and therefore relies heavily on the assumption of normally distributed returns. According to the CAPM, in equilibrium all (portfolios of) assets with the same beta will offer the same expected return. Any positive deviation therefore indicates superior performance.

Although both stemming from the CAPM, the above measures take a different perspective when looking at fund performance. The Sharpe ratio implicitly assumes that investors invest in nothing else than the fund in question, i.e. it evaluates fund performance on a stand-alone basis. Alpha on the other hand, evaluates fund performance in a portfolio context by incorporating the correlation characteristics of the fund in the evaluation (via the fund beta). A fund with a Sharpe ratio higher than that of the market index will also have a positive alpha. The reverse need not be true, however, i.e. underperformance on a stand-alone basis does not necessarily imply underperformance in a portfolio context. Although we will use a different performance measure, we will make the same distinction between evaluation on a stand-alone basis and evaluation in a portfolio context in this study.

Using monthly total return data from May 1990 to April 2000, we calculated the alphas and Sharpe ratios of the S&P 500, the 13 hedge fund indices and the 77 individual funds. We used 3-month USD LIBOR as a proxy for the risk-free rate and the S&P 500 as the relevant market index. The results can be found in the last four columns of table 4 and 5. Eleven indices show significant positive alphas. Twelve indices generate a Sharpe ratio higher than that of the S&P 500. Of the individual funds, 71 show positive alphas but only 32 test significantly different from zero. 28 funds produce a Sharpe ratio higher than that of the S&P 500.

<< Insert Figure 2 >>

We also plotted the means and standard deviations of the 13 indices in traditional mean-standard deviation space together with a number of other equity, bond and commodity indices. The results can be found in figure 2. From this graph it is clear that most of the hedge fund indices combine a relatively high mean return with a relatively low standard deviation. In terms of mean and standard deviation, the hedge fund indices are definitely more attractive than the other indices, which is in line with the message from these indices' alphas and Sharpe ratios.

Based on the above performance measures, hedge funds have shown superior performance over the last decade; a fact often quoted by hedge fund managers and marketers. But is this really the case? As we saw before, hedge fund return distributions tend to be significantly skewed and non-linearly related to the reference index. This is not unlike the return distribution that results from a so-called 'buy-write'. Suppose we had a stock index with a monthly price return that was normally distributed with an expected value of 1.24% (14.88% per annum) and a volatility of 3.59% (12.43% per annum). The index is worth $100 and pays a continuous dividend yield of 2.65% per annum. The risk free rate is 5.35%, yielding a Sharpe ratio for the index of 0.28. The reason behind this specific choice of parameter values will become clear in section VIII. According to the Black-Scholes (1973) model, an ordinary at-the-money call on the index with one month to maturity would cost $1.55. Now suppose we bought the index and wrote the call. Writing the call eliminates all upside potential but retains all downside risk. In addition, we receive \$1.55 for the call. Creating this payoff profile requires no special skills. However, this is not the conclusion one would draw from the portfolio's alpha and Sharpe ratio. By writing the call, alpha goes up from zero to 0.34 and the Sharpe ratio rises from 0.28 to 0.42. This is purely the result of the changed shape of the return distribution though. By giving up all upside, the monthly standard deviation drops from 3.59% to 1.67%. The expected return drops as well, but this is partially compensated by the option premium that is received. As a result, the Sharpe ratio goes up. Although the above is just a simple example, it makes it painfully clear that traditional evaluation methods may very easily reach a wrong conclusion when dealing with a non-normal distribution.[14]

VI. AN ALTERNATIVE PERFORMANCE MEASURE

To evaluate the performance of portfolios with a non-normal, skewed return distribution correctly, the entire distribution has to be considered. Ideally, this should be done without having to make any prior assumptions regarding the type of distribution. The performance measure that we will use in this study does exactly that. It is based on the following reasoning. When buying a fund participation, an investor buys participation in a certain investment strategy. In more abstract terms, the investor acquires a claim to a certain payoff distribution. If we wanted to investigate whether a fund manager had any superior investment skills the most direct line of attack would therefore be to re-create the payoff distribution that he offers to his investors by means of a dynamic trading strategy and compare the cost of that strategy with the price of a fund participation. If the manager in question indeed had superior skills, the strategy should be more expensive than the fund participation. Of course, the same payoff distribution can be generated in many different ways. The critical issue is therefore to find the strategy that does so most efficiently, i.e. at the lowest cost. We will return to this shortly but first we explain the procedure that we will follow.

<< Insert Figure 3 and 4 >>

We evaluate the performance of the hedge funds and hedge fund indices in our sample using the following 3-step procedure, which in the remainder of the paper we will refer to as 'the efficiency test'.

1. For every hedge fund and hedge fund index we use the available monthly returns over the period May 1990 – April 2000 to create an end-of-month payoff distribution, assuming we invest $100 at the beginning of each month. The same is done using S&P 500 price returns, except that we explicitly assume the latter to be normally distributed. An example of the resulting cumulative distributions can be found in figure 3. Of course, the S&P 500 distribution is smooth due to its assumed normality.

2. For every hedge fund and hedge fund index we construct a path independent payoff function that, in combination with the S&P 500 distribution, yields exactly the same end-of-month payoff distribution as produced by the hedge fund (index) in question. Of course, there are many functions that will map one distribution into the other. We therefore make the additional assumption that the payoff must be a non-decreasing function of the index value. An example can be found in figure 4. Details about the mapping procedure and the pricing procedure that follows can be found in the Appendix.

3. The third step consists of the pricing of the self-financing dynamic trading strategy, trading the S&P 500 and cash, that generates the above payoff function. We do so assuming we live in the world of Black and Scholes (1973), which explains why in step 2 we assume S&P 500 returns to be normally distributed. Prices are calculated as discounted risk neutral expected payoffs using standard Monte Carlo simulation with 20,000 simulation runs. If the price thus obtained is higher (lower) than $100, we take this as evidence of superior (inferior) performance.

The efficiency test has its theoretical foundation in the payoff distribution pricing model of Dybvig (1988a, 1988b). The important point that emerges from Dybvig's work is that inefficiencies in investment strategies do not only result from management fees, transaction costs and poor diversification across assets but also from poor diversification through time. By moving in and out of the equity market, investors miss out on a substantial part of the equity risk premium. A market timing fund manager will therefore need to have very substantial forecasting skills to make up for the opportunity loss.

We avoid the problem of inefficient diversification across assets by using a well-diversified market index like the S&P 500 as our risky asset. The problem of inefficient diversification through time is avoided by concentrating on path independent non-decreasing payoffs. Cox and Leland (2000) showed that in a Black-Scholes world all path dependent strategies are inefficient in the sense that the same payoff distribution can also be obtained by a path independent strategy, but at lower costs. In addition, from Dybvig (1988a, 1988b) we know that in a Black-Scholes world a strategy is efficient if and only if its payoff is a non-decreasing function of the index at maturity. Intuitively, this is a plausible result. A non-decreasing payoff will be positively correlated with the index. As a result, the rebalancing trades required by the strategy generating that payoff will tend to be relatively modest, which serves to keep the costs down.

In short, what we use as a benchmark is the cost of the cheapest self-financing dynamic trading strategy that generates the same payoff distribution as the hedge fund in question. By doing so we test whether a hedge fund manager has sufficient skill to compensate not only for transaction costs and management fees (which simply do not exist in a Black-Scholes world), but also for the inefficiency costs of potentially poor diversification across assets as well as through time. Implicit in the efficiency test is the assumption that investors are only interested in the end-of-month payoff of a strategy and not in its intermediate values. This is an adequate characterization of hedge fund investors as most hedge funds have strict lock-up and exit rules that effectively force investors to take a longer-term view.

Dybvig (1988b) uses a binomial version of the efficiency test to estimate the inefficiency costs of a number of popular path dependent investment strategies, such as stop-loss and lock-in strategies. Robinson (1998) uses it to estimate the inefficiency costs of so-called rolling guarantee funds and two path dependent equity-linked notes. Our study, however, is more ambitious as we aim to estimate the inefficiency costs of investment strategies the details of which are not known. In addition, we aim to capture all sources of inefficiency and not just the cost of inefficient time diversification.

We are not the first to approach performance evaluation from a contingent claims perspective. Glosten and Jagannathan (1994) approximate mutual fund payoffs by a portfolio consisting of the index and a limited number of ordinary index calls. Agarwal and Naik (2000b) show that simple option strategies are able to explain a significant part of the variation in hedge fund returns over time. Fung and Hsieh (2001) show that the returns from trend following strategies are similar to those from lookback straddles. Finally, Mitchell and Pulvino (2001) find that the returns from risk arbitrage strategies are very similar to the results from writing ordinary put options. All these researchers link fund payoffs with specific option payoffs. Our method does not do so, however. Apart from requiring the payoff to be a path independent non-decreasing function of the index it is fully determined by the empirically observed hedge fund return distribution.

VII. TWO TESTS OF THE METHODOLOGY

We only have 10 years of monthly data to estimate hedge funds' payoff distributions. As a result, the efficiency test will be confronted with sampling error. Since we do not make any assumptions about the nature of the distributions involved, a formal study is problematic. We can, however, obtain an indication of the possible extend of the error by studying the efficiency test's application on a payoff function that we know to be efficient. We therefore applied the efficiency test to the index plus short call package discussed in section V. Since the payoff of this package is neither hampered by transaction costs or management fees nor by inefficient diversification, the test should produce a value of exactly 100. With only 120 observations available, however, this need not always be the case. The procedure we followed is as follows. First, we generated 120 end-of-month index values and calculated the corresponding payoffs, assuming monthly index (price) returns to be normally distributed with a mean of 1.24% (14.88% per annum) and a standard deviation of 3.59% (12.43% per annum), and a monthly dividend yield of 0.22% (2.65% per annum). These estimates were obtained from monthly S&P 500 data over the period May 1990 - April 2000. Next, we applied the efficiency test to the 120 payoff values thus obtained, assuming the S&P 500 to follow a geometric Brownian motion with a volatility equal to the above standard deviation and a drift equal to the difference between the risk-free rate and the above S&P 500 dividend yield. The former is set equal to the 10-year historic mean of the 3-month USD LIBOR rate (5.35%). We repeated the above procedure 20,000 times. A frequency distribution of the annualised error, i.e. the difference between the actual test result and 100, can be found in figure 5

<< Insert Figure 5 >>

Figure 5 shows that with only 120 observations the efficiency test may produce an error that significantly differs from zero. The error distribution, however, has a high peak around zero, meaning that, compared to a normal distribution, there is a relatively high probability of a small error. In addition, figure 5 shows that the efficiency test is unbiased. The average error is –0.05. Obviously, with more observations the sampling error will drop. Given the currently available data on hedge funds, however, this is the best one can do. We repeated the above analysis for a number of other payoff profiles, which yielded similar results.

When the distribution of fund returns is (close to) normal, the efficiency test should reach the same conclusion as traditional performance measures. We tested this hypothesis using ten years of monthly total return data on the FTSE All Share index and 33 UK based equity mutual funds over the period May 1990 - April 2000. The return characteristics of the index and the 33 mutual funds can be found in table 6. As before, we numbered the funds in question and refer to them by number instead of by name. The last column contains the results of the Jarque-Bera normality test. This shows that at a 5% significance level, 22 of the 33 funds have normally distributed returns.

<< Insert Table 6 and 7 >>

For all 33 funds we calculated Jensen's alpha and performed the efficiency test. We used the 1-month T-bill rate as a proxy for the risk free rate and the FTSE All Share index as the relevant market index. For mapping purposes we assume monthly FTSE All Share price returns to be normally distributed with a mean of 0.85% (10.2% per annum) and a standard deviation of 4.28% (14.83% per annum). These estimates were obtained from monthly returns over the period May 1990 - April 2000. For pricing purposes we assume the FTSE All Share index to follow a geometric Brownian motion with a volatility equal to the above standard deviation and a drift equal to the difference between the risk-free rate and the FTSE All Share dividend yield. The risk-free rate is set equal to the 10-year historic mean of the 1-month T-bill rate (7.32%) and the dividend yield is set equal to its 10-year historic mean of 4.05%. The results are shown in Table 7. From table 7 we clearly see that both Jensen's alpha and the efficiency test indicate a high level of inefficiency for all funds in the sample. The average efficiency loss is 13.46% per annum. Of course, this result should be interpreted in light of the period under consideration. Over the period studied the ex-post risk premium has been relatively high, implying that the sample period offers the potential for relatively high inefficiency costs.

