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ESSAYS ON HEDGE FUNDS

by

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Abstract

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Most of the commonly used performance measures of hedge funds, such as the Sharpe ratio and the Jensen alpha, assume an *a priori* frequency distribution of returns, which, under certain conditions, may result in erroneous inferences. Meanwhile, a non-parametric method allows data to determine the shape of the functional form rather then imposing the parametric straightjacket of rigid distributional assumptions. Distribution of the error term, for example, is not viewed as taking a specific functional form, and the relationship between the dependent and independent variables is not forced into a constraining parametric structure. The parametric method might especially become problematic when the distribution has fat tails and a sharp peak around zero (i.e. there might be more downside risk than upside potential). With a non-parametric approach, on the other hand, the approximation of the distribution of the returns and thus the subsequent inference can be carried out without any guidance/constraints from the theory. The second chapter measures performance of hedge funds following a non-parametric approach and compares its findings with the parametric performance measurement methods.

Furthermore, it is a challenging task to identify the systematic risk factors of hedge funds because of the voluntary disclosure of information by hedge funds and the limited availability of data. The previous literature has typically identified risk factors using stepwise regression methods, with the single model selected by the procedure used for subsequent statistical analysis. A serious shortcoming of any such procedure is that the reported uncertainty for the values such as future predictions or parameter estimates reflects only within model uncertainty, ignoring between model uncertainty- the uncertainty associated with the model selection procedure itself. Hence, stepwise methods can result in the underestimation of the uncertainty about the parameters, overestimation of the confidence in a particular model being "correct" and riskier decisions and poorer predictive ability. Third chapter employs Bayesian Model Averaging (BMA) to account for model uncertainty in the selection of factors that explains the hedge fund returns using a multi-factor model. It is shown that BMA leads to a better evaluation of factors for hedge funds, as well as improved predictive ability.

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CHAPTER 1

PERFORMANCE OF HEDGE FUNDS: AN ANALYSIS OF RISK AND RETURN

The Securities and Exchange Commission defines a "hedge fund" as a private and unregistered investment pool[1], generally with fewer than 100 investors,[2] which are exempt from the registration and disclosure requirements that govern the issuance and trading of public securities. As private partnerships they may invest in any asset class as well as derivative securities, and use long and short positions and leverage. The recent increase in assets managed by hedge funds has sparked a corresponding proliferation of literature on hedge funds in general. Hedge fund assets grew from about $20 billion in 1990 to an estimated over $500 billion by 2001[3], which corresponds to an annual growth rate of 34 percent.

A couple of factors are usually stated as driving the growth of hedge funds. One of these factors has been argued to be the growth in the affluent population in the US. Affluent households, those with investable assets of more than $1 million, control about $5 trillion of the financial assets.[4] John Bogle (2000) once characterized the mutual funds

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[1] Hedge funds generally rely on Sections 3(c)(1) and 3(c)(7) of the Investment Company Act of 1940 to avoid registration and regulation as investment companies, and on Section 4(2) and Rule 506 of Regulation D of the Securities act of 1933 to avoid registration of the securities they offer with the SEC.

[2] National Securities Markets Improvement Act of 1996 allows a hedge fund to have as many as 500 investors and remain unregulated.

[3] Statistics on hedge fund growth appears in Ackermann, McEnally, and Ravenscraft (1999) and KPMG Consulting [1998].

[4] KPMG Consulting (1998).

as a medium of investment for middle-income households, and the United States as a middle-income society.[5] If the Unites States can be characterized as an affluent society today, then hedge funds might be the relevant medium of investment. Hedge funds are also considered as having low barriers to entry, which may have fueled the increase in the number of funds. The attractive compensation structure for the management and the flexibility of the positions that can be taken may also have attracted money managers into the hedge fund business.

1.1. General Characteristics of Hedge Funds

Hedge funds possess some important characteristics that distinguish them from other investment vehicles. As illiquid investments, they usually come with ‘lockup’ and ‘liquidity’ provisions. The lockup provision states the time period during which the investment cannot be redeemed. The liquidity provision, on the other hand, regulates the frequency and the advance-notice requirements of redemption after the initial lockup period. For example, an investor may not be able to withdraw any capital for the first six months after the investment, and then withdrawals could only be allowed at the end of each calendar quarter with a 45 days advance notice. This reduced liquidity allows managers to enter into less liquid positions. Figure 4 shows that, out of the 1,256 funds, 478 allows for monthly, while 499 allows for only quarterly redemption.

Unlike mutual fund managers, hedge fund managers usually charge an incentive fee as well as a fixed asset management fee. The norm in the industry is to charge, on average, 1 percent as an annual fixed charge and an additional 20 percent as an incentive fee. Of the 1255 funds in 2003, 679 charged a performance-based fee of 20%. The performance fees

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[5] Bogle (2001), p.353.

ranged from 0% to 50%. The annual management fees ranged from 0 to 6 percent, and 33 percent of the funds charged 1 percent. The incentive fee is a percentage of profit above a certain base amount, typically, assets under management at the beginning of the period. It is usually subject to a "high water mark" provision. The high water mark provision requires that the manager must make up losses from prior years before receiving any incentive fees. However, their nonlinear characteristics may induce the managers to change their investment strategy. If the losses are substantial then managers may simply prefer to close the "out-of-the-money" funds that do not promise to pay incentive fees or increase volatility to increase their chances of hitting the high water mark.[6] For example, George Soros' Quantum Fund charges an annual fee of one percent of net asset value with a high-water mark based performance fee of 20 percent of returns earned annually. As a result, the Quantum Fund returned 49 percent in 1995 on net assets of $3.7 billion resulting in an estimated total compensation of $393 million for that year, most of which was due to the incentive fees. However, in 1996 The Quantum Fund lost 1.5 percent, and thus, earned only their regular annual fee of $54 million (one percent of the $5.4 billion of assets).[7]

Goetzmann, Ingersoll and Ross (2003) find that the present value of fees and other costs could be as high as 33 percent of the amount invested, though the average is probably between 10 percent and 20 percent. How much skill must a fund manager have to justify such a significant transfer of wealth to the manager? Goetzmann, Ingersoll and

[6] Though there are countervailing forces which would control for excessive risk taking of hedge fund managers, especially for US based funds. Hedge fund managers usually invest a substantial amount of their own capital in the fund, and also as general partners they may have substantial liability if the fund goes bankrupt.

[7] Goetzmann, Ingersoll and Ross (2003).

Ross (2003) show that excess performance as small as an alpha of three percent would compensate the investors for such charges.

Some studies have claimed that the convex payoff structure of hedge fund fees may induce managers to take on excess risk, especially when the net asset value is substantially below the high-water mark. Carpenter (2000) has shown this to be the optimal behavior when the compensation is an option-like payoff based on the portfolio's terminal value. Starks (1987) also concludes that incentive fees induce managers to select more risk and expend less effort then investors desire. On the contrary, Goetzmann, Ingersoll and Ross (2003) state that the volatility would be reduced as the asset value drops near the liquidation level to ensure that liquidation does not occur, since the fee value is zero under liquidation. And at higher asset values, a larger volatility would be adopted to increase the value of the performance fee based on the high-water mark.

The return opportunities for hedge funds come from an expanded universe of investable securities, provided by the greater availability of trading strategies that can be implemented. This, in return, results in unique risk and return characteristics that are not accessible through traditional asset management strategies.

Over the last twelve years, the risk-adjusted performance of the hedge funds have been superior to the traditional active managers and the passive benchmarks when measured by the standard performance measurement methods such as the Sharpe ratio and the Jensen's alpha. Table 7 shows that all of the hedge fund style categories, except Global Emerging and Short Selling, had higher Sharpe ratios and lower variance of returns than that of the S&P 500 index during the period 1990 through 2001. Furthermore, all of the hedge fund categories have positive Jensen's alphas during the same period. These observations are consistent with the findings of Fung and Hsieh (2001), Brown, Goetzmann, and Ibbotson (1999), Liang (1999, 2001), and Edwards and Caglayan (2001) which find that hedge funds are able to hedge and diversify market risk and at the same time enhance return performance. However, Ackermann, McEnally, and Ravenscraft (1999) report mixed results. They find that hedge funds did not consistently outperform standard market indices during their sample period. The results varied with the time period, the hedge fund category, and the market index used. They add the fact that hedge funds do seem to be earning enough of a superior return to cover their costs. However, they report significantly positive Jensen's alphas for hedge funds, ranging from 6 to 8 percent per year. These findings are consistent with the claim that most of the hedge funds are designed to lower systematic risk rather than total risk.

However, the additional risk structure of the hedge funds complicates performance attribution and risk management. The most commonly cited benefit of hedge funds is their ability to lower the systematic risk of a well-diversified portfolio due to their low correlation with other asset classes. But from investors' perspective, it is important to realize that the low correlation between hedge funds and other asset classes may as well be a result of our misconceptions about this recently developing asset class. The correlation coefficient is a measure of the strength of the linear relationship between two variables, but when the relationship is nonlinear, the correlation coefficient will not represent the real magnitude of the relationship between two variables. Therefore, by using the correlation coefficient in asset allocation decisions one might be underestimating the nonlinear relationship, if it exists. Especially in times of trouble, markets become more closely linked and seemingly unrelated assets rise and fall together. Fung and Hsieh (2001), Mitchell and Pulvino (2001), and Agarwal and Naik (2002) show that hedge fund returns exhibit nonlinear risk-return characteristics and stress the importance of taking into account the option-like features of the hedge funds into account.

One possible explanation of the low correlation of hedge fund returns with the standard market indices can be the stale prices and non-synchronous price reactions of the illiquid assets held by hedge funds. The lack of market prices may give fund managers flexibility in marking these positions for month-end reporting. Asness, Krail, and Liew (2001) find that the presence of stale prices artificially reduces the estimates of hedge fund equity market risk and the actual hedge fund volatility, and overstates excess hedge fund returns.

The distribution of hedge fund returns has fat tails. This implies the occurrence of outlying events more often than a normal distribution would permit. The problem with outlying phenomena is the fact that "you cannot anticipate them on the basis of previous experience"[8]and such exposure to tail events in asset markets is not diversifiable. In the light of such exposure, Fung & Hsieh (1997) conclude that an in-depth due diligence on a case-by-case basis might be required for performance attribution. Underestimating tail events may potentially cost managers, thus investors, a huge loss of capital. In one of the most notorious cases of hedge fund industry's history, the Long-Term Capital Management lost $3.6 billion, most of their capital, in five weeks.[9]

[8] Lowenstein [2000], author's interview with George Soros, p. 149.

[9] Ibid., p. 143.

1.2. Data Conditioning Biases

This section analyzes the problems faced when measuring the performance of the hedge funds. The available datasets, consisting of the historical rate of returns of the hedge funds, have potential biases caused by the structure of the hedge fund industry. The complete history of every single hedge fund simply does not exist. Since the disclosure of information is voluntary, the available record is only a subset of the total hedge fund universe. Hence, it can be argued that the funds that choose to disclose information are anything but a random sample of that universe. In the performance attribution literature, the most commonly discussed data conditioning biases are the selection, survivorship, backfilling, and multi-period sampling biases.

Selection bias is a direct result of the way the hedge fund industry is organized. Due to the voluntary nature of disclosure, it can be argued that mostly the successful funds would voluntarily disclose their historical return information to the data vendors. If that is the case, then the hedge funds in the observable portfolio are no longer representative of the universe of hedge funds. The result of the selection bias, then, would be an upward bias in the returns of the hedge funds.

Backfilling bias (also known as the instant history bias) exists because when a data vendor adds a fund to its database, the vendor usually backfills the fund's historical return data into the database. This may result in a bias because only funds that survived the backlisting period are included. The backfilling bias occurs because in order to attract investors, hedge fund managers need a track record, and thus only funds that survive an incubation period would start reporting to database vendors. Fung and Hsieh (2000) find that the median incubation period for the hedge funds in the TASS database 343 days, and they estimate the backfilling bias to be 1.4 percent per year. A commonly employed approach to address this bias is to eliminate the first two years of data, as these years should contain the most backfilled data.