To see how much the conclusions from both performance measures differ, we tested for overall correlation as well as correlation in sign and rank. The overall correlation coefficient (Pearson) was 0.88. The sign correlation (Kendall) was 0.67 and the rank correlation (Spearman) was 0.84. All these were significant at a 5% significance level, which shows that for the mutual funds studied our method reaches conclusions that are similar to those based on fund alphas, overall as well as in sign and rank. It does so, however, without having to make any assumptions about the nature of fund returns.

VIII. APPLICATION TO HEDGE FUNDS

We proceed with the application of the efficiency test to the monthly returns of the 13 hedge fund indices and 77 individual hedge funds discussed earlier, using the same parameter values as in the previous section. Note again that over the period studied the ex-post risk premium has been relatively high, which potentially allows for the presence of significant inefficiency costs.

<< Insert Tables 8 and 9 >>

<< Insert Figure 6 >>

The evaluation results on the 13 indices can be found in table 8. Twelve of the 13 indices show signs of inefficiency with the average efficiency loss on these 12 indices amounting to 3.00% per annum. With an average efficiency loss of 4.15%, the three fund of funds indices make an important contribution to this figure. Excluding the latter, the average efficiency loss drops to 2.61%.

The evaluation results on the 77 individual funds are reported in table 9 and are sorted and graphically reproduced in figure 6. Of the 77 funds studied, 72 show signs of inefficiency. For these 72 funds the average efficiency loss amounts to 6.97% per annum. Five funds offer superior performance with an average efficiency gain of 1.49% per annum. Even without taking survivorship bias into account, these results clearly contradict the claim that hedge funds generate superior investment results on a stand-alone basis.

With an average efficiency gain over individual hedge funds of 3.66%, the hedge fund indices perform significantly better than the individual funds, indicating that a significant part of individual fund inefficiency is due to poor diversification. This means that inefficiency costs can be reduced by investing in a portfolio of hedge funds instead of a single individual fund. Combining different types of funds seems to offer additional gains. If we were to combine all 13 indices into an equally-weighted portfolio, the efficiency loss would drop to 1.82%. Without the three fund of funds indices the efficiency loss would come down to 1.40%.

<< Insert Table 10 >>

To see whether there are any significant differences between different types of hedge funds, we divided the 77 individual funds in the sample in seven groups: fund of funds, non fund of funds, event driven, global, market neutral, offshore and US based. The results are summarized in table 10. All of the 15 event driven funds show signs of inefficiency with an average efficiency loss of 3.76% per annum. Of the 28 global hedge funds, 24 show some level of inefficiency with an average cost of 8.51% per annum. Of the 11 market neutral funds studied, 10 show some level of inefficiency. For this group the average efficiency loss is 6.80% per annum. US based funds appear to be more efficient than offshore funds. Four out of 49 US based funds classify as efficient with an average efficiency gain of 1.54% per annum. This is in line with the results of Ackermann, McEnally and Ravenscraft (1999) and Liang (1999), who found offshore funds to be substantially more volatile than US funds.

It is worrisome to see funds of funds perform so badly. Despite the extra layer of diversification, the three fund of funds indices are almost 2% behind on the other 10 hedge fund indices. The efficiency loss of the average individual fund of funds is 7.51% per annum, meaning that the average fund of funds is 1.56% less efficient than the average non-fund of funds and 5.17% less efficient than the average non-fund of funds index. A priori one would expect funds of funds to show results similar to those obtained for the non-fund of funds indices. The above result therefore strongly suggests that the fees charged by fund of funds managers tend to outweigh the efficiency gains of additional diversification and potentially superior fund selection.

IX. TRANSACTION COSTS

So far we have used the S&P 500's historical volatility to price the payoff functions resulting from our mapping procedure. Given that it is this volatility that is used to map the hedge fund return distribution into a payoff function, this seems the obvious choice. Since our benchmark value equals the costs of a specific dynamic investment strategy, however, one might object that using the index's historical volatility is not correct as in practice we will be confronted with transaction costs.[15] As shown by Leland (1985), transaction costs can be incorporated in the form of a volatility adjustment.[16] For strategies generating a payoff that is a convex function of the index at maturity, transaction costs can be modelled as an increase in volatility. The reverse is true for strategies generating a payoff that is a concave function of the index. If we denote the volatility of the index as σ, round-trip transaction costs (as a percentage of the index value) as c, and the time between subsequent rebalancings as Δt, then Leland's transaction costs adjusted volatility σ_L is given by

$$\sigma_L = \sqrt{\sigma^2 \left(1 + D \sqrt{\frac{2}{\Pi}} \frac{c}{\sigma \sqrt{\Delta t}} \right)} \quad (4)$$

where D is +1 when dealing with a convex and –1 when dealing with a concave payoff. If we assume daily rebalancing and cash market execution at round trip transaction costs of 0.5%, the volatility to be used for convex strategies would be 15.34% and 8.74% for concave strategies. If we assumed futures market execution, transaction costs would of course be much lower, say 0.05% round trip. In that case convex strategies should be priced at 12.76% and concave strategies at 12.13%.

With futures market execution the adjusted volatilities are hardly different from the 12.43% we have used so far, implying that with futures market execution transaction costs will not change our previous conclusions. This is not the case with cash market execution. To see how cash market transaction costs change our results we investigated how high or low volatility needs to be to bring the value of the hedge fund payoff distributions to 100. This information can be found in the fourth column of table 8 and 9. The numbers indicate the volatility level at which the value of the payoff distribution offered reaches 100. Concentrating on the 72 funds that have a value below 100 at 12.43% volatility, there are three interesting observations to be made.

1. 42 out of 72 reach 100 at a volatility level higher than 12.43% (18.79% on average). The fact that the value of these funds' payoff distributions increases with volatility implies a convex payoff. The benchmark volatility is therefore 15.43%, meaning that 8 of these funds can no longer be classified as inefficient.

2. 21 out of 72 reach 100 at a volatility level lower than 12.43% (8.81% on average), implying a concave payoff. The benchmark volatility is therefore 8.74%, which means that 4 of these funds can no longer be classified as inefficient.

3. 9 out of 72 fail to reach 100 (denoted as 'DNT 100') even at 0% volatility. Apart from a concave payoff, this also implies that these funds are definitely inefficient.

In sum, with round-trip transaction costs at 0.5%, 12 of the 72 funds classified earlier as inefficient can no longer be classified as such. This still leaves us with 60 inefficient funds though. Looking at the 5 funds that show a value higher than 100 at 12.43% volatility, we see that 3 out of 5 show a decrease in value as volatility rises. Again, this implies a concave payoff.

The fact that the value of the payoff distribution offered by 33 out of 77 funds is a decreasing function of volatility is in line with the observation made in section IV that many hedge fund return distributions offer relatively limited upside potential. Since a concave payoff is the most efficient way to generate such a distribution, this is what the mapping procedure produces. However, this does not mean that the hedge funds studied actually offer investors a payoff that is a concave function of the index. All we are saying is that the payoff distributions offered by many hedge funds can be re-created cheapest by an investment strategy that aims to generate a payoff that is a concave function of the index. The last columns in table 8 and 9 show the correlation between the return calculated from the payoff function resulting from our mapping procedure and the actual hedge fund (index) return. These low correlation coefficients underline that although our payoffs replicate hedge funds' payoff distributions, they do not replicate their time series behaviour very well. In essence, this is exactly why we find hedge funds to be inefficient.

X. HEDGE FUNDS IN A PORTFOLIO CONTEXT

By construction, our mapped payoffs are heavily correlated with the index. In reality, however, the relationship between hedge fund and index returns is rather weak. For example, over the period studied the average correlation between the S&P 500 and individual hedge funds was only 0.29. The efficiency test used so far does not take this into account as it only aims to replicate hedge funds' payoff distribution and not their correlation profile. If we were to introduce an explicit correlation restriction into the efficiency test, i.e. require our trading strategies not only to replicate the funds' payoff distributions but also their correlation with the index, hedge funds would come out better as the additional restriction would make our replication strategies more expensive. There are two problems with this, however. First, incorporating an explicit correlation restriction into the procedure is technically complicated. Second, concentrating on correlation implicitly assumes a linear relationship between hedge fund returns and index returns. As discussed in section IV, however, the data suggest that this is not the case.

To solve the above problems we decided on the following procedure. First, we form portfolios of hedge funds and the S&P 500, with the fraction invested in the S&P 500 ranging from 0% to 100% in 1% steps. Subsequently, we run the same efficiency test as before on these portfolios' 120 monthly returns and check for the existence of a combination of hedge fund and S&P 500 that offers a risk-return profile that cannot be obtained with a mechanical trading strategy at a lower price. Roughly speaking, this procedure tests whether the relationship with the S&P 500 is sufficiently weak to make up for the efficiency loss observed on a stand-alone basis. Table 11 and 12 show for every hedge fund index and individual hedge fund respectively the correlation with the S&P 500, the highest efficiency value achieved, the mix at which this occurs, and the improvement in efficiency relative to the stand-alone result.

<< Insert Table 11 and 12 >>

From table 11 we see that when mixed with the S&P 500, 7 of the 12 indices that were found to be inefficient on a stand-alone basis are able to produce an efficient payoff profile, i.e. a payoff profile that cannot be obtained otherwise at a better price. In all 7 cases the most efficient mix consists of around 20% hedge fund index and 80% S&P 500. Given that the correlation coefficients of these indices with the S&P 500 (column 2) vary between 0.09 and 0.71, this again indicates that there is more between hedge fund index returns and S&P 500 returns than a simple linear relationship. The results on individual funds can be found in table 12. Of the 72 previously inefficient funds, 58 can be mixed with the S&P 500 to produce an efficient payoff profile. As with hedge fund indices, the most efficient mix varies much less than expected given the funds' varying correlations with the S&P 500. For all 58 funds the most efficient mix consists of 10-20% hedge fund and 80-90% S&P. It is interesting to note that, despite their marked inefficiency on a stand-alone basis, 13 out of 23 funds of funds are capable of producing an efficient payoff profile when mixed with the S&P 500. Another interesting result concerns the fact that with a 20/80 mix there is relatively little difference between the results for hedge fund indices and individual hedge funds. One might be inclined to conclude from this that in a portfolio context hedge fund diversification is much less of an issue than on a stand-alone basis. Such a conclusion could be premature, however, as it ignores the survivorship bias introduced by only including funds with at least 10 years of history.

XI. SENSITIVITY ANALYSIS

To gain insight in the sensitivity of the above results for outliers we removed the top and bottom 2.5% of the return observations, leaving 114 instead of 120 monthly returns. The overall results did not change much. The correlation between the results from 120 observations and 114 observations was 0.94.

To see how sensitive the above results are for the choice of reference index, we performed the same exercise using the Dow Jones Industrial (DJI) index instead of the S&P 500. The DJI is substantially different from the S&P 500. The former is made up of only 30 stocks, while the latter contains 500. In addition, instead of being value-weighted like the S&P 500 and most other major stock market indices, the DJI is one of the few price-weighted indices in the world. Using the DJI as our reference index, the results did not change very much. The correlation between the S&P 500 results and the DJI results was 0.99. Details are available upon request.

XII. CONCLUSION

In this paper we have used the payoff distribution pricing model introduced by Dybvig (1988a, 1988b) to evaluate hedge fund performance over the period 1990 - 2000. Our main results can be summarized as follows:

1. **Hedge fund returns and performance evaluation**. Because hedge fund returns tend to be non-normal, skewed and non-linearly related to equity returns, traditional performance measures such as Jensen's alpha and the Sharpe ratio are not suitable for the evaluation of hedge fund performance

2. **The proposed performance measure**. The efficiency test appears to be unbiased, while with 120 observations sampling error risk does not seem to be prohibitively high. When fund returns are (approximately) normal, the test yields results that are very similar to those obtained with traditional performance measures.