Table 6 provides another measure of the backfilling bias. It provides average monthly return and the standard deviation of monthly returns for funds established through 1991 to 2000, and follows their performance during the sample period. For example, in 1998 there were seven cohorts; group of funds established in 1991 through 1997. The average monthly return for the year for each cohort is given. The average monthly return of the funds established in 1997 was 0.88 percent in 1998. Similarly, it was 0.32, 0.79, -0.02, 0.01, -0.06, and 0.14 percent for the funds established in 1996, 1995, 1994, 1993, 1992, and 1991 respectively. The pattern, here, is that the new funds seem to be doing better than the seasoned funds. However, this is a direct consequence of the backfilling bias; new funds do better than the seasoned ones, because only the successful funds are able to complete the incubation period. In fact, if the performance of the new funds is followed through the following periods, their excess return relative to the seasoned funds disappears.

Figures 6a to 6h provide a visual representation of Table 6. Funds are divided into three categories; new funds with less than 24 months of return data, seasoned funds with more than 24 months return data, and seasoned funds with more than 5 years of return data. Compared to seasoned funds, new funds have higher average monthly returns during their first 24 months. Meanwhile, there is no significant difference between the performance of the seasoned funds with at least 2 years of data and the seasoned funds with at least 5 years of data.

Survivorship bias refers to the case when the existing sample database includes only the hedge funds that exist at the end of the sample period. Some funds exit the database because they either liquidate or discontinue reporting to the database vendor. If the funds that cease operation have, on average, lower performance, then the historical return performance of the sample is biased upward. However, if some funds discontinue reporting when they attract enough capital or grow aggressively, and assuming that these would be the funds with superior returns, then this may bias the historical return performance of the sample downward. If only the existing funds that are still in the database at the end of the sample period are used when calculating the return on a portfolio of hedge funds, then the portfolio, in essence, represents an investor who avoids all defunct funds. Ackermann, McEnally, and Ravenscraft (1999), Brown, Goetzmann, and Ibbotson (1999), Fung and Hsieh (2000), Liang (2000, 2001) report among others the existence of survival bias. Survival bias is believed to vary systematically with the age, size, and strategy of a fund. Most estimates of the average bias are between 2 and 3 percent a year. Fung and Hsieh (2000) find an annual survivorship bias of 1.5 percent for hedge funds. Brown, Goetzmann, and Ibbotson (1999) report an annual survivorship bias of 3 percent for offshore funds. However, Ackermann, McEnally, and Ravenscraft (1999) find that the average return of defunct funds is not lower than the return of surviving funds and report that the survivorship bias is at most 0.16 percent per year.

Liang (2000) argues that the conflicting results about survivorship bias in the previous studies were mainly due to the different amount of defunct funds contained in the hedge fund databases used. Ackermann, McEnally, and Ravenscraft (1999) use combined data from MAR and Hedge Fund Research, Inc. (HFR). Liang (2000) shows that HFR collects a lower number of defunct funds than TASS data, and concludes that it is not surprising to see a lower survivorship bias in the combined HFR/MAR database. Furthermore, both HFR and TASS started to collect data on dissolved funds beginning in 1994; fund attrition rates prior to 1994 should be zero. Ackermann, McEnally, and Ravenscraft (1999) use data from 1988 to 1995. However, studies that do not primarily cover years after 1994 would underestimate the survivorship bias.

Finally, the multi-period sampling bias stems from the research requirement that a fund must have sufficient history before it is included in the sample database. For example, Fung and Hsieh (1997) required 36 months and Ackermann, McEnally, and Ravenscraft (1999) required 24 months of return history for inclusion in their study. However, Fung and Hsieh (2000) argue that the multi-period sampling may not need to be problematic, depending on the context in which the information is used. For example, if an investor requires at least 36 months of return history as a condition of investment, then a study imposing the same restriction would not create an incorrect inference.

1.3. Hedge Fund Strategies

The average hedge fund return data mask a broad distribution of returns for different types of funds. While hedge funds are primarily focused on preserving capital and providing consistent positive returns, there are significant differences in the way the various strategies achieve this. It is important to understand the underlying strategies and the risk exposures when analyzing the appropriateness of hedge funds for a particular portfolio. This is the reason why hedge funds are often categorized according to the dominant strategy that they follow. However, the same fund may be put into a different category by different data vendors. In general, three broad strategies can be defined:

1.3.1. Convergence Strategies

Convergence strategies are based upon the speculation that two securities or market prices will converge over time. Under this strategy, market risk is kept to a minimum and managers often use leverage to magnify returns. The sub-categories are convertible arbitrage, index arbitrage, fixed-income arbitrage, and merger arbitrage.

Convertible arbitrage strategy tries to profit from mispricing of the embedded option in a convertible bond. It usually involves a long position in a convertible bond and a corresponding short position in the underlying security.

Index arbitrage tries to profit from mispricing of equity and equity derivatives. It often involves long positions in the stocks that underlie the index and a corresponding short position in the equity derivative security.

Fixed-income arbitrage profits from mispricing, or spread, across fixed income markets.

Merger arbitrage strategy exploits the change in security prices due to a takeover or merger. It usually involves a long position in the securities of the target firm and a short position in the securities of the acquiring firm.

1.3.2. Security Selection Strategies

Security selection strategies exploit the misvaluation of specific securities by combining long and short positions, primarily in equities. The sub-categories include equity long/short and market neutral funds.

Long/Short equity funds may have long and short positions in equity markets. Value is added primarily through superior security selection, and market exposure can vary substantially depending on the bias of the fund, i.e. it can have a long bias, short bias, or a variable bias.

Market neutral funds use long and short positions in equity markets and attempt to avoid systematic exposure to the capital markets, and are true diversifiers. They seek to generate portfolio performance regardless of the direction of the capital markets.

1.3.2. Directional Trading Strategies

Directional trading strategies bet on the direction of the change in overall market prices. The majority of the funds under this category are called "global macro" funds, which try to profit from changes in global financial markets to exploit changes in interest rates, foreign exchange rates, and other macroeconomic variables.

1.4. Data

This study uses the MAR/Hedge dataset. The sample period covers the period between January 1990 and July 2002. Tables 1 through 4 report descriptive statistics of the database. As of July 2002, MAR/Hedge has a database that contains 1,668 surviving funds with aggregate assets under management of about $180 billion. Zurich Capital Markets (hereafter, ZCM)[10] calculates 19 hedge fund indices. Each index reflects the median monthly, net of fee, returns of the funds in that strategy group. Only twelve of these indices are analyzed in this study as five of the remaining indices do not have enough observations and the other two are sub-indices for the Fund of Funds index with very similar characteristics to that index. The strategies with the most assets under

[10] Formerly, MAR/Hedge indices.

management were Market Neutral, Global Established, and Fund of Funds with $50 billion, $32.2 billion, and $32 billion respectively.[11]

Table 3 presents the descriptive statistics of hedge fund features. The median minimum purchase requirement for all hedge funds was $500,000, and the median size of assets under management was $29 million. However, the latter number is highly skewed as most of the assets are managed by a few dominant funds. As evidenced by Figure 1, about 20 percent of the total assets managed by hedge funds were controlled by the largest ten funds.

[11] As of May 2002. Source: Zurich Capital Markets.

CHAPTER 2

A NONPARAMETRIC ASSESSMENT OF THE DIVERSIFICATION BENEFIT OF HEDGE FUNDS

Most of the commonly used performance measures of hedge funds, such as the Sharpe ratio and the Jensen alpha, assume an *a priori* frequency distribution of returns, which, under certain conditions, may result in erroneous inferences. Meanwhile, a non-parametric method allows the data to determine the shape of the functional form rather then imposing the parametric straightjacket of rigid distributional assumptions. The distribution of the error term, for example, is not viewed as taking a specific functional form, and the relationship between the dependent and independent variables is not forced into a constraining parametric structure. The parametric method might especially become problematic when the distribution has fat tails and a sharp peak around zero (i.e. there might be more downside risk than the upside potential, and vice versa). With a non-parametric approach, on the other hand, the approximation of the distribution of the returns and thus the subsequent inference can be carried out without any guidance/constraints from the theory. This chapter measures the performance of the hedge funds following a non-parametric approach and compares its findings with the parametric performance measurement methods.

This paper extends the existing hedge fund literature by empirically testing the low systematic risk claim of hedge funds by using a nonparametric statistical method, which captures the potential non-linear relationship between hedge fund style categories and benchmark indices. The simple measures of systematic risk may lead to the underestimation of the true hedge fund risk. Almost all performance and risk measurements concentrate on only the first two moments of a distribution, mean and standard deviation. The mean-variance efficient portfolio decision involves choosing the portfolio with the highest expected mean return with the lowest possible risk captured by the standard deviation. In a normally distributed world this approach works very well. However, when the reality departs from the normality assumption, investors might actually be worse off by following these standard measurements. In such cases, one should also consider the third and the fourth moments, skewness and kurtosis, of a distribution. The former measures the asymmetry of a distribution. A negative skewness implies that the distribution has a long left tail, thus a higher probability of excessive negative returns than a normal distribution would justify.[12] Therefore, risk-averse investors do not like negative skewness. Kurtosis is a measure of the thickness of the tails of a distribution.[13]

As can be observed from Table 7, almost all hedge fund strategies, except global macro, market neutral and short selling, have negative skewness, and all strategies have a positive excess kurtosis. Brooks and Kat (2001) also document the high levels of skew and kurtosis associated with monthly hedge fund returns. This should warn investors that hedge fund returns would substantially deviate from normality, particularly in down markets.

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[12] A normal distribution has a skewness of zero.

[13] A normal distribution has a kurtosis of 3 and an excess kurtosis of zero.

2.1. Data

This study uses the Zurich Capital Markets (ZCM)[14] dataset. The dataset covers the period through January 1990 to January 2002. ZCM calculates 19 hedge fund indices. Each index reflects the median monthly, net of fee, returns of the funds in that strategy group. Only twelve of these indices are analyzed in this study as five of the remaining indices do not have enough observations and the other two are sub-indices for the Fund of Funds index with very similar characteristics to that index. The strategies with the most assets under management were Market Neutral, Global Established, and Fund of Funds with $50 billion, $32.2 billion, and $32 billion respectively.[15]

2.2. Local Polynomial Kernel Regression[16]

A nonparametric approach, the Kernel fit, allows us to analyze hedge fund indices by taking into account the nonlinear correlation between the hedge fund strategies and the other asset classes in general and the S&P 500 index in particular. Local polynomial estimators are easy to interpret because they generalize the most commonly used statistical method, linear regression, to allow local nonlinearity. A Kernel density estimate is much less sensitive to outliers than are maximum likelihood estimates like the sample mean and variance. Instead of fitting a linear model to a potentially nonlinear relationship, the following nonparametric regression model is specified

$$y_i = m(x_i) + e_i \qquad (1)$$

[14] Formerly Managed Account Reports (MAR). @Zurich Capital Markets 2001. No claim to orig. US Govt. works. All rights reserved. Reproduced from www.marhedge.com

[15] As of May 2002. Source: Zurich Capital Markets.

[16] For more information on Kernel fit, see Simonof [1996], chapter 5. This part was adapted mostly from that chapter.

where the regression curve $m(x_i)$ is the conditional expectation $m(x) = E(Y/X=x)$. Local polynomial kernel regressions fit Y, at each value of x, by choosing the parameters β to minimize the weighted sum-of-squared residuals:

$$m(x) = \Sigma (Y_i - \beta_0 - \beta_1(X-x_i) + \ldots + \beta_k(X-x_k)^k)^2 K((X-x_i)/h) \quad (2)$$

where N is the number of observations, K is a kernel function that integrates to one, and h is the bandwidth. For each data point in a sample, the Kernel function fits a locally weighted polynomial regression. The local polynomial regression corresponds to locally approximating m(x) with a constant, weighting values of y corresponding to x_is closer to x more heavily.