3. **Hedge funds as a stand-alone investment.** With an efficiency loss of 6.42%, the average hedge fund makes for quite an inefficient investment. The 3.66% lower average efficiency loss observed on hedge fund indices, however, suggests that a major part of the inefficiency costs of individual funds can be diversified away by investing in a portfolio of hedge funds instead of a single hedge fund.

4. **Hedge funds in a portfolio context.** Hedge funds score much better when seen as part of an investment portfolio. Due to their weak relationship with the index, 7 of the 12 hedge fund indices and 58 of the 72 individual funds classified as inefficient on a stand-alone basis are capable of producing an efficient payoff profile when mixed with the S&P 500. The best results are obtained when 10-20% of the portfolio value is invested in hedge funds.

5. **Funds of funds.** The average fund of funds manager seems unable to earn back his fees. The average stand-alone fund of funds efficiency loss exceeds that of the average non-fund-of-funds hedge fund index by 5.17%. On a stand-alone basis, the average fund of funds therefore makes for quite a wasteful investment. Despite this, 13 of the 23 funds classified as inefficient on a stand-alone basis are able to produce an efficient payoff profile when mixed with the S&P 500. Again, the best result is obtained with 10-20% invested in the fund in question.

6. **Comparison with mutual funds.** The sample of UK equity mutual funds studied shows levels of inefficiency that by far exceed those of the hedge funds in our sample. Given that hedge funds charge higher fees and are unlikely to be better diversified or to incur lower transaction costs than mutual funds, this suggests that hedge fund managers tend to be more skilled than mutual fund managers.

Our results make it clear that the main attraction of hedge funds lies in the weak relationship between hedge fund returns and the returns on other asset classes. It is interesting to note, however, that this is primarily the result of the general type of strategy followed by many hedge funds and not special manager skills. Any fund manager following a typical long/short type strategy can be expected to show low systematic exposure, whether he has special skills or not. This leads us to the question why investors should pay those high fees if the main attraction of hedge funds is not a manager specific feature? The answer of course is that investors have little choice. Only hedge funds provide hedge fund type returns.

APPENDIX

This appendix explains the details of the construction and pricing of the payoff functions used in the efficiency test.

The first step is to recover the cumulative probability distribution of the monthly hedge fund payoffs as well as the S&P 500 from the available data set. We construct these cumulative probability distributions using 500 bins, i.e. we divide the relevant outcome space in 500 intervals of 0.20 each. We then map each of these 500 points of the hedge fund distribution into a payoff function using the cumulative probability distribution of the S&P 500 as the common point of reference. The following example will clarify this. Suppose that the hedge fund distribution told us there was a 20% probability of receiving a payoff lower than 100. We would then look up in the S&P 500 distribution at which S&P 500 value X there was an 80% probability of finding an index value higher than X. If we found X=101, the payoff function would be constructed such that when the index was at 101 the payoff would be 100.

Having constructed the desired payoff function, we use standard Monte Carlo simulation to generate 20,000 end-of-month values for the S&P 500, using the following discretized and risk neutralized geometric Brownian motion.

$$S(t+\delta t) = S(t)\exp\left((r - q - \frac{1}{2}\sigma^2)\delta t + \sigma\sqrt{\delta t}\varphi\right)$$

Where $S(t)$ is the starting value of the index (100), r is the risk free rate (5.35%), q is the S&P 500 dividend yield (2.65%), σ is the S&P 500 volatility (12.43%), δt is the time step (one month) and φ is a random variable with a standard normal distribution. From the 20,000 S&P 500 values thus generated we subsequently calculate the corresponding 20,000 payoffs, average them and discount the resulting average back to the present at the risk free rate to give us the price of the payoff function in question. The theoretical motivation for this pricing procedure can be found in Harrison and Kreps (1979).

FOOTNOTES

1. See for example President's Working Group on Financial Markets (1999, p. 1).

2. Carol J. Loomis, *The Jones Nobody Keeps Up With,* Fortune, April 1966.

3. Julie Rohrer, *The Red-Hot World of Julian Robertson,* Institutional Investor, May 1986.

4. See Van Hedge Fund Advisors International, Inc. at www.vanhedge.com, September 1999.

5. See for example Fung and Hsieh (1997), Ackermann, McEnally and Ravenscraft (1999), Agarwal and Naik (2000a), and Liang (1999).

6. An alternative is to classify hedge funds based on empirical style categories. See Brown and Goetzmann (2001) for details.

7. A detailed analysis of the costs and benefits of high watermark compensation can be found in Goetzmann, Ingersoll and Ross (1998).

8. Although internally HFR monitors 4000 funds, the database available by subscription covers only 1400 funds.

9. On March 22, 2001, MAR sold its database operations to Zurich Capital Markets Ltd. For clarity, however, we will continue to refer to these data as the MAR/Hedge database.

10. Apart from failure, a fund may also leave a database because of a merger, a name change or lack of reporting. All of these, however, are often linked to poor performance.

11. Jarque-Bera (1987) test statistic:

$$JB = n\left[\frac{S^2}{6} + \frac{(K-3)^2}{24}\right]$$

Where S is the Skewness and K is the Kurtosis.

12. See for example Fung and Hsieh (1997, 2001) or Mitchell and Pulvino (2001).

13. An extensive bibliography on performance evaluation can be found on www.stern.nyu.edu/~sbrown/performance/bibliography.html.

14. Bookstaber and Clarke (1985) discuss the shortcomings of mean-variance analysis when used to evaluate the performance of optioned portfolios. Over the years there have been several at hoc attempts to solve this problem. Only recently, Leland (1999) has developed a skewness adjustment that has a sound theoretical basis in the early work of Rubinstein (1976).

15. Pelsser and Vorst (1996) analyse the effects of transaction costs in the binomial Dybvig (1988b) model.

16. Leland's adjustment is aimed at obtaining a zero expected hedging error as with positive transaction costs perfect replication not possible in a continuous time model. Strictly speaking, Leland's adjustment is only valid when gamma does not change sign, which need not be true in our case. If so, one should use the general result of Hoggard, Whalley and Wilmott (1994), which requires the solution of a non-linear parabolic PDE with the payoff function to be priced as a boundary condition. To avoid unnecessary complication, however, we decided for the Leland approximation.

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Table 1: Hedge Fund Classification

This table classifies the 77 individual hedge funds in our data set into different categories.

	Number of Hedge Funds		
Category	**Total**	**Onshore**	**Offshore**
Market neutral	11	11	0
Global	28	16	12
Event driven	15	11	4
Fund of funds	23	11	12

Table 2: Hedge Funds Index Return Characteristics

This table shows the mean, median, maximum, minimum, standard deviation (Std. Dev.), skewness, kurtosis and the results of the Jarque-Bera (1987) test calculated from the monthly returns of 13 hedge fund indices and the S&P 500 over the period May 1990 to April 2000. The hedge fund indices are: Event Driven (EVENT-DRIV), Event Driven: Distressed (EVENT DIST), Event Driven: Risk Arbitrage (EVENT RISK), Fund Of Funds (FUNDOFFUND), Fund Of Funds: Niche (FUND NICHE), Fund Of Funds: Diversified (FUND DIV), Global: Emerging (GL EMER), Global: Established (GL EST), Global: International (GL INTL), Global: Macro (GL MACRO), Market Neutral (MKT NEUTRAL), Market Neutral: Long/Short (MKT LONG), and Market Neutral: Arbitrage (MKT ARB).

	Mean (%)	Median (%)	Maximum (%)	Minimum (%)	Std. Dev. (%)	Skewness	Kurtosis	Jarque-Bera
S&P 500	1.4594	1.7237	12.0853	-11.1118	3.6460	-0.2373	1.0581	19.9825*
GL EST	1.5176	1.4950	9.4000	-9.4200	2.6817	-0.4860	5.2187	29.3373*
GL EMER	1.2913	1.0550	19.3300	-26.2500	4.9667	-1.0786	11.2347	362.3179*
MKT ARB	1.2417	1.1100	14.1300	-4.7800	2.1551	4.3819	27.2839	3332.556*
EVENT DIST	1.2068	1.3650	6.0500	-9.2200	2.1938	-0.9483	6.5708	81.7394*
GL MACRO	1.1863	0.6650	8.6100	-5.3600	2.1264	0.7830	4.8976	30.2674*
GL INTL	1.1669	1.3600	7.9200	-10.1500	2.0618	-1.1506	9.9069	265.003*
EVENT-DRIV	1.1162	1.1350	4.7400	-5.6100	1.2454	-1.3217	10.3978	308.5748*
EVENT RISK	1.0768	1.0750	4.6800	-6.9100	1.3404	-1.6370	12.6030	514.6788*
FUND DIV	0.9558	1.0000	6.1500	-6.4200	1.4860	-0.6267	8.4144	154.4364*
FUNDOFFUND	0.9130	0.8850	4.5000	-6.4000	1.3809	-1.1858	9.0826	213.1098*
MKTNEUTRAL	0.9124	0.9500	2.3400	-0.6100	0.4348	-0.0557	4.4526	10.6118**
FUND NICHE	0.8827	0.8750	5.9300	-5.8700	1.5453	-0.2789	7.0183	82.2909*
MKT LONG	0.8682	0.8500	2.7600	-1.0300	0.4962	0.3005	5.4686	32.2763*

* Significant at 1%
**Significant at 5%

Table 3: Hedge Fund Return Characteristics

This table shows the mean, median, maximum, minimum, standard deviation (Std. Dev.), skewness, kurtosis and the results of the Jarque-Bera (1987) test calculated from the monthly returns of 77 individual hedge funds over the period May 1990 to April 2000.

	Mean (%)	Median (%)	Maximum (%)	Minimum (%)	Std. Dev. (%)	Skewness	Kurtosis	Jarque-Bera
Fn1	0.5933	0.9150	6.5100	-11.1800	2.6989	-0.7992	5.2409	37.8824*
Fn2	0.8784	0.7050	14.3900	-8.2700	2.7496	0.5955	7.7702	120.8654*
Fn3	-0.6978	-1.0700	15.8100	-14.7600	4.8439	0.4884	3.8438	8.3304**
Fn4	1.3943	1.3600	10.6600	-6.6700	2.4832	0.5101	5.1797	28.9587*
Fn5	1.2974	1.0850	10.1300	-7.9200	3.0415	0.0899	4.0830	6.0264**
Fn6	1.1413	1.0300	8.1900	-4.8700	2.0201	0.4500	4.0559	9.6235*
Fn7	0.8883	0.7600	10.6200	-10.5200	3.1579	-0.2551	4.7090	15.9051*
Fn8	1.3908	1.4900	9.5000	-9.0000	3.0048	-0.3927	4.4835	14.0876*
Fn9	0.8415	0.7700	6.1700	-5.6700	1.8535	-0.2170	4.2361	8.582**
Fn10	1.4275	1.5750	13.0300	-11.4500	3.6041	-0.4645	5.2340	29.2678*
Fn11	1.1820	0.9800	11.4700	-6.2700	2.7268	0.6819	5.4211	38.6084*
Fn12	0.7214	0.2100	16.1900	-9.3600	3.9007	0.7146	4.8748	27.7875*
Fu1	0.7245	0.8700	4.8800	-7.1000	1.5926	-0.9484	7.1002	102.0488*
Fu2	1.0588	1.1100	4.9200	-6.6900	1.5827	-1.0051	6.8298	93.5441*
Fu3	0.7651	0.8500	3.6100	-7.9500	1.5220	-1.5462	10.7330	346.8139*
Fu4	0.6905	0.7400	4.3900	-3.1200	1.0517	0.3314	5.8627	43.1727*
Fu5	0.2459	0.3800	8.6600	-15.8100	2.9422	-1.1879	9.4512	236.3118*
Fu6	0.9288	0.8900	15.1400	-4.6600	1.9829	3.0112	24.5401	2501.224*
Fu7	1.1529	0.9650	8.8900	-4.4900	1.8369	0.4175	6.3395	59.2458*
Fu8	1.1983	1.3100	8.5100	-8.8100	2.7429	-0.1258	4.0595	5.9289
Fu9	0.6762	0.8750	2.2900	-6.0000	1.0669	-3.1553	17.4050	1236.648*
Fu10	1.1562	1.0250	12.0000	-7.0300	2.6788	0.7379	6.5696	74.598*
Fu11	0.7013	0.8750	2.2000	-6.4100	0.9871	-4.1730	26.8179	3184.744*
En1	1.0808	0.9700	9.8000	-7.4200	2.4373	-0.0252	6.3614	56.5061*
En2	2.1936	1.3850	49.5500	-34.1000	10.2818	0.6333	7.4691	107.8842*
En3	0.9460	0.8500	4.5600	-2.2700	1.0123	0.6133	6.1707	57.7875*
En4	1.0195	1.0300	5.2200	-2.8900	1.2443	0.4171	4.9168	21.8515*
Eu1	1.0246	1.0000	5.5000	-4.0000	1.3093	-0.6518	6.0132	53.8934*
Eu2	1.6062	1.4650	15.9000	-7.2900	3.3568	0.9318	6.4198	75.8389*
Eu3	1.2591	1.1950	8.4300	-5.4900	1.9104	-0.3399	6.0269	48.1202*
Eu4	1.2056	0.9450	8.2800	-7.1600	2.2449	0.0299	4.9321	18.6832*
Eu5	1.0508	1.0900	4.5500	-5.9400	1.5368	-1.2848	7.6501	141.1336*
Eu6	0.9640	0.8450	10.2800	-4.6500	2.0529	0.8605	6.8447	88.7153*
Eu7	1.1713	0.9150	14.2800	-8.3700	2.4594	0.8720	10.4106	289.7907*
Eu8	1.1957	1.0050	11.8800	-6.0100	2.9859	0.4543	3.8807	8.0048**
Eu9	1.2967	1.3500	7.2400	-6.4900	1.9080	-0.8082	6.0344	59.1009*
Eu10	1.4892	1.3850	16.5300	-7.6300	3.8640	0.4462	3.9347	8.3513**
Eu11	1.6796	1.6700	12.2000	-16.2800	3.7866	-0.6288	7.5396	110.948*
Gn1	1.8239	1.5150	18.7300	-9.2900	4.3069	0.7270	4.8635	27.9349*
Gn2	1.6083	2.0350	25.5100	-34.3900	7.2916	-0.8904	8.5983	172.5597*

Gn3	0.8155	0.4550	21.7000	-17.5400	5.1440	0.1257	5.8922	42.1388*
Gn4	1.4398	1.6650	13.3900	-17.0700	3.6883	-0.9493	7.7460	130.6454*
Gn5	1.6355	1.5600	21.4100	-10.9100	3.8282	1.0274	9.9821	264.8629*
Gn6	1.2909	1.6600	16.9900	-13.3700	4.5514	-0.2223	4.2144	8.3619**
Gn7	1.0066	1.2050	5.5100	-7.7100	1.6377	-1.6883	10.7421	356.704*
Gn8	1.9994	1.8650	17.4400	-21.1700	4.7655	-0.5472	8.7880	173.4955*
Gn9	1.2393	1.8200	9.2600	-12.3200	4.0185	-0.7035	3.8926	13.8819*
Gn10	0.7661	0.9800	12.2900	-17.8600	4.8589	-0.4113	4.1995	10.5768*
Gn11	0.7625	0.8550	6.7300	-8.9300	2.3672	-0.5541	4.6522	19.7887*
Gn12	1.1594	1.4000	14.5200	-11.9800	4.0177	-0.2112	4.0940	6.8758**
Gu1	1.2274	0.7800	18.4500	-22.0000	6.2050	-0.0399	4.1737	6.92**
Gu2	1.8898	1.0000	17.7000	-17.0000	5.8311	0.1245	3.4002	1.1107
Gu3	1.2838	1.2500	34.6800	-27.4100	9.4486	0.2024	5.1765	24.5046*
Gu4	1.8128	2.1100	22.2000	-13.2900	5.0111	0.1785	5.1926	24.6738*
Gu5	1.8949	1.6050	22.1000	-11.3300	5.0935	0.5766	4.5995	19.441*
Gu6	1.3473	1.5750	20.3300	-16.6500	5.1416	-0.2199	5.2588	26.4787*
Gu7	1.4451	1.6600	9.5300	-13.7500	3.9177	-0.6683	4.5415	20.8146*
Gu8	1.8539	1.6450	8.2000	-5.3000	2.7404	-0.0465	2.8179	0.2090
Gu9	1.5804	1.7150	12.9700	-13.7000	4.2395	-0.2814	3.8691	5.3605
Gu10	2.4195	2.1950	26.7000	-19.8400	6.4496	0.8487	7.2078	102.9321*
Gu11	1.1868	1.1700	6.2000	-5.7000	1.7049	-0.1619	5.0479	21.4936*
Gu12	1.7454	2.3000	17.6000	-14.3000	6.0593	-0.0487	3.1855	0.2195
Gu13	1.6736	1.9950	14.6600	-13.8300	5.1497	-0.1405	3.1844	0.5648
Gu14	1.4404	1.8100	25.7900	-16.4200	7.5175	-0.0069	3.4173	0.8715
Gu15	1.9435	1.5750	19.1000	-22.8700	4.9724	-0.4543	9.7516	232.0461*
Gu16	1.2165	1.3200	13.6400	-13.8500	4.8197	-0.2970	4.2707	9.8377*
Mu1	0.5749	0.8050	10.5800	-7.5700	2.8327	0.1525	3.5809	2.1523
Mu2	0.9262	0.9950	9.4500	-5.5400	2.4273	0.0675	3.9410	4.5182
Mu3	0.7092	0.8750	3.6200	-11.3900	1.8808	-4.4288	28.5829	3664.72*
Mu4	1.1640	1.5450	11.0000	-15.5200	4.3587	-0.9191	5.4121	45.9851*
Mu5	0.9301	1.0050	5.0900	-5.2000	1.3103	-1.0363	7.2130	110.2234*
Mu6	0.5477	0.5450	2.2400	-0.8200	0.5570	-0.0022	3.3785	0.7165
Mu7	1.4609	1.3850	5.1400	-3.6100	1.4913	-0.3443	3.8356	5.8625
Mu8	0.6696	0.8000	2.3400	-1.6900	0.6511	-1.0695	5.1554	46.1039*
Mu9	0.5120	0.5600	2.1400	-1.6600	0.5441	-0.9135	6.3785	73.7578*
Mu10	1.9438	1.4650	45.4600	-7.3900	5.6902	3.9535	30.3490	4052.437*
Mu11	1.7548	2.0250	18.2100	-19.6100	5.6526	-0.2537	4.3694	10.6634*

* Significant at 1%
**Significant at 5%

Table 4: Traditional Performance Measures Hedge Fund Indices

Columns 2 to 5 show the results from the regression $(R_h - R_f) = (1-\delta)\{\alpha_L + \beta_L (R_{S\&P} - R_f) + e\} + (\delta)\{\alpha_H + \beta_H (R_{S\&P} - R_f) + e\}$ and columns 6 to 8 show the results from the regression $(R_h - R_f) = \alpha + \beta(R_{S\&P} - R_f) + e_h$ estimated from the monthly returns of 13 hedge fund indices over the period May 1990 to April 2000. R_h and $R_{S\&P}$ denote the hedge fund index return and the S&P 500 return respectively. R_f denotes the short term USD interest rate (3-month USD LIBOR). The last column shows the funds' Sharpe ratios. The hedge fund indices are: Event Driven (EVENT-DRIV), Event Driven: Distressed (EVENT DIST), Event Driven: Risk Arbitrage (EVENT RISK), Fund Of Funds (FUNDOFFUND), Fund Of Funds: Niche (FUND NICHE), Fund Of Funds: Diversified (FUND DIV), Global: Emerging (GL EMER), Global: Established (GL EST), Global: International (GL INTL), Global: Macro (GL MACRO), Market Neutral (MKT NEUTRAL), Market Neutral: Long/Short (MKT LONG), and Market Neutral: Arbitrage (MKT ARB).

	Alpha Low (%)	Beta Low	Beta high	R^2	Alpha(%)	Beta	R^2	Sharpe Ratio
S&P 500	0.0000	1.0000*	1.0000*	1.0000	0.0000	1.0000*	1.0000	0.2796
MKT ARB	0.7875**	0.1278	-0.1839	0.0393	0.7443*	0.0481	0.0066	0.3720
GL EST	0.7738*	0.6678*	0.2688*	0.5252	0.5445*	0.5188*	0.4956	0.4018
EVENT RISK	0.9635*	0.3174*	-0.0112	0.2412	0.5357*	0.1303*	0.1389	0.4751
GL MACRO	0.8118*	0.4083*	0.0009	0.2077	0.4998*	0.2353*	0.1598	0.3510
EVENT-DRIV	0.9544*	0.3678*	-0.0094	0.2870	0.4713*	0.1552*	0.1710	0.5429
EVENT DIST	0.9326*	0.5476*	-0.0210	0.3281	0.4591*	0.2958*	0.2393	0.3495
GL INTL	0.8994*	0.4752*	0.0685	0.2727	0.4501*	0.2652*	0.2180	0.3526
MKTNEUTRAL	0.5718*	0.0861*	0.0081	0.1257	0.4319*	0.0314*	0.0640	1.0865
MKT LONG	0.4017*	0.0353	0.0208	0.0493	0.3901*	0.0291*	0.0481	0.8629
FUND DIV	0.7706*	0.3600*	0.0674	0.2517	0.3283*	0.1768*	0.1856	0.3471
FUNDOFFUND	0.7955*	0.3628*	0.0742	0.2718	0.2971*	0.1654*	0.1869	0.3425
FUND NICHE	0.6815*	0.3343*	0.1902**	0.2308	0.2464	0.1855*	0.1893	0.2865
GL EMER	1.5746**	1.1472*	0.5228**	0.2619	0.1965	0.6392*	0.2183	0.1714

* Significant at 1%
**Significant at 5%

Table 5: Traditional Performance Measures Hedge Funds

Columns 2 to 5 show the results from the regression $(R_h - R_f) = (1-\delta)\{\alpha_L + \beta_L(R_{S\&P} - R_f) + e\} + (\delta)\{\alpha_H + \beta_H(R_{S\&P} - R_f) + e\}$ and columns 6 to 8 show the results from the regression $(R_h - R_f) = \alpha + \beta(R_{S\&P} - R_f) + e_h$ estimated from the monthly returns of 77 individual hedge funds over the period May 1990 to April 2000. R_h and $R_{S\&P}$ denote the hedge fund return and the S&P 500 return respectively. R_f denotes the short term USD interest rate (3-month USD LIBOR). The last column shows the funds' Sharpe ratios.