The advantage of the Kernel fit is that one does not need to assume a specific model *a priori*. The only assumption needed is that whatever the true density of hedge fund returns might be, it is to be a smooth one. Therefore it is possible to let the data tell us what the pattern truly is. An estimate of m(x) superimposed on the scatter plot can be a highly effective way to check the appropriateness of the model and help us identify potentially unexpected structure. Simonoff (1996) states that by "being able to free oneself from the *parametric straitjacket* of rigid distributional assumptions", the local polynomial regression provides an analysis that is both flexible and robust.

The appearance of a local polynomial regression estimate depends strongly on the bandwidth h; the larger the bandwidth, the smoother the estimate. This paper uses a data-based automatic bandwidth selection method, where the bandwidth is specified as follows:

$$h = 0.15(X_U - X_L) \tag{3}$$

where $(X_U - X_L)$ is the range of X.

For all of the hedge fund indices, the Gaussian kernel was used. The reason for that choice is that using an unbounded Kernel yields local linear estimators with finite conditional and unconditional variance. The use of a bounded kernel, like the Epanechnikov kernel, leads to estimators with infinite unconditional variance, which can translate into roughness of the estimate. Another way to achieve finite variance is to require at least four points in the interval covered by the kernel, by using a bandwidth based on nearest neighbors (Loess).[17]

2.3. Results

This section analyzes the 10 ZCM hedge fund indices using Kernel fit to determine the ones that add diversification to a portfolio that consists of S&P 500. For each hedge fund strategy, first a figure of the Kernel fit is provided. Then with the help of the visualized relationship between the hedge fund returns and S&P 500 returns, the nature of the relationship is determined, i.e. linear, quadratic, or third degree polynomial. The significance of the regression is tested by using the adjusted R^2. The adjusted R^2 gives us explanatory power of the independent variables, in our case the S&P 500 index, in explaining the hedge fund index returns, taking the number of independent variables into account.

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[17] For an application of the Loess fit to hedge fund returns, see Favre and Galeano (2002)

Table 9 presents the correlation between hedge fund indices and the S&P 500 index during down and up markets. The monthly returns during the analyzed period were divided into two states of the market: the months when the market had positive returns and the months when it had negative returns. The table shows that the correlation is not symmetric. Particularly, the event driven, global macro, market neutral-arbitrage, and the fund of funds indices experienced a remarkable increase in correlation during down markets. During the months when the market returns were positive, all of the above-mentioned indices had correlations with the market that were not significantly different than zero. However, during down markets, the correlations ranged between 15 and 46 percent. These are the indices for which one would expect to have the nonlinear models.

The regression results presented at Table 10 are consistent with the preceding results. When a hedge fund index has an asymmetric correlation with the market, the nonparametric method generally chooses a nonlinear model for that index. The event driven, market neutral, and fund of funds indices all have significant con-linear coefficients. The notorious exception is the global macro index, which has a linear fit but an asymmetric correlation with the market.

2.3.1. ZCM Event-Driven Index

ZCM defines event-driven strategy as being dominated by events that are seen as special situations or opportunities to capitalize from price fluctuations. Two of the mainstream strategies followed by these hedge funds are merger arbitrage (which is also known as risk arbitrage) and distressed securities. Merger arbitrage funds invest in companies involved in a merger or an acquisition. Manager simultaneously buys stock in a company being acquired and sells stock in its acquirers, and the return of the funds depends on three factors: the locked-up initial spread, the probability that the proposed merger will succeed, and the return if the merger fails.[18] Mitchell and Pulvino (2001) find that the risk of merger arbitrage strategy resembles that of writing a naked put option on the market and having a long exposure to Fama-French's Size factor. Distressed securities focus on securities of companies that are in reorganization or bankruptcy.

Figure 7 shows the local regression obtained with the kernel fit method. As the graph shows the relation between the S&P 500 index and the Event-Driven index is nonlinear. Since this strategy is event-driven, the funds can theoretically make positive returns in any market environment, however merger arbitrage is an equity-based strategy and overall merger and acquisition volume is affected by the equity market returns and the general level of economic activity. The Kernel fit captures this nonlinear relationship with a quadratic model specification. Furthermore, when one looks at the correlation between the equity markets and the event-driven index in both down and up markets, it is observed that they are not symmetric. The correlation is –0.04 in up markets, but increases to 0.46 in down markets,[19] increasing exposure to negative benchmark returns.

The relation between the two indices can also be analyzed by using Table 10. The explanatory power of the quadratic regression is good (adjusted R^2 is 0.38), and all the coefficients are strongly significant. However, when the regression is ran for the down and up markets separately, the explanatory power of the quadratic regression increases (adjusted R^2 increases to 0.57) for the negative S&P 500 returns, while it decreases significantly during up markets (with an adjusted R^2 of 0.014).

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[18] Yang and Branch (2001).

[19] The correlation for the whole sample period is 0.47. Investors would, in fact, like to see the opposite; a positive correlation in up markets and negative correlation in market downturns.

In Figure 8, monthly returns are divided into five states, ranging from severe market declines to market rallies, and the average return for each quintile is calculated, which illustrates the option like payoff of the event driven strategy.

2.3.2 ZCM Global Emerging Index

Emerging market funds invest in the equity markets and the sovereign debt of developing markets. Investments are generally long biased, because in most of these markets short selling is not allowed and derivative markets are nonexistent or less developed. Funds may shift their weighting among regions according to market conditions or alternatively concentrate on specific regions.

Figure 9 shows the relationship between the Global Emerging index and the S&P 500 index by using polynomial third degree regression. The payoff for the Global Emerging index is concave for negative S&P 500 returns and convex for the positive S&P 500 returns. Thus, investing in the Global Emerging index for negative S&P 500 returns can increase portfolio returns. For positive S&P 500 returns, on the other hand, investors would be better off by not investing in the Global Emerging index. However, the return structure deviates from the above observation for extreme values of the S&P 500 index, signs of the $(S\&P\ 500)^2$ and $(S\&P\ 500)^3$ coefficients prove the increasing exposure to negative independent variable values. The correlation increases to 0.32 for negative S&P 500 returns, from 0.20 for positive S&P 500 returns.

In Table 10 the relationship between two indices is estimated by a third degree regression.

2.3.3 ZCM Global International Index

Global International funds are focused on profit opportunities around the world. Unlike Global Macro funds, Global International funds are mostly focused on microeconomic variables and pick stocks in the markets that they like.

Figure 10 provides a quadratic Kernel fit between the Global International index and S&P 500. When the S&P 500 returns are between the range of –10% and 6%, the relationship is almost linear and the Global index is not much sensitive to the equity market returns. However, the relationship begins to change at the tails and correlation increases, especially at the downside.

2.3.4 ZCM Global Established Index

Global Established funds focus on opportunities in established markets like U.S., Europe, and Japan. Out of all the hedge fund indices provided by the Zurich Capital Markets, one would expect this one to have the highest correlation with the S&P 500 index and the best-fit model.

Figure 11 provides a quadratic Kernel fit between the Global Established index and S&P 500. As seen in the figure, the Global Established index is highly sensitive to the changes in S&P 500 index. Table 10 also confirms this robust relationship, where the relationship between the two indices is estimated by a second-degree regression. The explanatory power of the quadratic model is good, with an adjusted R^2 of 0.62, and all the coefficients are significant.

2.3.5 ZCM Market Neutral Index

Market neutral strategy attempts to neutralize systematic risk by exploiting pricing inefficiencies between related securities. One example of this strategy is to build portfolios made up of equal allocations on the long and short sides of the market. By definition, this strategy should have a beta of zero with the market[20].

Figure 12 shows the polynomial third degree Kernel fit for the market-neutral index. As seen, the market–neutral index is insensitive to changes in the S&P 500 index, in the sense that the relation between them is not well defined. The coefficient of determination of the polynomial model is 0.13, and only the coefficient of the cubic term is significant.

This strategy's beta of zero can also be confirmed by Figure 13, where the S&P 500 returns are listed in an ascending order from lowest to the highest and corresponding returns for the market-neutral index during the sample period. There were no significantly negative returns realized by the market neutral index during the sample period. Therefore, it can be concluded that this strategy provides very good diversification.

2.3.6. ZCM Market Neutral -Arbitrage Index

The Market Neutral-Arbitrage sub-index consists of the convertible arbitrage, stock arbitrage, and fixed income arbitrage strategies. The overall motive here is to profit from pricing inefficiencies between related securities. Of the 312 funds in the ZCM Market Neutral index, 153 are classified as arbitrage funds[21].

Convertible arbitrage strategy involves purchasing a portfolio of convertible securities and selling short the underlying equities, profiting from mispricing in the relationship of the two. Convertible bonds have both fixed income and equity characteristics. When the underlying equity appreciates, the value of the convertible bond would also increase accordingly and behave more like equity than a fixed income asset. At the same time,

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[20] In practice it is difficult to be market neutral, because the markets themselves are long-biased.

[21] As of May 2002. Source: Zurich Capital Markets

downside risk is minimized as the default risk of the company is hedged by shorting the underlying common stock

Stock arbitrage strategy involves purchasing a basket of common stocks and hedging by selling short stock index futures.

Fixed-income arbitrage strategy involves buying bonds and selling short instruments that replicate the owned bond. Most commonly used strategies include corporate versus Treasury yield spreads, yield-curve arbitrage, and municipal bond versus Treasury yield spreads.

Figure 14 provides a quadratic Kernel fit between the arbitrage index and S&P 500. The relationship is not well defined, and the arbitrage index is quite insensitive to the S&P 500 index, which is also confirmed by the quadratic regression estimated at Table 10. Even though all the coefficients are significant, adjusted R^2 is only 0.05.

2.3.7. ZCM Market Neutral-Long/Short Index

In this strategy, manager tries to minimize market risk by having equal allocations on the short and long side of the market. About 42% of the funds in the Market Neutral index are categorized as long/short funds.

Figure 15 shows that if a relationship exists between these two asset classes, it would be a linear one, however a very weak one. This week relationship is observed better at Figure 16 when one plots the returns starting from the lowest S&P 500 index monthly return to the highest one. During the whole sample period, there was only one month where the return of the long/short index was significantly negative.

2.3.8 ZCM Global Macro Index

Global macro managers invest in any market using any instrument to participate in expected market movements. They follow a directional strategy making leveraged bets on the fluctuation of stock market prices, foreign exchange rates and commodities markets. Some of the largest and well-known funds, like George Soros' Quantum Fund, are global macro funds.

Figure 17 shows a linear Kernel fit between S&P 500 and the Global Macro index, however the model does not fit the sample data well (adjusted R^2 is 0.20). The returns of the global macro index also depend on the equity market returns, especially on the downside, with a correlation of 0.27, versus a correlation of -0.07 on the upside.

2.3.9. ZCM Short Index

The short-seller funds sell securities that are not owned by the seller. It is a directional strategy betting that the stock prices will go down. These funds are generally marketed as a hedge for long-only portfolios.

Figure 18 provides a quadratic Kernel fit between the Short-Sellers index and S&P 500. As expected, there is an inverse relation between these two indices, and the regression estimate of the model is good with an adjusted R^2 of 0.54.

Given the high cost structure of hedge funds in general, cheaper options may be available for investors to get downside protection through alternative sources.

2.3.10. ZCM Fund of Funds Index

Fund of Funds provides diversification among hedge funds by investing in multitude of hedge funds. The manager of the fund has discretion in choosing which strategies to invest in for the portfolio. The goal of this strategy is to lower the risk of investing in hedge funds.

The quadratic Kernel fit provided at Figure 19 shows the nature of the relationship between the Fund of Funds index and the S&P 500. The volatility of this index is not significantly lower than the standard deviation of the monthly returns of the other hedge fund indices studied above, which makes us conclude that Funds of Funds were not able to significantly decrease the risk in investing in hedge funds.