	Alpha Low (%)	Beta Low	Beta high	R^2	Alpha(%)	Beta	R^2	**Sharpe Ratio**
Fn1	0.4974	0.4438*	-0.0913	0.1130	-0.0396	0.1822*	0.0597	0.0568
Fn2	0.4415	0.4051*	0.0797	0.1367	0.1670	0.2599*	0.1181	0.1594
Fn3	0.1532	-0.9439*	-0.3256	0.5111	-0.2256	-0.9112	0.4695	-0.2349
Fn4	1.4648*	0.3523*	-0.1221	0.0697	0.8592*	0.0854	0.0154	0.3843
Fn5	1.1291*	0.6341*	0.1644	0.2211	0.4866	0.3583*	0.1833	0.2819
Fn6	0.7662*	-0.0346	0.0006	0.0054	0.7297*	-0.0367	0.0044	0.3472
Fn7	0.8415	0.4814*	0.0074	0.0936	0.2255	0.2117*	0.0592	0.1419
Fn8	0.9521*	0.6602*	0.1114	0.3061	0.5151**	0.4225*	0.2619	0.3164
Fn9	0.5272	0.1888**	0.1233	0.0541	0.2830	0.1086*	0.0450	0.2166
Fn10	0.8801**	0.8707*	0.5245*	0.4422	0.3262	0.6457*	0.4254	0.2740
Fn11	0.4156	0.4473*	0.1834	0.2630	0.3557	0.3736*	0.2489	0.2721
Fn12	1.0561	0.1279	0.1615	0.0279	0.3331	-0.0598	0.0031	0.0721
Fu1	0.7287*	0.4171*	0.0471	0.2511	0.1056	0.1683*	0.1476	0.1786
Fu2	1.0596*	0.2751*	-0.0565	0.0981	0.5449*	0.0645	0.0217	0.3910
Fu3	0.7921*	0.4667*	0.1557**	0.3683	0.1015	0.2125*	0.2537	0.2136
Fu4	0.3759**	0.1053	0.0419	0.0385	0.1979**	0.0434	0.0230	0.2382
Fu5	-0.0914	0.2763	0.3270	0.0725	-0.4072	0.2022*	0.0625	-0.0660
Fu6	0.7645*	0.2751*	-0.0605	0.0725	0.3806**	0.0983	0.0321	0.2465
Fu7	1.2294*	0.4076*	-0.1070	0.1698	0.5822*	0.1207*	0.0554	0.3881
Fu8	0.8469*	0.6852*	0.1539	0.3703	0.3183	0.4266*	0.3192	0.2764
Fu9	0.5368*	0.2698*	-0.0420	0.2286	0.1335	0.0929*	0.0994	0.2213
Fu10	0.5220	0.4546*	0.0983	0.2329	0.3684	0.3354*	0.2083	0.2674
Fu11	0.3993*	0.1365*	-0.0624	0.0807	0.2101**	0.0420	0.0245	0.2647
En1	0.6661	0.3904*	-0.2260	0.1731	0.4362	0.1938*	0.0833	0.2629
En2	-0.1616	0.8812	0.0357	0.1381	0.7832	0.9515*	0.1135	0.1706
En3	0.347**	0.0817	0.0588	0.1122	0.4043*	0.0919*	0.1080	0.4998
En4	0.8228*	0.1429**	0.0373	0.0422	0.5296*	0.0407	0.0137	0.4657
Eu1	0.9779*	0.1992*	-0.0950	0.0858	0.5547*	0.0209	0.0033	0.4465
Eu2	1.3789*	0.4387*	-0.1333	0.0848	0.9556*	0.1997*	0.0466	0.3474
Eu3	1.35122*	0.4116*	-0.1001	0.1581	0.6881*	0.1211*	0.0516	0.4288
Eu4	1.4955*	0.4479*	-0.1489	0.1338	0.6628*	0.0930	0.0223	0.3410
Eu5	1.1449*	0.3555*	-0.0843	0.1727	0.5122*	0.0888**	0.0426	0.3974
Eu6	0.8845*	0.2517*	-0.1537	0.0606	0.4647*	0.0500	0.0077	0.2552
Eu7	1.1392*	0.5245*	-0.0675	0.1858	0.4978**	0.2223*	0.1061	0.2973
Eu8	0.9617**	0.4284*	0.1639	0.1053	0.4985	0.2458*	0.0895	0.2531
Eu9	0.8741*	0.3089*	0.1661	0.1724	0.6329*	0.2127*	0.1618	0.4490
Eu10	0.9259	0.4709*	-0.0609	0.1076	0.7341**	0.3031*	0.0809	0.2715

Eu11	2.5068*	0.7783*	-0.0659	0.1354	1.0324*	0.1963**	0.0356	0.3274
Gn1	1.2848	-0.1987	0.5421**	0.0463	1.3852*	-0.0099	0.0001	0.3213
Gn2	2.5596**	1.0791*	-0.0337	0.0743	0.7954	0.3603**	0.0323	0.1602
Gn3	0.9687	0.8609*	0.0940	0.1216	-0.0551	0.4174*	0.0870	0.0730
Gn4	0.7008	0.9476*	0.4571*	0.5275	0.2613	0.7221*	0.5040	0.2711
Gn5	1.1525*	0.6051*	0.1801	0.1669	0.7725**	0.4098*	0.1505	0.3123
Gn6	-0.0799	0.9591*	0.7013*	0.5359	-0.0610	0.9079*	0.5302	0.1870
Gn7	0.8514*	0.2892*	0.1462	0.1330	0.4158*	0.1405*	0.0962	0.3460
Gn8	1.8292*	0.8524*	0.1145	0.1702	1.0613*	0.4842*	0.1369	0.3272
Gn9	0.9412	0.0577	-0.2517	0.0181	0.4588	-0.1400	0.0109	0.1989
Gn10	0.3757	-0.0382	-0.0069	0.0039	0.3519	-0.0378	0.0034	0.0671
Gn11	0.6088	0.0993	-0.5055	0.0427	0.7148	-0.0041	0.0000	0.1362
Gn12	1.4743**	1.1955*	0.4096	0.2953	0.1059	0.6548*	0.2426	0.1791
Gu1	-0.3825	-0.0452	0.4157	0.0410	0.4859	0.2896	0.0289	0.1269
Gu2	1.3104	0.6678**	-0.2165	0.0956	1.0360	0.4008*	0.0624	0.2486
Gu3	1.4046	1.3251*	1.2795*	0.1393	-0.0874	0.9126*	0.1233	0.0893
Gu4	1.3207	1.0098*	-0.0062	0.2636	0.7289	0.6284*	0.2085	0.2739
Gu5	0.8372	0.7141*	0.2689	0.2057	0.8257	0.6139*	0.1929	0.2856
Gu6	0.0997	0.9911*	0.4255	0.3828	0.0384	0.8511*	0.3635	0.1765
Gu7	0.8253	0.8766*	0.2952	0.3665	0.3643	0.6254*	0.3373	0.2566
Gu8	1.1787*	0.6084*	0.2492	0.4030	0.9358*	0.4645*	0.3802	0.5159
Gu9	1.8978*	1.1732*	0.0981	0.3371	0.5504	0.5751*	0.2415	0.2690
Gu10	2.9926*	0.8372*	0.1214	0.0592	1.6489*	0.3185**	0.0322	0.3069
Gu11	1.1433*	0.2704*	0.1892	0.1121	0.6242*	0.1121*	0.0592	0.4381
Gu12	-0.3901	0.9512*	0.6803*	0.4182	0.2268	1.0585*	0.4033	0.2154
Gu13	0.2601	1.0153*	0.8336*	0.4725	0.2433	0.9711*	0.4705	0.2395
Gu14	-0.0779	0.9676*	0.3730	0.1963	0.0972	0.8851*	0.1835	0.1331
Gu15	1.7415*	0.8532*	0.0900	0.1593	1.0023**	0.4872*	0.1272	0.3024
Gu16	0.7955	1.0534*	0.5309*	0.4720	0.0456	0.7371*	0.4442	0.1611
Mu1	-0.5262	-0.1666	-0.0662	0.0283	0.1013	0.0246	0.0010	0.0476
Mu2	0.1267	0.4256*	0.2972*	0.3400	0.0865	0.3868*	0.3360	0.2003
Mu3	0.4404	0.1307	-0.3866	0.1105	0.2848	-0.0241	0.0022	0.1431
Mu4	0.5986	0.6455*	0.1508	0.1552	0.2634	0.4471*	0.1383	0.1661
Mu5	0.8173*	0.2441*	0.0793	0.1222	0.3881*	0.0923*	0.0650	0.3740
Mu6	0.0492	0.0575**	0.0355	0.1282	0.0464	0.0519*	0.1256	0.1933
Mu7	0.8514*	0.0628	0.1924**	0.0778	0.9054*	0.1056*	0.0672	0.6846
Mu8	0.2445*	0.0723**	-0.0559	0.0813	0.1907*	0.0298	0.0276	0.3526
Mu9	0.1105	0.0573**	0.0257	0.0510	0.0333	0.0296**	0.0398	0.1323
Mu10	1.4804	-0.0877	-0.4273	0.0142	1.6204*	-0.1241	0.0063	0.2643
Mu11	1.1987	1.2000*	0.6163**	0.3263	0.4312	0.8656*	0.3099	0.2326

* Significant at 1%
**Significant at 5%

Table 6: Mutual Fund Return Characteristics

This table shows the mean, median, maximum, minimum, standard deviation (Std. Dev.), skewness, kurtosis and the results of the Jarque-Bera (1987) test calculated from the monthly returns of 33 UK mutual funds and the FTSE All Share Index over the period May 1990 to April 2000.

	Mean (%)	Median (%)	Maximum (%)	Minimum (%)	Std. Dev. (%)	Skewness	Kurtosis	Jarque-Bera
FTSE	1.1562	1.5941	11.4864	-12.4810	4.2353	-0.2178	0.8303	25.6326*
MF1	0.5745	1.1302	12.7233	-13.3911	4.3836	-0.2897	3.9243	5.9511
MF2	0.8026	1.3320	12.2707	-10.3896	4.1582	-0.1731	3.4915	1.8073
MF3	0.4794	0.8890	10.2739	-15.2461	4.2257	-0.6299	4.5019	19.2148*
MF4	0.5299	0.4993	10.4709	-13.0031	4.2672	-0.3881	3.6079	4.8603
MF5	0.7569	1.5103	14.3133	-13.9257	4.8427	-0.3488	3.5904	4.1762
MF6	0.7468	1.0550	11.6782	-13.1010	4.1842	-0.2811	3.6722	3.8393
MF7	0.8249	1.2540	11.7698	-12.9874	4.2079	-0.3671	3.6678	4.9249
MF8	0.8037	1.0732	11.3461	-12.8029	4.0983	-0.2694	3.8377	4.9594
MF9	0.5354	0.4681	12.6339	-10.9871	4.0761	-0.1454	3.8485	4.0222
MF10	0.6085	1.1117	13.8119	-10.5344	4.3701	-0.1244	3.4038	1.1249
MF11	0.6322	0.8121	12.9542	-12.3969	4.3168	-0.2991	3.4746	2.9150
MF12	0.7729	1.1869	10.5244	-13.5461	4.0775	-0.3647	3.7710	5.6300
MF13	0.6838	1.4265	13.6269	-15.7035	4.6659	-0.5251	4.4027	15.3524*
MF14	0.6635	1.1664	14.4597	-13.9048	4.4133	-0.1802	4.3899	10.3079*
MF15	0.8459	1.1644	11.7663	-11.8766	4.2416	-0.2090	3.3811	1.6002
MF16	0.4246	0.3225	14.7797	-12.0566	4.4995	0.0205	3.9710	4.7228
MF17	0.6157	0.9603	14.9940	-13.7875	4.5426	-0.2847	4.2019	8.8432**
MF18	0.6087	0.7218	11.5153	-12.8073	4.3318	-0.2684	3.5857	3.1566
MF19	0.9896	1.0429	12.6770	-12.9176	4.2797	-0.2725	3.8023	4.7037
MF20	0.9279	0.7066	10.9037	-11.9453	4.1386	-0.2395	3.6080	2.9959
MF21	0.7737	0.4598	12.0205	-10.6270	4.1913	-0.0772	3.5167	1.4541
MF22	0.9293	1.4364	12.4897	-11.6977	4.3306	-0.2201	3.4777	2.1103
MF23	0.4869	0.5591	13.9987	-16.4805	5.2136	-0.1663	3.6460	2.6394
MF24	0.5143	0.8602	13.8657	-12.5495	4.5755	-0.0576	3.6515	2.1886
MF25	0.4896	0.5974	12.0121	-15.0977	3.9863	-0.3407	4.5646	14.5618*
MF26	0.5846	0.8970	13.2891	-11.0688	4.1092	-0.0859	3.6894	2.5240
MF27	0.8935	1.2749	11.5186	-15.3807	4.2076	-0.5598	4.5381	18.0955*
MF28	0.6046	0.2985	12.4691	-13.7668	4.2162	-0.0226	4.4789	10.9455*
MF29	0.9102	1.1144	11.3475	-13.3193	4.1368	-0.4326	3.8380	7.2544**
MF30	0.6454	0.9014	12.0697	-13.2273	4.1799	-0.4488	3.9493	8.5347**
MF31	1.1268	1.3145	10.5015	-12.1687	3.9147	-0.4185	3.9172	7.7079**
MF32	0.6102	0.8846	12.2111	-12.5849	4.3999	-0.3751	3.6065	4.6530
MF33	1.0742	1.4946	11.3572	-10.4444	4.0288	-0.2752	3.8737	5.3320

* Significant at 1%
**Significant at 5%

Table 7: Mutual Fund Efficiency

This table shows the monthly and annual (monthly times 12) efficiency loss of 33 UK mutual funds based on monthly return data from May 1990 to April 2000. The alphas in the last column were obtained by running the regression $(R_h - R_f) = \alpha + \beta(R_{S\&P} - R_f) + e_h$ on the monthly returns of the 33 funds over the period May 1990 to April 2000. R_h and $R_{S\&P}$ are the mutual fund return and the FTSE All Share Index return respectively. R_f is the short term GBP interest rate (1 month T-Bill mid rate) .

	Efficiency Monthly	Efficiency Yearly	Alpha (%)
MF1	-1.2624	-15.1486	-0.2340
MF2	-1.0436	-12.5231	-0.0043
MF3	-1.3211	-15.8535	-0.1669
MF4	-1.3146	-15.7751	-0.1444
MF5	-1.1366	-13.6398	-0.1000
MF6	-1.0722	-12.8668	-0.0281
MF7	-1.0033	-12.0397	0.0659
MF8	-0.9057	-10.8685	-0.0898
MF9	-1.1786	-14.1437	-0.1123
MF10	-1.2462	-14.9546	-0.0361
MF11	-1.1598	-13.9179	0.3024
MF12	-0.8496	-10.1955	-0.0243
MF13	-0.9287	-11.1438	-0.1510
MF14	-1.4284	-17.1411	0.0174
MF15	-1.3675	-16.4098	-0.0250
MF16	-1.2869	-15.4428	-0.1733
MF17	-1.2598	-15.1173	-0.0291
MF18	-1.2178	-14.6142	-0.1703
MF19	-0.7778	-9.3341	0.1920
MF20	-1.0326	-12.3915	0.1588
MF21	-1.1633	-13.9593	0.2040
MF22	-1.0012	-12.0143	0.2479
MF23	-1.4420	-17.3045	-0.1122
MF24	-1.2387	-14.8650	-0.0756
MF25	-0.7454	-8.9449	-0.2098
MF26	-1.0009	-12.0108	-0.2244
MF27	-1.1923	-14.3081	0.2772
MF28	-1.2336	-14.8038	-0.1635
MF29	-0.6740	-8.0883	0.1892
MF30	-0.9265	-11.1175	-0.0533
MF31	-1.0763	-12.9150	0.3301
MF32	-1.28006	-15.3607	-0.1056
MF33	-1.24169	-14.9003	0.3252

Table 8: Hedge Fund Index Efficiency

This table shows the monthly and annual (monthly times 12) efficiency loss (-) or gain (+) of 13 hedge fund indices based on monthly return data from May 1990 to April 2000. The fourth column shows how high/low implied volatility needs to be for the value of the indices' payoff distribution to reach 100. DNT 100 stands for 'does not touch 100'. The last column shows the correlation between the actual hedge fund index return and the return calculated from the payoff function resulting from the efficiency test.

	Efficiency Monthly	Efficiency Yearly	Volatility	Correlation
EVENT DIST	-0.2390	-2.8685	DNT 100*	0.4920
EVENT RISK	-0.0930	-1.1157	0.19	0.3777
EVENT-DRIV	-0.1401	-1.6807	DNT 100*	0.3862
FUND DIV	-0.3051	-3.6614	DNT 100*	0.4515
FUND NICHE	-0.4063	-4.8756	DNT 100*	0.5011
FUNDOFFUND	-0.3269	-3.9225	0.05*	0.4784
GL EMER	-0.6056	-7.2672	0.09*	0.4893
GL EST	-0.0616	-0.7388	0.19	0.6844
GL INTL	-0.2070	-2.4846	0.16	0.4669
GL MACRO	-0.2528	-3.0333	0.18	0.4308
MKT ARB	0.0115	0.1380	0.29*	-0.0777
MKT LONG	-0.2070	-2.4836	DNT 100*	0.3045
MKTNEUTRAL	-0.1549	-1.8591	DNT 100*	0.3574

* Inverse relationship between implied volatility and value payoff distribution

Table 9: Hedge fund Efficiency

This table shows the monthly and annual (monthly times 12) efficiency loss (-) or gain (+) of 77 hedge funds based on monthly return data from May 1990 to April 2000. The fourth column shows how high/low implied volatility needs to be for the value of the funds' payoff distribution to reach 100. DNT 100 stands for 'does not touch 100'. The last column shows the correlation between the actual hedge fund return and the return calculated from the payoff function resulting from the efficiency test.

	Efficiency Monthly	Efficiency Yearly	Volatility	Correlation
Fn1	-0.9840	-11.8074	DNT 100*	0.4435
Fn2	-0.7049	-8.4584	0.16	0.4153
Fn3	-2.7927	-33.5125	DNT 100*	-0.5951
Fn4	-0.1304	-1.5647	0.25	0.1724
Fn5	-0.3987	-4.7847	0.21	0.4908
Fn6	-0.3002	-3.6023	0.18	0.0151
Fn7	-0.8157	-9.7881	DNT 100*	0.3042
Fn8	-0.2929	-3.5152	0.04*	0.5820
Fn9	-0.5609	-6.7306	DNT 100*	0.2205
Fn10	-0.3931	-4.7176	0.10*	0.6916
Fn11	-0.4212	-5.0544	0.08*	0.4894
Fn12	-1.1641	-13.9695	0.20	0.0248
Fu1	-0.5775	-6.9299	0.06*	0.4234
Fu2	-0.2515	-3.0182	0.08*	0.2115
Fu3	-0.4949	-5.9387	0.11*	0.5405
Fu4	-0.5006	-6.0076	0.20	0.2435
Fu5	-1.2919	-15.5024	DNT 100*	0.2624
Fu6	-0.4141	-4.9686	0.21	0.0907
Fu7	-0.2315	-2.7776	0.15	0.2026
Fu8	-0.4048	-4.8574	0.17	0.6398
Fu9	-0.4682	-5.6178	0.08*	0.5076
Fu10	-0.4120	-4.9446	0.17	0.4251
Fu11	-0.3955	-4.7463	0.04*	0.3947
En1	-0.4239	-5.0871	0.15	0.2456
En2	-0.9454	-11.3449	0.14	0.3573
En3	-0.2356	-2.8266	0.17	0.2631
En4	-0.2334	-2.8010	0.19	0.1958
Eu1	-0.2321	-2.7851	0.03*	0.1767
Eu2	-0.1170	-1.4041	0.20	0.2006
Eu3	-0.1477	-1.7720	0.18	0.2336
Eu4	-0.2591	-3.1087	0.17	0.1186
Eu5	-0.2434	-2.9212	0.08*	0.2688
Eu6	-0.4693	-5.6319	0.19	0.0338
Eu7	-0.2975	-3.5697	0.16	0.2753
Eu8	-0.5079	-6.0954	0.19	0.2638
Eu9	-0.1032	-1.2385	0.11*	0.3701
Eu10	-0.4479	-5.3747	0.18	0.2578
Eu11	-0.0417	-0.4999	0.25	0.2943
Gn1	-0.1712	-2.0539	0.15	0.0498

Gn2	-0.8433	-10.1198	0.05*	0.2038
Gn3	-1.3025	-15.6298	0.21	0.2625
Gn4	-0.3043	-3.6516	0.09*	0.6148
Gn5	-0.1279	-1.5353	0.15	0.3052
Gn6	-0.7908	-9.4891	0.18	0.6693
Gn7	-0.2823	-3.3880	0.19	0.2816
Gn8	0.1078	1.2936	0.29*	0.2938
Gn9	-0.7203	-8.6432	0.04*	-0.0491
Gn10	-1.3222	-15.8663	DNT 100*	-0.0544
Gn11	-0.7490	-8.9879	DNT 100*	0.1530
Gn12	-0.7858	-9.4294	DNT 100*	0.4642
Gu1	-1.1431	-13.7170	0.17	0.1235
Gu2	-0.4657	-5.5885	0.13	0.3828
Gu3	-1.8642	-22.3700	0.23	0.3737
Gu4	-0.3545	-4.2534	0.15	0.4390
Gu5	-0.3068	-3.6816	0.16	0.4092
Gu6	-0.8287	-9.9442	0.21	0.6025
Gu7	-0.4436	-5.3228	0.05*	0.5553
Gu8	0.1821	2.1847	DNT 100	0.6250
Gu9	-0.3932	-4.7188	0.18	0.4788
Gu10	0.1338	1.6055	DNT 100	0.2257
Gu11	-0.1577	-1.8923	0.06*	0.2122
Gu12	-0.7378	-8.8535	0.18	0.6012
Gu13	-0.5717	-6.8602	0.03*	0.6670
Gu14	-1.4385	-17.2618	0.25	0.4052
Gu15	0.0663	0.7961	0.28*	0.2756
Gu16	-0.9163	-10.9957	DNT 100*	0.6500
Mu1	-1.0849	-13.0194	0.24	0.1472
Mu2	-0.6414	-7.6970	0.16	0.5719
Mu3	-0.5011	-6.0134	0.11*	0.2817
Mu4	-0.8331	-9.9971	0.05*	0.3104
Mu5	-0.3178	-3.8130	0.25	0.1512
Mu6	-0.5571	-6.6852	0.19	0.4362
Mu7	0.1296	1.5556	0.45*	0.1458
Mu8	-0.4443	-5.3320	0.15	0.2888
Mu9	-0.5728	-6.8739	0.07*	0.2009
Mu10	-0.1848	-2.2178	0.20	-0.0469
Mu11	-0.5314	-6.3766	0.02*	0.4886

* Inverse relationship between implied volatility and value payoff distribution

Table 10: Hedge Fund Efficiency: Summary

This table summarizes the efficiency test results on hedge fund indices and individual hedge funds. With regards to the latter we distinguish between the following categories: Fund of Funds (FOF), Non-Fund of Funds (Non FOF), Global, Market Neutral, Event Driven, Offshore and US Based.

	Overall			Efficient			Inefficient		
	No.	Avg. Monthly	Avg. Yearly	No.	Avg. Monthly	Avg. Yearly	No.	Avg. Monthly	Avg. Yearly
Indices	13	-0.2298	-2.7579	1	0.0115	0.1380	12	-0.2499	-2.9992
FOF Indices	3	-0.3461	-4.1532	0	-	-	3	-0.3461	-4.1532
Non FOF Indices	10	-0.1949	-2.3393	1	0.0115	0.1380	9	-0.2179	-2.6146
Individual Funds	77	-0.5348	-6.4171	5	0.1239	1.4871	72	-0.5805	-6.9660
FOF	23	-0.6261	-7.5137	0	-	-	23	-0.6261	-7.5137
Non FOF	54	-0.49584	-5.9501	5	0.123923	1.48708	49	-0.55908	-6.7088
Global	28	-0.5904	-7.0848	4	0.1225	1.4700	24	-0.7092	-8.5106
Market Neutral	11	-0.5036	-6.0427	1	0.1296	1.5556	10	-0.5669	-6.8025
Event Driven	15	-0.3137	-3.7641	0	-	-	15	-0.3137	-3.7641
Offshore	28	-0.6460	-7.7523	1	0.1078	1.2936	27	-0.6739	-8.0874
US Based	49	-0.4712	-5.6542	4	0.1280	1.5354	45	-0.5244	-6.2932

Table 11: Hedge Funds Index Portfolio Efficiency

This table shows the efficiency test results on portfolios constructed by investing in varying proportions in the hedge fund indices and the S&P 500. The second column shows the correlation between hedge fund index returns and S&P 500 returns. Column 3 shows the maximum efficiency level achieved. Column 4 gives the percentage to be invested in the S&P 500 to obtain that maximum efficiency level. The last column gives the improvement in efficiency relative to the stand-alone result as reported in table 8.

	Correlation with S&P 500	Maximum Efficiency	Investment in S&P 500	Improvement in Efficiency
EVENT DIST	0.4918	0.2790	79%	3.1474
EVENT RISK	0.3795	0.3142	81%	1.4299
EVENT-DRIV	0.4200	0.1936	78%	1.8743
FUND DIV	0.4358	0.0000	100%	3.6614
FUND NICHE	0.4398	0.0000	100%	4.8756
FUNDOFFUND	0.4381	0.0000	100%	3.9225
GL EMER	0.4663	0.3844	83%	7.6517
GL EST	0.7056	0.7331	82%	1.4718
GL INTL	0.4699	0.3475	81%	2.8321
GL MACRO	0.4017	0.1363	78%	3.1696
MKT ARB	0.0850	0.6032	77%	0.4652
MKT LONG	0.2342	0.0000	100%	2.4836
MKTNEUTRAL	0.2777	0.0000	100%	1.8591

Table 12: Hedge Fund Portfolio Efficiency

This table shows the efficiency test results on portfolios constructed by investing in varying proportions in the hedge funds and the S&P 500. The second column shows the correlation between hedge fund returns and S&P 500 returns. Column 3 shows the maximum efficiency level achieved. Column 4 gives the percentage to be invested in the S&P 500 to obtain that maximum efficiency level. The last column gives the improvement in efficiency relative to the stand-alone result as reported in table 9.