2.4. Implications

The nonparametric local polynomial regression analysis presented at the previous section demonstrates that eight out of the ten hedge fund indices have nonlinear properties. However, even after the nonlinear terms are added, the robustness of the models did not improve much. Compared to other actively managed funds like mutual funds, R^2s are still low, and with the exception of global established and the short-selling indices, the beta coefficients of the indices are also quite low. Fung and Hsieh (1997) also find low R^2s after adding five hedge fund styles to Sharpe's (1992) asset class factor model, and conclude that hedge fund returns are much harder to explain and replicate using simple trading rules.

In this section, the implications of the findings for portfolio construction and risk management are discussed. As shown in the hedge fund literature, hedge fund returns exhibit option-like characteristics and have left skew and excess kurtosis.[22] There is a consensus that, qualitatively, nonlinearity does exist, but the question that investors care perhaps more about is whether nonlinearity is quantitatively significant or not.

[22] Fung and Hsieh (1997, 2001), Mitchell and Pulvino (2001), Agarwal and Naik (2002), Asness, Krail, and Liew (2001), and Brooks and Kat (2001).

First, the signs of the coefficients of the nonlinear terms are important, because under certain conditions, nonlinearity might as well be what hedge fund investors are looking for. As presented in Table 10, coefficients of the quadratic terms are always negative (except the short-selling index). Furthermore, if the model is third degree polynomial, the coefficient of the cubic term is positive. This type of nonlinearity means that the hedge fund index returns become less sensitive to the market returns at the extreme tails of the market return distribution; as S&P 500 index returns go into the negative territory, the Kernel fit of hedge fund index returns become flatter and hedge fund indices do not lose as much as the benchmark S&P 500 index. On the other end of the distribution, when S&P 500 index have large positive returns, the Kernel fit again becomes flatter, and hedge fund indices do not return as much as the market. One of the important properties of the above payout structure is that it is generally not available through traditional money managers like mutual funds. But if investors are willing to give up some of the gains in a strongly rising market in return for a decrease in the downside risk in a rapidly falling one, then the mean-variance approach may not reflect investors' true risk-return preferences.[23]

Second, does nonlinearity change the conclusion that hedge funds have excess returns? In order to compare the nonlinear model with the linear one, the regression results of the linear model are reported at Table 11. When a nonlinear model is specified instead of a linear one, in all cases, except for the short-selling index, the intercept term, the regression alpha, increases. If alpha had reduced to zero after adding the nonlinear terms, it would have meant that the excess returns of the indices were spurious. But in

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[23] When investors have nonquadratic preferences Fung and Hsieh (1997) state that it is unclear whether mean-variance tools are appropriate for portfolio construction and risk management, especially when the dynamic trading strategies exhibit non-normal distribution.

this case the excess returns persist even when a nonlinear model is specified. One caveat is in order here. Given the option-like feature of hedge fund strategies, the standard asset pricing models cannot be used to assess the risk-adjusted performance of hedge funds. The alphas derived from such models do not represent excess returns. Glosten and Jagannathan (1994) suggest using a contingent claims approach that explicitly values the nonlinearity.

Third, is it optimal to hold hedge funds in a portfolio? Elton, Gruber, and Rentzler (1987) show that a new asset group should be added to a portfolio only if the Sharpe ratio of the new asset group exceeds the product of the Sharpe ratio of the existing portfolio (i.e. S&P 500 index) and the correlation of the new asset group and the current portfolio. For the hedge fund strategies analyzed during the whole sample period, all of them have Sharpe ratios that are greater than the product of the Sharpe ratio of the S&P 500 index and the correlation of the S&P 500 index and the hedge fund indices. However, when the sample period is divided into six consecutive 2-year periods, only two strategies, market neutral and global established, are chosen to be added to a portfolio consisting of the S&P 500 index, in all of the six sub-periods.[24]

2.5. Conclusion

There has been a significant increase of interest in hedge funds during the last decade. However, the potential to enhance risk-adjusted return profile of traditional portfolios comes with a complex risk structure. Given the complexity of hedge fund strategies, there is a need for new tools for measuring risk.

[24] Brealey and Kaplanis (2001) find that the out-of-sample forecasting accuracy of the hedge fund return generating process is maximized at around 24 months.

Most of the commonly used performance measures of hedge funds, such as the Sharpe ratio and the Jensen alpha, assume an *a priori* frequency distribution of returns. Meanwhile, a non-parametric method allows the data to determine the shape of the functional form rather then imposing the parametric straightjacket of rigid distributional assumptions. The parametric method might especially become problematic when the distribution has fat tails. With a non-parametric approach, on the other hand, the approximation of the distribution of the returns and thus the subsequent inference can be carried out without any guidance/constraints from the theory. Using a non-parametric approach, this study found that out of the ten hedge fund indices analyzed, eight had a nonlinear payoff structure. Generally speaking, positive S&P 500 returns do not explain hedge fund returns, and most of the strategies have option like payoffs. However, during negative market returns, all hedge fund strategies experienced a remarkable increase in correlation, and volatility. Hedge funds still provide diversification benefits as they act akin to portfolio insurance by dampening the effect of the S&P 500 at the tails of the distribution. Fung and Hsieh (1997) state that this diversification is achieved at an implicit cost. The flexibility of the hedge fund managers in the types of trades and markets that they can enter allows them to deliver an uncorrelated set of return. But when analyzing these dynamic trading strategies, they add that investors should put greater effort in due diligence and risk monitoring. In the end, the exposure to tail events in asset markets is not completely diversifiable.

These conclusions warrant several caveats. First of all, hedge fund indices are believed to be considerably less representative of the time series performance characteristics of the funds they proxy for than equity indices are for stocks and mutual funds. This is important because investors face the risks of individual hedge funds rather then the index-replicating portfolios. Second, many findings in finance have been sensitive to the time period analyzed and the time series data for hedge funds cover a short period of time.

CHAPTER 3

AN ALTERNATIVE METHODOLOGY IN THE IDENTIFICATION OF SYSTEMATIC RISK FACTORS OF HEDGE FUNDS

The first task in performance evaluation is to determine whether the past performance was superior or not, and then to determine whether such performance was due to skill or luck. Performance evaluation and attribution models typically regress the historical returns of the analyzed portfolio on one or more asset benchmarks. The essential idea is that if the manager had superior performance, the fund return would be higher than the returns that could have been obtained by investing in another alternative portfolio. That alternative portfolio is usually chosen to be a broad market index, which represents the universe of assets that the manager can choose. For example, if the fund invests in large US corporations, then it would be compared to the S&P 500 index. The fund manager will be considered to have superior skill only if the returns achieved by the fund are higher that of the S&P 500 for the period analyzed. However, for this comparison to be viable, the selected benchmark should be relevant, transparent, and feasible. The benchmark should exhibit similar risk characteristics to that of the analyzed portfolio. Failing to meet these conditions will generally cause erroneous inferences about the performance attribution.

The original work of Jensen (1968) used a single benchmark, called thereafter the single-factor model, to analyze performance. The constant term, “Jensen’s alpha”, measures superior performance and skill of the manager. The slope term measures the extent that returns were explained by the benchmark. The slope, thus, measures exposure to the benchmark risk.

Sharpe (1992) extended the Jensen (1968) analysis by using multiple factors as explanatory variables in the regression. He showed that a significant amount of the cross-sectional variation of mutual fund returns could be explained by a limited number of asset classes. Agarwal and Naik (2002), Fung and Hsieh (1997, 2001b), and Liang (1999) applied the Sharpe's (1992) style analysis to hedge funds. The asset-based measures of portfolio performance provide an estimate of a portfolio's risk-adjusted return. Following Shape's (1992) steps, hedge fund returns are regressed on market indices. However, linear-factor models that utilize the traditional asset benchmarks are not very successful in explaining the hedge fund returns. Linear factor models are more suitable for analyzing buy-and-hold strategies, rather than dynamic trading strategies. Due to the regulatory restrictions, mutual funds generally follow the former, while the hedge funds follow the later strategy. Therefore, *a priori* one would expect a higher explanatory power of this model when applied to mutual fund returns than hedge fund returns. In fact, previous studies show that mutual fund returns can be explained by a couple of asset classes. Using multi-factor linear model, Fung and Hsieh (1997) show that more than half of the mutual funds in their study had R^2s above 75% while less than five percent of the hedge funds had R^2s above 75%. The style regression can attribute a fund's return to traditional asset classes only if their returns are correlated. The difficulty is finding a set of asset classes that capture the return characteristics of the underlying hedge fund strategies. Furthermore, this approach is sensitive to the nonlinearities between the fund's returns and the benchmarks. It is well documented in the literature that hedge fund returns have nonlinear characteristics. Fung and Hsieh (1999) state that returns on global macro funds and the trend-following CTAs display a collar and a straddle like payoff on the US equity indices respectively. Glosten and Jagannathan (1994) suggest adding excess returns on benchmark indices that have option-like features as additional factors. Agarwal and Naik (2002) extend the traditional linear-factor model by adding option-based strategies to the linear-factor model.

Typically, the risk factors are analyzed using the stepwise regression method (Liang 1999; Fung and Hsieh 2000 and 2001; and Agarwal and Naik 2002). The stepwise regression procedure involves selecting variables sequentially depending on the F-value. The model selected is then used for subsequent statistical analysis. An advantage of the stepwise method is its parsimonious selection of factors. However, a serious shortcoming of any such procedure is that the reported uncertainty for the values such as future predictions or parameter estimates reflect only within- model uncertainty, ignoring between-model uncertainty - the uncertainty associated with the model selection procedure itself. This becomes an even more serious problem with hedge funds since they can, in practice, implement an infinite number of dynamic trading strategies. Till we have better benchmarks that explain most of the major strategies followed by hedge funds[25], the factors will be chosen *ad hoc*, and model uncertainty will continue to be an important problem. Hence, stepwise methods can result in the underestimation of the uncertainty about the parameters, overestimation of the confidence in a particular model being "correct" and riskier decisions and poorer predictive ability (Draper, 1995; Chatfield, 1995; Madigan and Raftery, 1994; Volinsky, 1997, Volinsky *et. al.*, 1997).

[25] Recently a couple of papers took a step in that direction. Mitchell and Pulvino (2001) constructed returns of merger arbitrage strategy from 1963 to 1998; Fung and Hsieh (2001a) model the returns of trend-following hedge funds as "lookback straddles"; and Gatev et al (1999) model the returns on "pairs-trading".

This paper extends previous research on hedge funds in a number of directions. An alternative methodology in the identification of systematic risk factors of hedge funds is presented. One possible approach to model uncertainty is to obtain several potential "best" models, each of which is strongly supported by the data. Though this approach addresses model uncertainty, it does not offer a way to combine the results of different models and to interpret the results when the models indicate qualitatively different conclusions. The standard Bayesian solution to this problem is to combine the results from different models by averaging with weights based on the posterior probabilities of the most likely models, a method known as Bayesian Model Averaging (BMA). This paper employs BMA to account for model uncertainty in the selection of the factors in the Sharpe's (1992) linear-factor model. Methodologically, it is shown that Bayesian Model Averaging (BMA) leads to a better evaluation of risk factors for hedge funds, as well as improved risk assessment for potential investors.

The empirical analysis in this study points to the fact that hedge funds follow dynamic trading strategies and that the factor loadings change frequently. For half of the indices, the model selected by the stepwise procedure was not among the three best models chosen by the BMA approach.

The balance of the paper is as follows. Section 2 presents Sharpe's (1992) linear-factor model. In section 3, the Bayesian Model Averaging is introduced, and its application to variable selection is discussed. Section 4 introduces the data set. Section 5 interprets the results of the BMA analysis, discusses some of the interesting results of the study and how they relate to portfolio construction and risk management. Conclusions follow.

3.1. Model

The finance literature is replete with papers on the systematic risk of hedge funds and mutual funds. Most of these papers stem from William Sharpe's (1992) seminal work, *Asset Allocation: Management Style and Performance Measurement.* In his analysis of the mutual funds, he showed that the multitude of strategies and styles followed by thousands of funds could be explained by a limited number of asset classes. The first step in this approach is the identification of the significant factors that explain the performance of the hedge funds. The Sharpe (1992) multi-factor model is specified as follows:

$$R_t = \alpha + \sum_{k-1}^{n} \beta_k F_{k,t} + \varepsilon_t \qquad (1)$$

where

R_t	=	the fund's return in month t
$F_{k,t}$	=	the return of k^{th} factor in month t
β_k	=	the factor loading of the k^{th} factor
ε_t	=	a random error term in month t

In the Sharpe (1992) model, returns are adjusted for risk. The constant term of the regression (commonly known as the Jensen's alpha) captures the excess risk-adjusted return of the fund manager. The slope coefficients of the regression are the factor loadings. They tell us the allocation of fund capital to each strategy. However, linear factor models are not capable of capturing the nonlinear return features. Grinblatt and Titman (1989) showed that a fund manager could generate positive Jensen's alphas by simply selling call options on the underlying benchmark. Glosten and Jagannathan (1994) point out that it is possible to characterize the risk in managed portfolios by using derivative pricing methods. They suggest including returns on options on certain indices as additional factors to the linear factor model.

3.2. Bayesian Model Averaging

To proceed with the identification of the systematic risk factors of hedge funds, a specific collection of factors (a specific model) should be selected. The standard approach to model selection is to search over many classes of models, usually through stepwise methods and then pick the one that "best" fits the data. Once the model is "found", then it is used for the subsequent statistical analysis, the results are reported and interpreted. The reported uncertainty for the values such as the future predictions or the parameter estimates, however, reflects only *within* model uncertainty. Ignoring *between* model uncertainty-uncertainty associated with the model selection procedure itself-results in the underestimation of overall uncertainty, overestimation of a particular model being "correct" and poorer predictive ability (Draper, 1995; Chatfield, 1995; Madigan and Raftery, 1994; Volinsky, 1997; Volinsky, *et al.* 1997).[26]

It should also be noted that empirical models are often taken too seriously, and that poor models are sometimes accepted merely because they fit data better than other models that are even worse. A striking example of this is given in Rencher and Pun (1980). It is well worth repeating their example here. They show that when subset selection is used in regression, the expected value of R-square is substantially inflated above its value without selection. They perform a Monte Carlo simulation by generating, say, n random variables on a normally distributed response variable and on k independent additional

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[26] For striking examples of this, see Draper (1995), Regal and Hook (1991), Madigan and York (1995), Kass and Raftery (1995), and Raftery (1996). Some of the recent work on model uncertainty includes among others Clyde *et al.* (1995), George and McCulloch (1993), and Madigan and York (1995). See Kass and Raftery (1995), Chatfield (1995), and Draper (1995) for reviews.

variables, which will be treated as if they were potential explanatory variables. Thus the true model here is the null model (where $\beta = 0$ for all k). Nevertheless, the best subset of p 'explanatory' variables is selected using stepwise method, and the resulting coefficient of determination, R-square, is evaluated. This procedure can be repeated many times to obtain the null distribution of R-square. When n=20, k=10, and p=4 (i.e. when we choose four factors out of a possible 10 using approximately two years of monthly data), the average value of R-square is found to be 0.42 with upper 95th percentile (R-square $_{0.95}$) = 0.66.[27] Thus an observed relationship obtained by the above procedure could look 'interesting' and be judged significant by the usual tests, but could, in fact, be spurious.

A model M, which formalizes judgments about how the known variables x and the unknown variables y are related, can be expressed by two parts M=(S, θ): the structural assumptions S and the parameters θ. It is common, in practice, to acknowledge parametric uncertainty about θ given a particular assumed structure S, however, it is much less common to acknowledge structural uncertainty about S itself. Traditional inference generally assumes that a model is known *a priori*, and takes no account of possible uncertainty regarding its structure. It is assumed that the model is prespecified based on the accepted theory and prior knowledge obtained from previous similar studies. However, in practice, the models are not specified *a priori*. They are rather formulated partially by looking at the same data set as those later used to fit the model. Draper (1995) states that it is misleading to make inferences as if a model is known to be true when, in fact, it has been selected from the same data to be used for estimation purposes, alas the dreaded data-mining. Furthermore, the least squares theory does not apply under

[27] The expected value of R-square without selection when $\beta = 0$ is $p / (n-1)$ if it was obtained from p variables chosen randomly from the k available predictor variables. Thus E[R-square | p=4, n=20] = 0.21.

these conditions. The estimated model parameters and residual variance will be biased and the researcher will think that the fit is better than it really is. In retrospect, one notices that uncertainty bands were not sufficiently wide. Chatfield (1995) suggests that in any data-instigated procedure, one must be clear what the analysis is conditioned on.

One possible solution to model uncertainty is to obtain several potential "best" models, each of which is strongly supported by the data. Though this approach addresses model uncertainty, it does not offer a way to combine the results of different models and to interpret the results when the models indicate qualitatively different conclusions.

Bayesian solution to this problem is to select a number of most likely models from a set of potential candidates and then to combine the results from the former by averaging with weights based on the posterior probabilities, a method known as Bayesian model averaging (BMA). BMA approach accounts for model uncertainty in both prediction and parameter estimates. The resulting estimates of uncertainty incorporate between model uncertainty and thus may better reflect the true uncertainty in the parameter estimates. The following section provides a brief overview of how BMA can be extended to linear regression as suggested by Raftery (1995), Madigan and Raftery (1994), Chatfield (1995), and Draper (1995).

3.2.1 Bayesian Model Averaging for Linear Regression

Let y be any unknown quantity of interest, i.e. monthly hedge fund returns, and $M = \{M_1,\ldots, M_K\}$ be a finite set of all structural alternatives under consideration. The posterior distribution of y given the data x is

$$\Pr\langle y|x\rangle = \sum_{k=1}^{K} \Pr\langle y|M_k, x\rangle \Pr\langle M_k|x\rangle \quad (2)$$

This accounts for the uncertainty about model form by weighting the conditional posterior densities according to the posterior probabilities of each model. The posterior probability for model M_k is given by

(3) $$\Pr\langle M_k|x\rangle = \frac{\Pr\langle x|M_k\rangle \Pr(M_k)}{\sum_{l=1}^{K} \Pr\langle x|M_l\rangle \Pr(M_l)}$$

where

(4) $$\Pr\langle x|M_k\rangle = \int \Pr\langle x|\theta_k, M_k\rangle \Pr\langle \theta_k|M_k\rangle d\theta_k$$

is the integrated likelihood of model M_k, θ_k is the vector of parameters of model M_k, Pr (θ_k | M_k) is the prior density of θ_k under model M_k, Pr (x | θ_k, M_k) is the likelihood, and Pr (M_k) is the prior probability that M_k is the true model. In the absence of any prior information all models are generally assumed to be equally likely. The same approach is taken here and it is assumed that $\Pr(M_k) = K^{-1}$. All probabilities are implicitly conditional on *M*, the set of all models under consideration.

Hoeting (1994) showed that the integral in Eq. (4) may be evaluated analytically in some special cases. For more general situations, Raftery (1995) proposed using the *Bayes Information Criterion* (BIC) as an accurate approximation to the integrated likelihood. For normal linear regression,

(5) $$BIC_j = n \ln(1 - R_j^2) + k_j \ln n$$

for model j, where R_j^2 is the usual *R*-square for the model j, k_j is the number of regressors in model j, and *n* is the number of observations. The marginal likelihood of model *j* is then approximated by

(6) $$\Pr\langle M_j|x\rangle \alpha e^{-0.5 BIC_j}$$

After the maximum likelihood is approximated, the posterior probability of each model can be approximated using Eq. (3). The individual models are then weighted by their posterior probabilities so that the various quantities of interest may be estimated (Eq. (2)).

This way of averaging over all the models provides better predictive ability, as measured by a logarithmic scoring rule[28], than using any single model M_j (Raftery *et al.* 1997):

(7) $$-E\left[\log\left\{\sum_{k=1}^{K} \Pr\langle y \mid M_k, x\rangle \Pr\langle M_k \mid x\rangle\right\}\right] \leq -E\left[\log\left\{\Pr\langle y \mid M_j, x\rangle\right\}\right],$$ (j = 1,...,K)

where x is the observable to be predicted and the expectation is with respect to $\sum$ Pr (y | M_k, x) Pr (M_k | x). This follows from the nonnegativity of the Kullback Leibler information divergence.

When there are many potential predictors, the finite sum (2) can quickly become unmanageable. A general algorithmic approach to solving this problem, known as "Occam's window" was proposed by Madigan and Raftery (1994). They suggest averaging only over the "best" models as an approximation to averaging over all models, where "best" is determined by the posterior model probability. They argue that if a model is far less likely *a posteriori* than the most likely model, then it should no longer be considered. Thus, only models belonging to the set below are included in the sum (2).

[28] The efficacy of a modeling strategy can be assessed by how well the resulting predictive distributions predict future observations. Madigan and Raftery (1994) measured predictive performance by splitting data into two subsets, one for calculating model probability and the other for testing. Then, predictive performance of the modeling strategies can be measured using the logarithmic scoring rule of Good (1952). This method can be used to assess the performance of any method that generates predictive distributions.

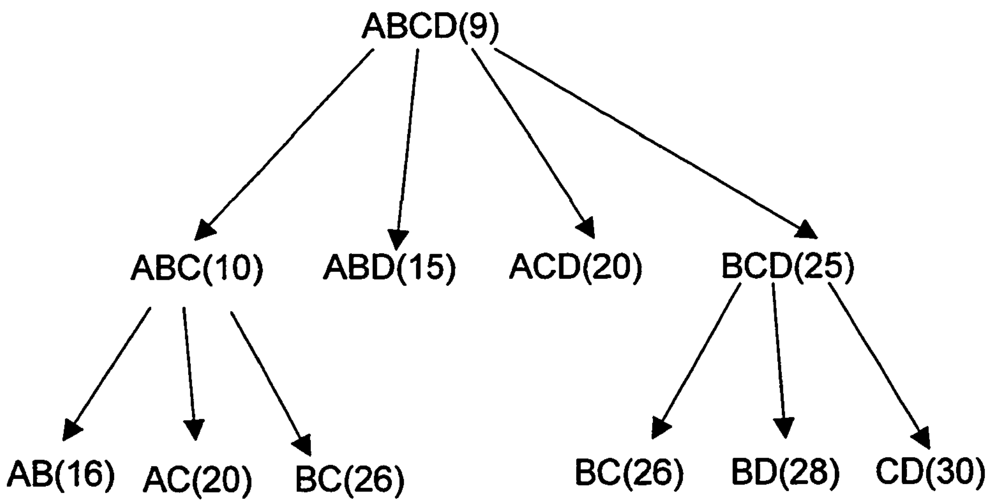
$$A = \left\{ M_k : \frac{\max_l \{\Pr\langle M_l \mid y\rangle\}}{\Pr\langle M_k \mid y\rangle} \leq C \right\}$$

(8)

where C is chosen by the data analyst and $\max_l\{\Pr(M_l \mid x)\}$ denotes the model with the highest posterior model probability. In the following BMA analysis of hedge funds, $C = 20$ is used, by analogy with the popular 0.05 cutoff point for P values. The number of models in Occam's Window increases as the value of C decreases. Note that $\Pr(M_k \mid x)$ rather than $\Pr(x \mid M_k)$ is used as the measure of how well the model predicts the data.

This greatly reduces the number of models in the sum in equation (2) and now all that is required is a search strategy to identify the models in *A*. One such search strategy consists of a sequence of pairwise comparisons of nested models. If a model is rejected in favor of a larger one, then all the models nested within it are also rejected. To efficiently identify the models in *A*, the "leaps and bounds" algorithm of Furnival and Wilson (1974) is used as in Raftery (1995).