	Correlation with S&P 500	Maximum Efficiency	Investment in S&P 500	Improvement in Efficiency
Fn1	0.2449	0.0000	100%	11.8074
Fn2	0.3460	0.1234	96%	8.5818
Fn3	-0.6787	0.0000	100%	33.5125
Fn4	0.1224	1.0053	80%	2.5700
Fn5	0.4297	0.3420	82%	5.1266
Fn6	-0.0621	0.3866	78%	3.9889
Fn7	0.2444	0.0000	100%	9.7881
Fn8	0.5136	0.4878	78%	4.0030
Fn9	0.2152	0.0000	100%	6.7306
Fn10	0.6534	0.3004	78%	5.0180
Fn11	0.5013	0.4012	96%	5.4556
Fn12	-0.0519	0.0000	100%	13.9695
Fu1	0.3888	0.3024	96%	7.2323
Fu2	0.1502	0.2912	81%	3.3093
Fu3	0.5090	0.0000	100%	5.9387
Fu4	0.1609	0.0000	100%	6.0076
Fu5	0.2523	0.0000	100%	15.5024
Fu6	0.1807	0.0000	100%	4.9686
Fu7	0.2356	0.3282	78%	3.1058
Fu8	0.5666	0.2191	96%	5.0765
Fu9	0.3230	0.1163	98%	5.7341
Fu10	0.4592	0.0953	89%	5.0399
Fu11	0.1666	0.0000	100%	5.2981
En1	0.2906	0.0555	94%	5.1426
En2	0.3387	0.7931	89%	12.1379
En3	0.3370	0.2285	97%	3.0551
En4	0.1198	0.0938	82%	2.8948
Eu1	0.0630	0.2149	76%	3.0000
Eu2	0.2164	1.3597	78%	2.7637
Eu3	0.2268	0.6177	80%	2.3897
Eu4	0.1483	0.4611	78%	3.5698
Eu5	0.2075	0.1318	93%	3.0530
Eu6	0.0877	0.0516	91%	5.6835
Eu7	0.3253	0.1987	80%	3.7684
Eu8	0.3012	0.2290	79%	6.3244
Eu9	0.4049	0.6641	80%	1.9026
Eu10	0.2838	0.9104	78%	6.2850
Eu11	0.1916	1.8296	78%	2.3295
Gn1	-0.0067	1.9820	77%	4.0360
Gn2	0.1805	0.5607	90%	10.6805

Gn3	0.2953	0.0000	100%	15.6298
Gn4	0.7097	0.3487	89%	4.0003
Gn5	0.3869	1.0281	78%	2.5634
Gn6	0.7269	0.1217	96%	9.6108
Gn7	0.3139	0.1911	96%	3.5790
Gn8	0.3722	2.2509	79%	0.9573
Gn9	-0.1058	0.2729	96%	16.1392
Gn10	-0.0555	0.1805	96%	9.1684
Gn11	-0.0015	0.3810	96%	9.8104
Gn12	0.4905	0.0000	100%	10.9957
Gu1	0.1717	0.4147	96%	14.1317
Gu2	0.2503	1.2430	76%	6.8315
Gu3	0.3500	0.0000	100%	22.37
Gu4	0.4583	1.1370	82%	5.3904
Gu5	0.4418	1.3494	81%	5.0310
Gu6	0.6044	0.0000	100%	9.9442
Gu7	0.5818	0.4580	76%	5.7808
Gu8	0.6184	2.1847	0%	0.0000
Gu9	0.4896	0.7908	79%	5.5096
Gu10	0.1796	2.8748	78%	1.2693
Gu11	0.2506	0.4995	74%	2.3918
Gu12	0.6345	0.3215	90%	9.1750
Gu13	0.6861	0.4677	89%	7.3278
Gu14	0.4294	0.5209	96%	17.7827
Gu15	0.3585	2.1840	77%	1.3879
Gu16	0.6667	0.1512	96%	8.7944
Mu1	0.0358	0.1888	97%	13.2081
Mu2	0.5819	0.2436	96%	7.9406
Mu3	-0.0451	0.3093	96%	6.3227
Mu4	0.3703	0.3604	96%	10.3574
Mu5	0.2606	0.1798	96%	3.9928
Mu6	0.3609	0.3956	96%	7.0808
Mu7	0.2654	1.8706	15%	0.3150
Mu8	0.1795	0.5204	96%	5.8525
Mu9	0.2150	0.2867	96%	7.1607
Mu10	-0.0755	2.1405	78%	4.3582
Mu11	0.5565	0.8625	76%	7.2390

Figure 1: Normality Plots

This figure shows normality plots for four hedge fund indices (Global Macro, Event Driven, Fund of Funds and Market Neutral) and two individual hedge funds based on monthly returns from May 1990 to April 2000. In the plot, the curve shows the distribution of the actual return data, while the straight line shows how the distribution would have been if it were normal.

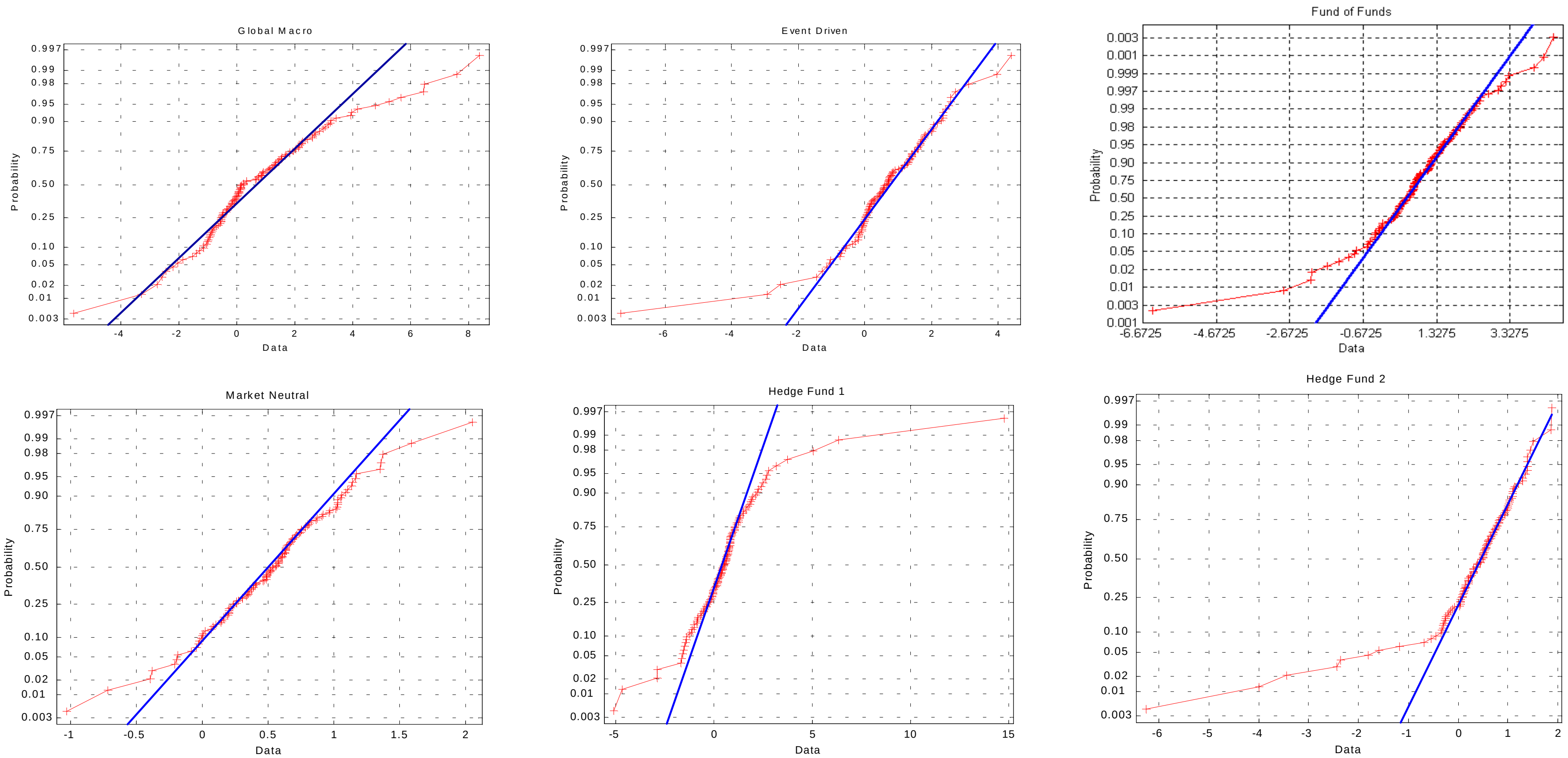

Figure 2: Mean-Standard Deviation Plot

This figure plots the 13 hedge fund indices as well as some other market indices into mean-standard deviation space. All parameter estimates are based on monthly return data from May 1990 to April 2000. The hedge fund indices are: Event Driven (EDRI), Event Driven: Distressed (EDSec), Event Driven: Risk Arbitrage (Erarb), Fund Of Funds (FF), Fund Of Funds: Niche (FFNic), Fund Of Funds: Diversified (FFDiv), Global: Emerging (GLEmer), Global: Established (GLEst), Global: International (GLInt), Global: Macro (Mac), Market Neutral (MkNeu), Market Neutral: Long/Short (MNL/S) and Market Neutral: Arbitrage (MNStAr). The other indices are: S&P 500 (S&P), Nasdaq (NASDq), Russell 2000 (Rus 2000), Morgan Stanley World index excluding US (WorldIdxUS), and Goldman Sachs Commodities index (Comm).

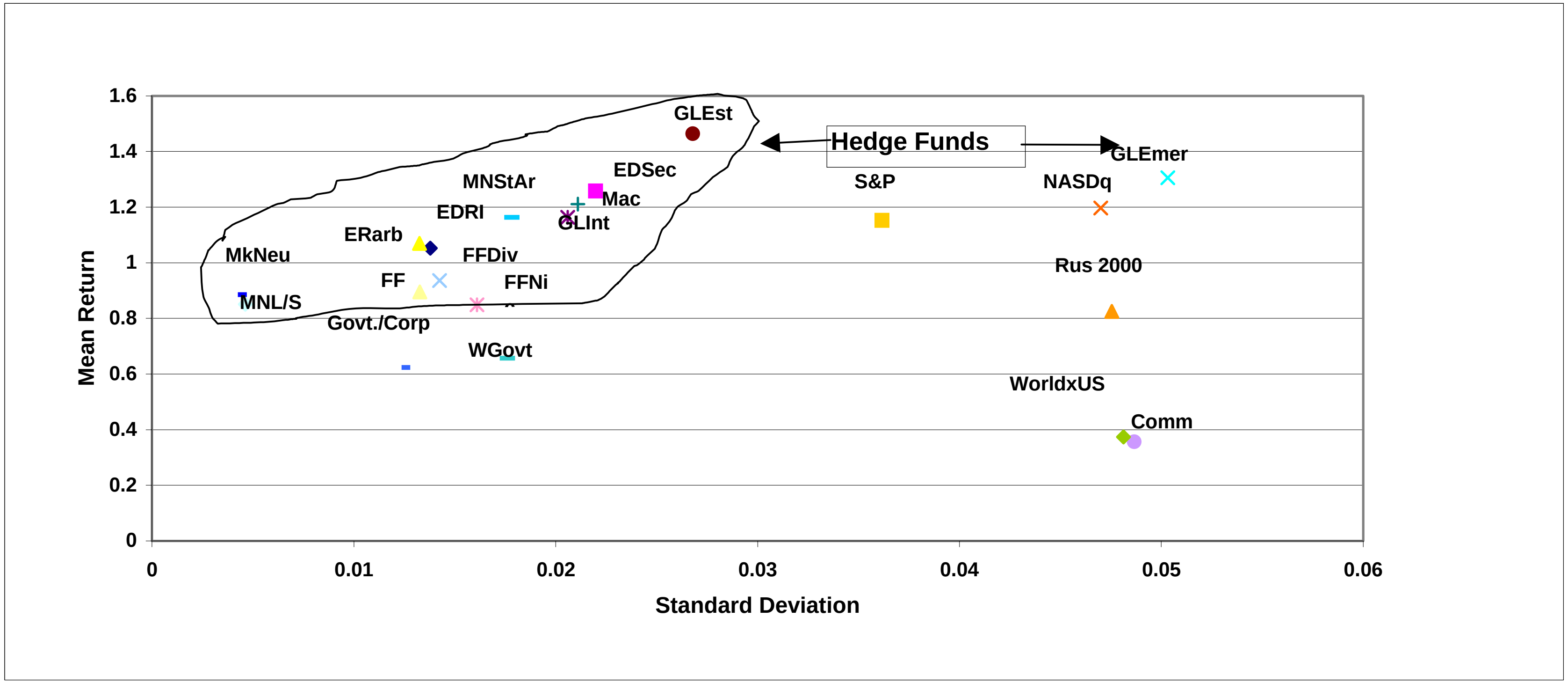

Figure 3: Cumulative Probability Distribution

This figure shows the cumulative probability distribution of the end-of-month payoff of a hedge fund and the S&P 500 (excluding dividends). Both graphs are based on monthly return data from May 1990 to April 2000. S&P 500 returns are assumed to be normally distributed.