Linear regression by leaps and bounds uses the fact that for two models A and B, where A and B are each subsets of the full parameter set, if A xxx B then RSS (A) xxx RSS (B). The model space is represented as tree, with the full model at the top. To see how the leaps and bounds algorithm works, let us consider the following example from Volinsky (1997). Imagine a situation with four potential variables labeled *A*, *B*, *C*, and *D*. A partial representation of the tree of the model space for this model selection problem is shown in Figure 3.1. The residual sum of squares for each model is in parenthesis. Say, one is interested in the best two-variable model. *ABC* is the best of three-parameter models (the one with the smallest RSS), so one looks at the subsets of it. Of these, *AB* has a lower RSS than the three-parameter model *BCD*, which indicates that *AB* must have a lower RSS than any two-parameter subset of *BCD*. So without fitting any other two-parameter model, *AB* is found to be the best model.



Due to the convenient matrix representation of the normal regression problem, the leaps and bounds easily provides the top q models of each model size, where q is chosen by the user. The MLE θ_k, var (θ_k), and R^2 for each model M_k are also returned. As long as q is large enough, this procedure returns the models in A plus many models not in A. The returned models are then estimated, the BIC value for each is computed, and those that are not in A are eliminated. The posterior model probabili'ies are then normalized over the selected set.

The posterior probability that a regression coefficient, say Δ, is nonzero is calculated by adding the posterior probabilities from all the models that contain Δ.

(9) $$\Pr\langle \Delta \neq 0 \mid x\rangle = \sum_{A_1} \Pr\langle M_k \mid x\rangle$$

where $A_1 = \{ M_k : k = 1,\ldots, K : \Delta \neq 0 \}$, i.e. the set of models that include β_1. The interpretation of a posterior probability is as follows: less than 50%: evidence against the effect; 50-75%: weak evidence for the effect; 75-95%: positive evidence; 95-99%: strong evidence; and greater than 99%: very string evidence (Kass and Raftery, 1995).

Of interest, also the size of the effect, given that it is non-zero. The posterior distribution of this is

(10)
$$\Pr\langle \Delta \neq 0 \mid x, \Delta \neq 0 \rangle = \sum_{A_1} \Pr\langle \Delta \mid M_k, x \rangle \Pr\langle M_k \mid x \rangle$$

This can be summarized by its posterior mean and standard deviation, which may be viewed as, respectively, a Bayesian point estimator and Bayesian analogue of the standard error. The convenient approximations of these are (Raftery, 1994)

(11)
$$E\langle \Delta \mid x, \Delta \neq 0 \rangle \approx \sum_{A_1} \hat{\Delta}(k) \Pr\langle M_k \mid x \rangle$$

(12)
$$SD^2\langle \Delta \mid x, \beta_1 \neq 0 \rangle \approx \sum_{A_1} \left[se_1^2(k) + \hat{\Delta}(k) \right] P\langle M_k \mid x \rangle - E\langle \Delta \mid x, \Delta \neq 0 \rangle^2$$

where $\hat{\Delta}(k)$ and se(k) are respectively the MLE and the standard error of Δ under model M_k.

3.2.2. Data

This study uses the MAR hedge fund indices. The dataset covers the period between January 1990 and December 1999 The indices analyzed are the Event Driven, Global Emerging, Global International, Global Established, Global Macro, Market Neutral, Short, and Fund of Funds index.[29] Each index reflects the median monthly, net of fee, returns of the funds in that strategy group.

The factors consist of the S&P 500 index, MSCI World excluding USA index, MSCI Emerging Markets index, JP Morgan United States Government Bond index, JP Morgan non-US Government Bond index, United States Federal Reserve Bank Trade-Weighted

[29] Appendix provides a detailed definition of the MAR hedge fund indices.

Dollar index, and Goldman Sachs Commodity index. These indices cover a broad spectrum of the equity, bond, currency, and commodity markets. In addition to these, two Fama-French (1992) strategy factors are included in the analysis. These are Fama-French's Size (Small-minus-Big, SMB) and Book-to-Market (High-minus-Low, HML) factors. The choice of the factors is consistent with the previous literature on hedge funds. In order to account for the nonlinear return features of hedge funds, Agarwal and Naik's (2002) option-based strategies are added to the factors above.[30] The option-based strategies involve trading once a month in short-maturity European call and put options on the S&P 500 index that are listed on the Chicago Mercantile Market. Agarwal and Naik's (2002) strategy involves buying a one-month at-the-money call option on the S&P 500 index (SPCa) at the beginning of the month. On the first trading day of the following month, sell the option and buy another one-month at-the-money call option. They calculate the monthly return on this trading strategy by using the Futures Industry Institute price data. The returns on the out-of-the-money call option on the S&P 500 index (SPCo), at-the-money put option (SPPa) and out-of-the-money put option (SPPo) are also calculated in a similar way.

Table 4.1 presents the descriptive statistics of the hedge fund indices and the factors.

3.3. Results

The models are first specified using the stepwise regression procedure for each hedge fund index. The stepwise regression results for the whole period are presented at Table 12. Tables 14a-14g present the results of the BMA approach for the whole and the six two-year sub-periods for the event driven index. BMA selects a number of most likely models from the set of potential independent variables and then combine the results from

[30] I am grateful to Vikas Agarwal and Narayan Naik for providing the data on options.

the former by averaging with weights based on posterior probabilities. Thus, the resulting estimates of uncertainty incorporate between model uncertainty and may better reflect the true uncertainty in estimates. Therefore, through Tables 14a through 14g, the mean values of the coefficients are the weighted average value of the respective coefficients of the most likely models.

The results strongly support that hedge funds follow dynamic trading strategies and that the factor loadings change frequently. Our results are also consistent with the findings of Agarwal and Naik (2002) that the option-based strategies characterize the systematic risk of hedge fund strategies.

The evidence from the data is inconclusive as to the effects of some factors on the hedge fund returns. Especially when the stepwise regression is not among the three most likely models chosen by the BMA, the factors chosen by the two methods usually differ. This does not necessarily mean that these factors could be discarded. In fact, with BMA, they are included in any prediction with weights proportional to their posterior probabilities. Posterior probabilities can make one distinction that P-values cannot: One may fail to reject the null hypothesis of 'no effect' because, either there are not enough data to detect an effect, or the data provide evidence for the null hypothesis. The posterior probabilities of 'no effect' can be considered as an approximation to the posterior probability of the effect being small, namely $P(|\Theta| < \varepsilon)$ provided that ε is at most about one half of a standard error (Berger and Delampady, 1987).

For the whole sample period the MAR Event Driven hedge fund index shows significant relationship with the Fama-French's Size (SMB) and book-to-market (HMB) factors. Furthermore, the size and the book-to-market factors are significant during the five and three periods out of the six sub-periods respectively. This suggests that event driven strategies are similar to having a long position in small stocks and a short position in large stocks. The positive coefficient for the book-to-market factor suggests that the event driven strategy returns resemble to that of having a long position in value stocks and a short position in growth stocks. The economic intuition behind these results is that in a takeover the target company is more likely to be smaller and have a higher book-to-market ratio than the acquiring company. The merger arbitrage strategy involves shorting the acquiring company and having a long position in the target company. If the merger succeeds, the share price of the target company generally increases while the share price of the acquiring company decreases. The hedge fund manager is betting on the probability that the merger transaction will be completed successfully.

For the whole sample period, the event-driven index had positive exposure to the MSCI Emerging Markets index and the Goldman Sachs Commodity index. However, these coefficients were quantitatively insignificant. During the period analyzed, the event driven strategy had a significantly negative coefficient for the out-of-the-money put option on the S&P 500 index (SPPo). Therefore, the event driven strategy's payoff resembles that of writing an out-of-the-money put option on the market.[31] The intuition is that even though the returns of the event driven strategy are unrelated to the overall equity market returns, the correlation increases during extreme down markets. The probability that the merger deal will fail increases during extreme down markets. The individual merger's occurrence in generally not related to the equity markets. However, there have been several instances in which "arbitrage returns were related to the equity

[31] This result is consistent with that of Agarwal and Naik (2002). Note that our measurement unit (percentage) is different than theirs (in decimals). To compare the coefficient values, option coefficients in this study need to be multiplied by 100.

market. For instance, during the Crash of 1987 and the Mini-Crash of 1989, many announced merger transactions were reevaluated by the acquiring companies' boards of directors" (Moore, 1999). In fact, the stepwise method picks up that relationship and assigns a significantly negative coefficient for SPPo usually during down markets. The difference of the BMA is that it utilizes the same information during all sub-periods, and assigns a significant coefficient for SPPo for most of the sub-periods.

Additionally, the event driven-distressed securities sub-index has a significantly negative factor loading on the at-the-money put option (SPPa) and a significantly positive factor loading on the out-of-the-money put option. This means that the distressed securities strategy's payoff resembles that of a bull spread on the S&P 500 index.[32] A bull spread limits the upside as well as the downside risk.

[32] A bull spread can be created by simultaneously buying a put option with a low strike price and writing a put option with a high strike price.

APPENDIX 1

MAR/Hedge Hedge Fund Styles *

Event-Driven

Investment theme is dominated by events that are seen as special situations or opportunities to capitalize from price fluctuations.

Distressed Securities. Focused on securities of companies in reorganization and/or bankruptcy, ranging from senior secured debt (low risk) to common stock (high risk).

Risk Arbitrage. Manager simultaneously buys stock in a company being acquired and sells stock in its acquirers. If the takeover falls through, traders can be left with large losses.

Fund of Funds

Capital is allocated among funds, providing investors with access to managers with higher minimums than individual might afford.

Diversified. Allocates capital to a variety of fund types.

Niche. Allocates capital to a specific type of fund.

Global

International. Manager pays attention to economic change around the world (except US); bottom-up-oriented in that they tend to be stock-pickers in markets they like. Use index derivatives much less than macro managers.

Regional-Emerging. Manager invests in less mature financial markets. Because shorting is not permitted in many emerging markets, managers must go cash or other markets when valuations make being long unattractive. Focus on specific regions.

Regional-Established. Focuses on opportunities in established markets.

Global Macro

Opportunistic; the 'classic' Soros-Steinhardt-Robertson type hedge fund, manager profiting wherever they see value. Use leverage and derivatives to enhance positions, which will have varying time frames, from short (less than one month) to long (more than 12 months).

Long-Only Leveraged

Traditional equity fund structured like a hedge fund; i.e. uses leverage and permits manager to collect an incentive fee.

Market Neutral

Manager attempts to lockout or neutralizes market risk. In theory, market risk is greatly reduced but it is difficult to make a profit on a large diversified portfolio, so stock picking is critical.

Long/Short. Net exposure to market risk is believed to be reduced by having equal allocations on the long and short sides of the market.

Convertible Arbitrage. One of the more conservative styles. Manager goes long convertible securities and short underlying equities, profiting from mispricing in the relationship of the two.

Stock Arbitrage. Manager buys a basket of stocks and sells short stock index futures contracts, or reverse.

Fixed Income Arbitrage. Manager buys bonds – often T-bonds, but also sovereign and corporate bonds – and goes short instruments that replicate the owned bond. Manager aims to profit from mispricing of relationship between the long and short sides.

Sector

Follows specific economic sectors and/or industries: Managers can use a wide range of methodologies (e.g. bottom-up, top-down, discretionary, technical) and primary focus (e.g. large-cap, mid-cap, small-cap, micro-cap, value growth, opportunistic).

Short-Sellers

Manager takes a position that stock prices will go down. A hedge fund borrows stock and sells it, hoping to buy it back at a lower price. Manager shorts only overvalued securities. A hedge for long-only portfolios and those who feel market is approaching a bearish trend.

*Source: MAR/Hedge web site (http://www.marhedge.com)

APPENDIX 2

Tables

Table 1: Number of Defunct and Surviving Funds by Inception Year

First Year	Defunct*		Live*		Total
	#	%	#	%	
1980		0%	2	100%	2
1981	1	100%		0%	1
1982	3	50%	3	50%	6
1983	5	71%	2	29%	7
1984	9	64%	5	36%	14
1985	11	85%	2	15%	13
1986	14	64%	8	36%	22
1987	18	69%	8	31%	26
1988	19	73%	7	27%	26
1989	18	44%	23	56%	41
1990	41	59%	28	41%	69
1991	61	64%	35	36%	96
1992	80	61%	51	39%	131
1993	137	65%	73	35%	210
1994	200	63%	119	37%	319
1995	142	52%	129	48%	271
1996	193	53%	171	47%	364
1997	197	55%	161	45%	358
1998	126	40%	188	60%	314
1999	109	32%	230	68%	339
2000	65	25%	198	75%	263
2001	11	6%	167	94%	178
2002	4	12%	29	88%	33
Total	**1464**	**47%**	**1639**	**53%**	**3103**

*Number of funds as of July, 2003.

Table 2: Distribution of Funds by Investment Strategy

Defunct Funds by Investment Category

	Off-shore	US	Total #	Total %
Event-Driven	27	65	92	6%
Global Macro	76	48	124	9%
Global Emerging	48	30	78	5%
Global Established	81	129	210	14%
Global International	20	6	26	2%
Long Only	4	16	20	1%
Market Neutral	131	146	277	19%
Sector	36	58	94	6%
Short-Sales	5	16	21	1%
Global	98	113	211	15%
US Opport.	11	42	53	4%
Natural Resources		3	3	0%
Total	**537**	**672**	**1209**	**83%**
Fund of Funds	152	92	244	17%
Grand Total	**689**	**764**	**1453**	**100%**

Live Funds by Investment Category

	Off-shore	US	Total #	Total %
Event-Driven	78	87	165	10%
Global Macro	29	28	57	3%
Global Emerging	63	28	91	6%
Global Established	141	208	349	21%
Global International	30	25	55	3%
Long Only	3	17	20	1%
Market Neutral	185	195	380	23%
Sector	34	87	121	7%
Short-Sales	7	11	18	1%
Total	**570**	**686**	**1256**	**76%**
Fund of Funds	219	168	387	24%
Grand Total	**789**	**854**	**1643**	**100%**

Table 3: Descriptive Statistics of Hedge Fund Features

This table presents summary statistics on four features of hedge funds. The sample consists of 1,643 hedge funds in the MAR database as of July, 2003. Annual management fee is the percentage of the fund's net assets under management that is paid annually to fund management. Incentive fee is the percentage of the profits that is given to fund management in reward for good performance. Size is the amount of the fund's net assets under management as of July, 2003.

	All Hedge Funds	Event-Driven	Global Macro	Global Emerging	Global Established
Number of Funds	1,643	165	57	91	349
Average Minimum Purchase ($)	778,602	873,000	468,618	397,582	674,327
Median Minimum Purchase ($)	500,000	500,000	250,000	250,000	250,000
Average Incentive Fee (%)	13.73	13.36	13.82	17.18	10.77
Median Incentive Fee (%)	20.00	20.00	20.00	20.00	15.00
Average Std. Dev. Incentive Fee (%)	9.20	9.48	9.97	6.78	9.75
Max. Incentive Fee (%)	50.00	33.00	30.00	33.00	25.00
Average Admin. Fee (%)	0.89	0.96	1.09	1.24	0.76
Median Admin. Fee (%)	1.00	1.00	1.00	1.00	1.00
Average Std. Dev. Admin. Fee (%)	0.72	0.69	1.07	0.57	0.64
Average Size of Funds ($ millions)	110.05	116.31	52.66	53.49	108.41
Median Size of Funds ($ millions)	29.00	36.00	15.92	25.30	28.50

Table 3: Descriptive Statistics of Hedge Fund Features (continued)

This table presents summary statistics on four features of hedge funds. The sample consists of 1,643 hedge funds in the MAR database as of July, 2003. Annual management fee is the percentage of the fund's net assets under management that is paid annually to fund management. Incentive fee is the percentage of the profits that is given to fund management in reward for good performance. Size is the amount of the fund's net assets under management as of July, 2003.

	Global International	Long Only	Market Neutral	Sector	Short-Sales	Fund of Funds
Number of Funds	55	20	380	121	18	387
Average Minimum Purchase ($)	386,636	305,250	1,199,766	567,810	381,944	718,618
Median Minimum Purchase ($)	150,000	250,000	500,000	500,000	250,000	250,000
Average Incentive Fee (%)	12.65	9.50	14.53	11.17	10.28	16.30
Median Incentive Fee (%)	20.00	10.00	20.00	20.00	15.00	20.00
Average Std. Dev. Incentive Fee (%)	9.15	9.45	10.14	9.81	10.77	6.07
Max. Incentive Fee (%)	25.00	20.00	50.00	25.00	25.00	25.00
Average Admin. Fee (%)	0.79	0.73	0.96	0.88	0.56	0.83
Median Admin. Fee (%)	1.00	1.00	1.00	1.00	1.00	1.00
Average Std. Dev. Admin. Fee (%)	0.62	0.82	0.71	0.68	0.62	0.76
Average Size of Funds ($ millions)	149.29	17.60	169.09	40.15	85.56	94.82
Median Size of Funds ($ millions)	21.50	8.00	44.71	16.00	15.05	32.03

Table 4: Descriptive Statistics of Assets under Management by Hedge Fund Category

	Number of Funds	Mean	Median	Total Assets	Largest 10 Funds	Largest 10 Funds as % of Total Assets
All Hedge Funds	1,643	110.05	29.00	180.81	32.20	17.81%
Event-Driven	165	116.31	36.00	19.20	10.13	52.76%
Global Macro	57	52.66	15.92	3.00	2.20	73.33%
Global Emerging	91	53.49	25.30	4.87	2.59	53.18%
Global Established	349	108.41	28.50	37.84	15.63	41.31%
Global International	55	149.29	21.50	8.21	6.54	79.66%
Long Only	20	17.60	8.00	0.35	0.33	92.59%
Market Neutral	380	169.09	44.71	64.25	23.03	35.84%
Sector	121	40.15	16.00	4.86	2.18	44.86%
Short-Sales	18	85.56	15.05	1.54	1.49	96.75%
Fund of Funds	387	94.82	32.03	36.69	10.67	29.08%

Table 5: Average Monthly Performance of Hedge Funds: 1990:1 – 2003:7

	Surviving Hedge Funds			Defunct Hedge Funds		
	EW Average Monthly Return	VW Average Monthly Return	Average Std. Dev. Of Monthly Returns	EW Average Monthly Return	VW Average Monthly Return	Average Std. Dev. Of Monthly Returns
1990	0.80	1.48	4.48	0.41	-	-
1991	1.95	2.64	4.50	1.98	2.94	4.95
1992	1.28	1.19	3.59	1.17	1.01	4.22
1993	1.98	2.07	3.64	2.30	1.82	8.27
1994	0.28	-0.06	3.71	0.12	0.35	7.12
1995	1.57	1.55	3.54	1.36	0.95	5.07
1996	1.80	1.39	3.97	1.53	1.02	5.66
1997	1.73	1.65	4.26	2.05	0.65	16.76
1998	0.52	0.27	5.66	-0.03	0.21	7.45
1999	2.57	1.68	5.77	2.49	0.70	7.61
2000	1.03	1.02	6.37	-0.62	-0.26	9.71
2001	0.53	0.50	4.51	-0.73	-0.01	7.37
2002	-0.32	0.08	4.01	-	-	-

Table 6: Monthly Return and Standard Deviation of Hedge Funds by Inception Year

Average Monthly Return

Cohort	1992	1993	1994	1995	1996	1997	1998	1999	2000	2001
1991	1.37	2.22	0.28	1.49	1.60	1.44	0.14	2.31	0.22	0.23
1992		2.20	0.06	1.45	1.69	1.80	-0.06	2.16	1.06	0.52
1993			0.50	1.27	1.55	1.68	0.01	2.39	0.30	0.42
1994				1.78	1.95	1.81	-0.02	2.51	0.49	0.56
1995					2.06	1.59	0.79	2.43	0.91	0.47
1996						1.80	0.32	2.45	1.00	0.53
1997							0.88	2.92	1.05	0.45
1998								2.95	1.14	0.38
1999									1.33	0.42
2000										0.86

Average Monthly Standard Deviation

Cohort	1992	1993	1994	1995	1996	1997	1998	1999	2000	2001
1991	3.25	2.74	3.31	2.48	2.55	3.42	5.25	4.30	4.99	3.83
1992		2.97	2.77	2.59	2.85	3.56	4.62	3.99	3.74	2.91
1993			3.33	3.03	2.83	3.40	5.09	4.57	4.84	3.91
1994				2.91	3.35	3.64	5.43	4.62	4.94	3.37
1995					3.22	3.23	4.64	3.99	4.85	3.30
1996						4.06	5.54	4.90	5.61	4.22
1997							6.26	5.26	6.16	4.30
1998								4.18	4.77	3.04
1999									5.02	3.21
2000										2.93

Table 7: Hedge Fund Index Return Distributions

This table presents the descriptive statistics of the 14 hedge fund style indices of the ZCM database for the 145 month period between January 1990 and January 2002. The single index alpha is generated according to $(R_t - R^*) = \alpha + \beta_t (R_M - R^*)$, where R_t, R^*, R_M are the monthly return of the hedge fund, the risk free rate of return (30 day US$ LIBOR rate), and the S&P 500 monthly total return respectively. A positive alpha (α) indicates that the fund manager had overperformed on a risk-adjusted basis. The Sharpe Ratio is defined as $S_t = (r_t - r^*) / \sigma_t$ where r_t is the average monthly return of the hedge fund, r^* is the average monthly risk free rate, and σ_t is the standard deviation of fund monthly returns.

	Mean	Std. Dev.	Skewness	Kurtosis	Alpha (%)	Sharpe Ratio
Event-Driven	1.00	1.32	-1.49	11.39	0.4594	0.4177
Event-Driven: Distressed Securities	1.15	2.07	-0.88	6.83	0.5554	0.3405
Event-Driven: Risk Arb.	1.01	1.27	-1.43	9.92	0.4764	0.4427
Global Emerging	1.15	4.76	-1.07	11.53	0.3423	0.1478
Global International	0.96	2.03	-0.85	8.58	0.3565	0.2525
Global Established	1.28	2.66	-0.38	4.83	0.5232	0.3140
Global Macro	1.11	2.02	0.89	5.28	0.5202	0.3256
Market Neutral	0.89	0.42	0.03	4.42	0.4182	1.0391
Market Neutral: Arbitrage	1.10	2.08	4.09	27.46	0.5911	0.3138
Market Neutral: Long/Short	0.84	0.50	0.45	5.14	0.3747	0.7911
Short	0.27	5.28	0.46	4.55	0.4058	-0.0337
Fund of Funds	0.83	1.31	-1.03	9.01	0.2783	0.2890
Fund of Funds: Diversified	0.86	1.41	-0.49	8.47	0.3027	0.2917
Fund of Funds: Niche	0.84	1.49	-0.16	7.18	0.2967	0.2617
S&P 500	1.08	4.19	-0.46	3.70	-	0.1502

Table 8: Correlation Matrix for Hedge Fund Index Returns

	1	2	3	4	5	6	7	8	9	10	11	12	13	14
1.Event-Driven	1.00													
2.Event-Driven: Distressed Sec.	0.75	1.00												
3.Event-Driven: Risk Arb.	0.93	0.58	1.00											
4.Global Emerging	0.59	0.55	0.51	1.00										
5.Global International	0.68	0.61	0.59	0.65	1.00									
6.Global Established	0.68	0.65	0.62	0.65	0.68	1.00								
7.Global Macro	0.52	0.54	0.44	0.46	0.52	0.56	1.00							
8.Market Neutral	0.66	0.56	0.59	0.48	0.55	0.52	0.45	1.00						
9.Market Neutral: Arbitrage	0.35	0.30	0.31	0.37	0.46	0.56	0.23	0.39	1.00					
10.Market Neutral: Long/Short	0.41	0.37	0.38	0.25	0.45	0.46	0.31	0.55	0.45	1.00				
11.Short	-0.56	-0.53	-0.52	-0.53	-0.51	-0.80	-0.40	-0.41	-0.43	-0.31	1.00			
12.Fund of Funds	0.73	0.63	0.67	0.65	0.80	0.72	0.67	0.59	0.42	0.46	-0.51	1.00		
13.Fund of Funds: Diversified	0.70	0.62	0.63	0.67	0.84	0.76	0.64	0.58	0.57	0.50	-0.53	0.97	1.00	
14.Fund of Funds: Niche	0.56	0.52	0.52	0.52	0.49	0.53	0.54	0.51	0.26	0.33	-0.43	0.73	0.69	1.00
15.S&P 500	0.47	0.48	0.45	0.50	0.51	0.78	0.46	0.31	0.20	0.29	-0.72	0.52	0.52	0.42