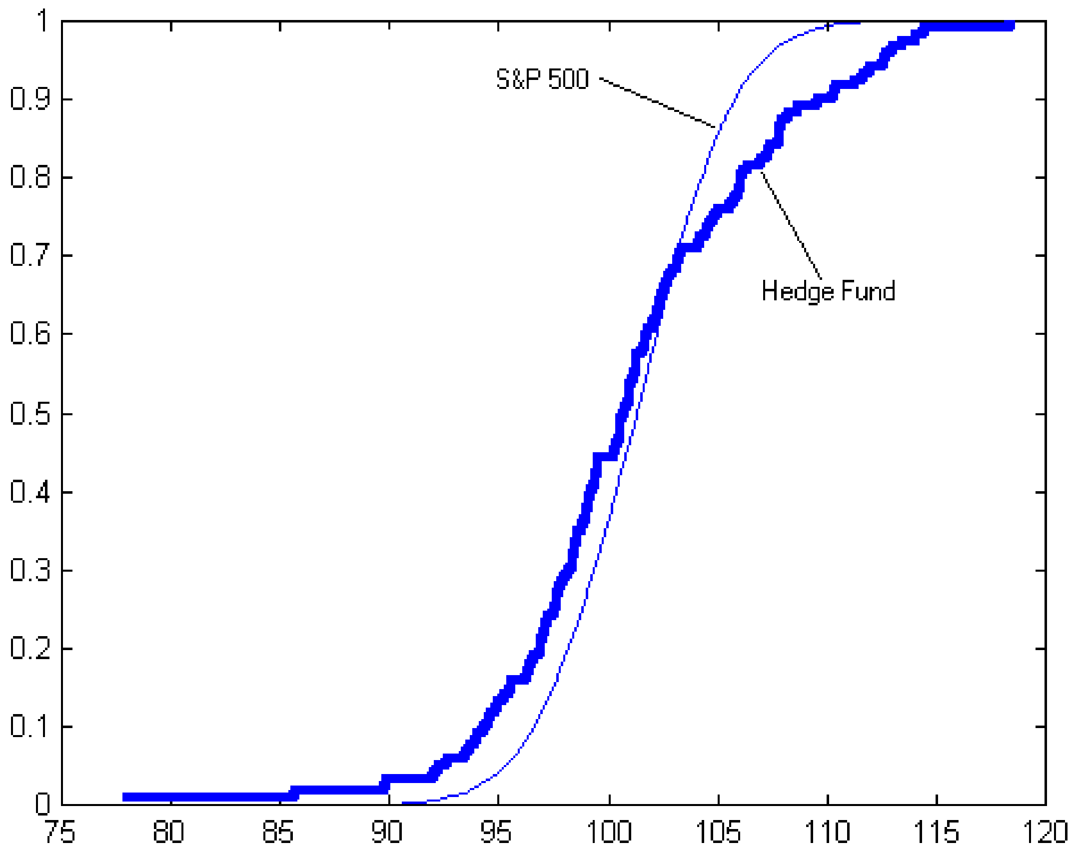

Figure 4: Payoff Function

This figure shows an example of a payoff function resulting from the mapping procedure discussed in Section VI. Given the S&P 500 distribution, this payoff function implies the same payoff distribution as the hedge fund (index) in question.

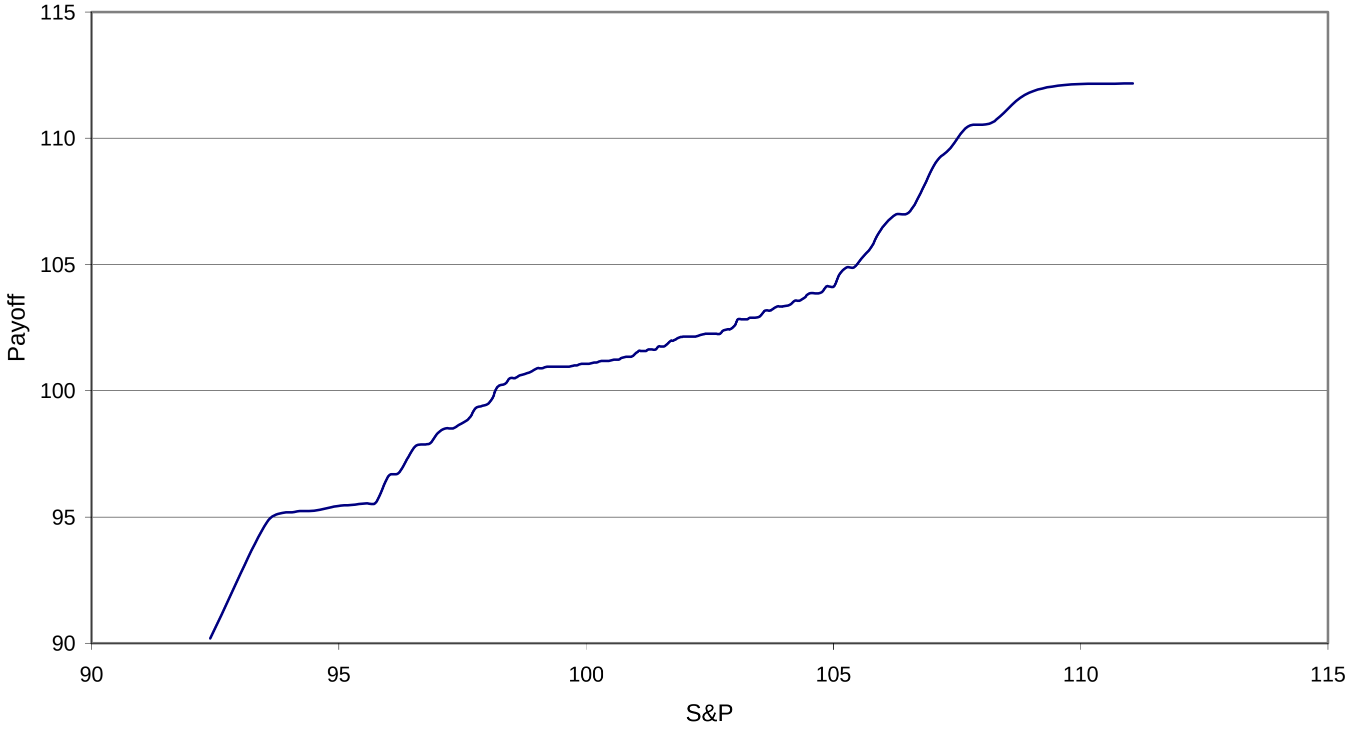

Figure 5: Sampling Error

This figure shows the frequency distribution of the annualised errors from performing the efficiency test on a combination of the index and a short at-the-money call. To calculate the errors we first sampled 120 end-of-month index values, assuming a monthly mean return of 1.24% and a standard deviation of 3.59%, and calculated the corresponding payoffs from the combination (including 0.22% dividend yield). Subsequently, we applied the efficiency test to these data and calculated the sampling error as the difference between the actual test result and 100. To obtain the frequency distribution shown, this procedure was repeated 20,000 times. The normal distribution shown has the same mean (-0.05) and standard deviation (2.14) as the sampling error distribution.

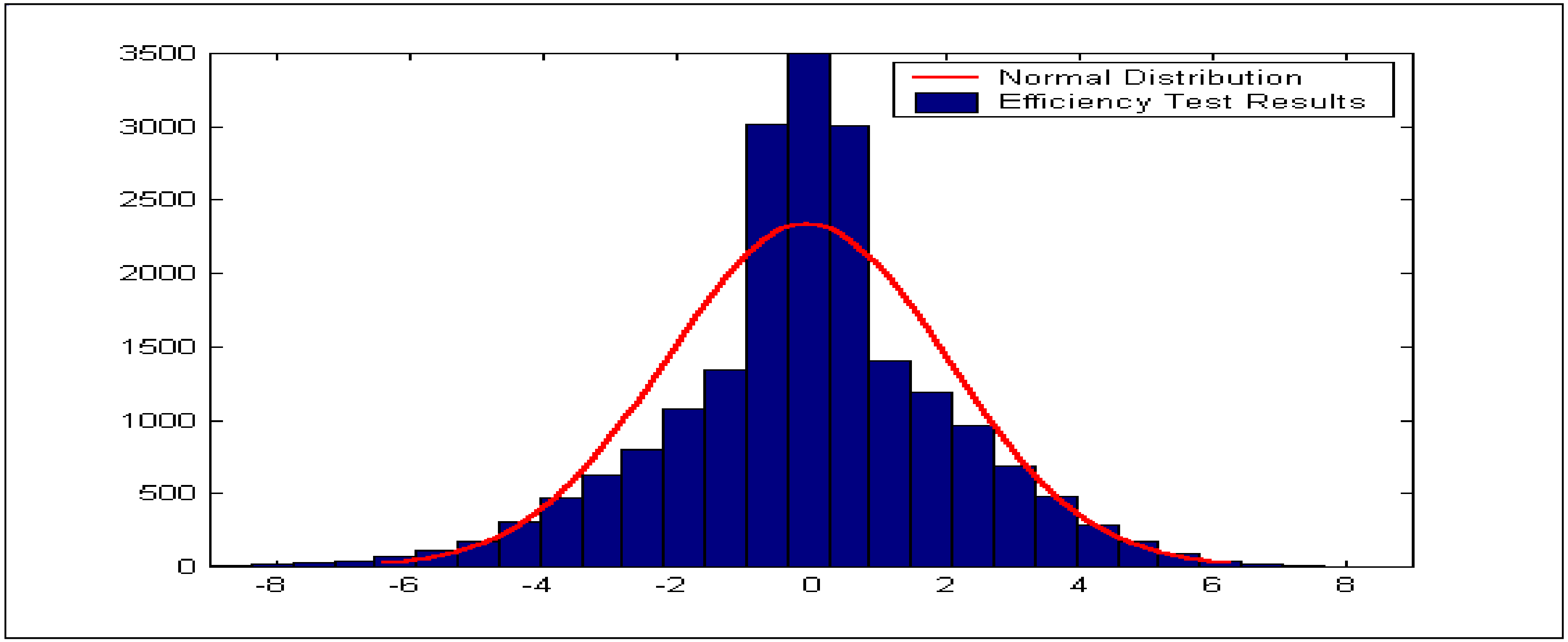

Figure 6: Hedge Fund Efficiency

This figure shows the annual efficiency loss (-) or gain (+) of 77 individual hedge funds based on monthly return data from May 1990 to April 2000. The entries are taken from the third column of table 9.