Note: Monthly data, January 1990-January 2002

Table 9: Correlation between Hedge Fund Indices and the S&P 500 Index

This table presents the correlation between the hedge fund indices and the S&P 500 index for the whole sample, r. In the second and third columns, the dataset was divided into two periods, first the periods when the S&P 500 index returns were negative and later when the S&P 500 index returns were positive. Therefore, r^{neg} measures the correlation in downmarkets and r^{pos} measures the correlation in upmarkets. Standard errors are given in parenthesis.

	r	r^{neg}	r^{pos}
Event-Driven	0.47	0.46	-0.04
	(0.07)	*(0.13)*	*(0.10)*
Event-Driven: Distressed Sec.	0.48	0.15	-0.07
	(0.07)	*(0.14)*	*(0.10)*
Event-Driven: Risk Arb.	0.45	0.42	-0.05
	(0.07)	*(0.13)*	*(0.10)*
Global Emerging	0.50	0.32	0.20
	(0.07)	*(0.13)*	*(0.10)*
Global International	0.51	0.10	0.13
	(0.07)	*(0.14)*	*(0.10)*
Global Established	0.78	0.53	0.45
	(0.05)	*(0.12)*	*(0.09)*
Global Macro	0.46	0.27	-0.07
	(0.07)	*(0.14)*	*(0.10)*
Market Neutral	0.31	0.26	0.06
	(0.08)	*(0.14)*	*(0.10)*
Market Neutral: Arbitrage	0.20	0.26	-0.03
	(0.08)	*(0.14)*	*(0.10)*
Market Neutral: Long/Short	0.29	0.13	0.16
	(0.08)	*(0.14)*	*(0.10)*
Short	-0.72	-0.56	-0.39
	(0.06)	*(0.12)*	*(0.10)*
Fund of Funds	0.52	0.32	0.08
	(0.07)	*(0.13)*	*(0.10)*
Fund of Funds: Diversified	0.52	0.31	0.11
	(0.07)	*(0.13)*	*(0.10)*
Fund of Funds: Niche	0.42	0.24	0.15
	(0.08)	*(0.14)*	*(0.10)*

Table 10: Hedge Fund Regressions on S&P 500 Index – Nonlinear Model

Regression estimates of hedge fund index returns on the S&P 500 is provided. The models are generated according to $R_t = \alpha + \beta_1 SP + \beta_2 SP2 + \beta_3 SP3 + \varepsilon$, where R_t is the percentage monthly return of the hedge fund index, SP, SP2, and SP3 are the percentage monthly return of the S&P 500 index, and quadratic and cubic term of that index respectively.

	Intercept	S&P 500	$(S\&P\ 500)^2$	$(S\&P\ 500)^3$	Adjusted R^2
Event-Driven	1.201 (0.11)	0.155*** (0.02)	-0.020*** (0.003)		0.39
Global Emerging	1.108 (0.39)	0.147 (0.12)	-0.015 (0.01)	0.007*** (0.001)	0.37
Global International	1.016 (0.17)	0.253*** (0.03)	-0.018*** (0.005)		0.31
Global Established	0.985 (0.17)	0.495*** (0.03)	-0.013** (0.005)		0.62
Global Macro	0.869 (0.15)	0.221*** (0.04)			0.20
Market Neutral	0.895 (0.04)	0.008 (0.01)	-0.001 (0.001)	0.0004** (0.0002)	0.14
Market Neutral: Arbitrage	1.223 (0.21)	0.102** (0.04)	-0.012** (0.006)		0.05
Market Neutral: Long/Short	0.806 (0.04)	0.035*** (0.009)			0.08
Short	0.776 (0.37)	-0.917*** (0.07)	0.026** (0.01)		0.53
Fund of Funds	0.90 (0.11)	0.165*** (0.02)	-0.013*** (0.003)		0.34

***Significant at the 1 percent level
**Significant at the 5 percent level.
*Significant at the 10 percent level.

Table 11: Hedge Fund Regressions on S&P 500 Index – Linear Model

Regression estimates of hedge fund index returns on the S&P 500 is provided. The models are generated according to $R_t = \alpha + \beta\ SP + \varepsilon$, where Rt is the percentage monthly return of the hedge fund index, SP is the percentage monthly return of the S&P 500 index.

	Intercept	S&P 500	Adjusted R^2
Event-Driven	0.841 (0.10)	0.149*** (0.02)	0.22
Global Emerging	0.538 (0.35)	0.568*** (0.08)	0.25
Global International	0.693 (0.15)	0.249*** (0.03)	0.26
Global Established	0.751 (0.14)	0.492*** (0.03)	0.60
Global Macro	0.869 (0.15)	0.221*** (0.04)	0.20
Market Neutral	0.853 (0.03)	0.03*** (0.008)	0.09
Market Neutral: Arbitrage	0.995 (0.18)	0.099** (0.04)	0.03
Market Neutral: Long/Short	0.806 (0.04)	0.035*** (0.009)	0.08
Short	1.258 (0.314)	-0.91*** (0.07)	0.52
Fund of Funds	0.654 (0.09)	0.16*** (0.02)	0.26

***Significant at the 1 percent level
**Significant at the 5 percent level.
*Significant at the 10 percent level.

Table 12: Descriptive Statistics of the Hedge Fund Indices and the Explanatory Factors

This table presents the mean monthly returns, standard deviations (SD), medians, skewness (Skew), kurtosis, minimum, and maximum for the hedge fund indices and the factors during January 1990 and December 2001. SPCa, SPCo, SPPa, and SPPo are the at-the-money call, out-of-the-money call, at-the-money put, and out-of-the-money put options on the S&P 500 index respectively.

	Mean	SD	Median	Skew	Kurtosis	Minimum	Maximum
Hedge Fund Indices							
Event Driven	1.01	1.33	0.99	-1.50	8.68	-6.91	4.68
Event Driven: Distressed Securities	1.15	2.08	1.20	-0.88	3.97	-9.22	6.05
Event Driven: Risk Arbitrage	1.02	1.27	1.10	-1.46	7.19	-5.61	4.74
Global Emerging	1.14	4.77	1.05	-1.07	8.80	-26.65	19.33
Global International	0.97	2.03	1.05	-0.87	5.81	-10.15	7.92
Global Established	1.29	2.66	1.45	-0.39	1.92	-9.42	9.40
Global Macro	1.11	2.03	0.63	0.89	2.37	-5.36	8.61
Market Neutral	0.89	0.42	0.93	0.02	1.50	-0.61	2.34
Market Neutral: Arbitrage	1.10	2.09	1.07	4.12	25.17	-4.78	14.13
Market Neutral: Long/Short	0.85	0.50	0.82	0.45	2.31	-1.03	2.76
Short	0.26	5.29	0.11	0.47	1.64	-12.12	22.17
Fund of Funds	0.83	1.32	0.82	-1.04	6.22	-6.40	4.50
Factors							
S&P 500	1.10	4.20	1.32	-0.47	0.76	-14.46	11.44
MSCI World ex-US	0.20	4.84	0.47	-0.13	0.35	-13.66	14.45
MSCI Emerging	0.52	6.98	0.92	-0.70	1.80	-29.29	16.45
JP Morgan Global Gov't Bond	0.55	1.71	0.45	0.19	0.02	-3.34	5.22
JP Morgan USA Gov't Bond	1.24	2.56	1.18	-0.22	1.61	-8.26	8.82
Fed Trade-Weighted Dollar index	0.44	1.15	0.37	0.41	0.96	-2.78	3.96
Goldman Sachs Commodity index	0.41	5.31	0.23	0.91	2.62	-12.12	22.94
Fama-French SMB	0.12	3.60	0.02	0.57	2.41	-11.66	15.40
Fama-French HML	0.06	4.26	-0.23	-0.85	6.09	-21.51	14.23
SPCa	0.70	84.22	-20.34	0.78	-0.23	-99.04	236.24
SPCo	-1.35	93.24	-30.56	1.10	0.65	-99.35	300.60
SPPa	-16.26	91.50	-54.37	1.85	3.67	-95.30	386.02
SPPo	-18.99	97.33	-60.69	2.26	5.91	-96.21	422.34

Table 13: Stepwise Regression Results of Hedge Fund Strategies

This table shows the results of the stepwise regression results for the hedge fund strategies for the whole sample period (Jan. 1990-Dec. 2001). The coefficients are significant at the five percent level. Standard errors are in parentheses. The factors are the S&P 500 index (SP500), MSCI World excluding USA index (MSXUS), MSCI Emerging Markets index (MSEM), JP Morgan Global Government Bond index (JPGB), JP Morgan USA Government Bond index (JPGBUS), Federal Reserve Bank Trade-Weighted Dollar index (FED$I), Goldman Sachs Commodity index (GSCI), Fama-French Size factor (SMB), Fama-French Book-to-Market factor (HML), at-the-money call option (SPCa), out-of-the-money call option (SPCo), at-the-money put option (SPPa), out-of-the-money put option (SPPo) on the S&P 500 index.

	Constant	SP500	MSXUS	MSEM	JPGB	JPGBUS	FED$I	GSCI	SMB	HML	SPCa	SPCo	SPPa	SPPo	Adj-R2
Event Driven	0.84			0.05				0.03	0.14	0.05				-0.0060	0.54
	(0.08)			(0.01)				(0.01)	(0.02)	(0.02)				(0.00)	
Event Driven- Dist.	0.99			0.07					0.18	0.07			-0.0343	0.0242	0.48
	(0.13)			(0.02)					(0.04)	(0.03)			(0.01)	(0.01)	
Event Driven- Risk Arb.	0.85								0.14	0.07				-0.0077	0.47
	(0.08)								(0.02)	(0.02)				(0.00)	
Global Emerging	0.88			0.50											0.54
	(0.27)			(0.04)											
Global International	0.80			0.14				0.07		-0.08			-0.0047		0.50
	(0.12)			(0.02)				(0.02)		(0.03)			(0.00)		
Global Established	0.75	0.47							0.31	-0.06					0.82
	(0.10)	(0.02)							(0.03)	(0.03)					
Global Macro	0.52			0.17		0.26	0.42								0.38
	(0.16)			(0.02)		(0.05)	(0.12)								
Market Neutral	0.87			0.02					0.03						0.24
	(0.03)			(0.00)					(0.01)						
Market Neutral- Arbitrage	1.18		0.09		-0.18				0.18	-0.18					
	(0.14)		(0.03)		(0.08)				(0.04)	(0.04)					(0.44)
Market Neutral- L/S	0.72	0.08				0.06			0.05				0.0024		0.28
	(0.04)	(0.02)				(0.01)			(0.01)				(0.00)		
Short	1.32	-0.90							-0.67						0.73
	(0.24)	(0.06)							(0.06)						
Fund of Funds	0.60			0.07		0.07		0.04	0.09					-0.0040	0.54
	(0.09)			(0.01)		(0.03)		(0.01)	(0.02)					(0.00)	

Table 14a: Event Driven / Whole Sample Period

Posterior parameter estimates, standard deviations and probabilities that the coefficients are non-zero.

	Mean	St. Dev	$\Pr(\beta \neq 0 \mid D)$	1st Best Model	2nd Best Model	3rd Best Model/Stepwise Selected Model
Intercept	0.85	0.08				
S&P 500	0.00	0.01	2.7	F	F	F
MSCI World ex-US	0.00	0.00	4	F	F	F
MSCI Emerging	0.05	0.02	97.8	T	T	T
JP Morgan Global Gov't Bond	0.00	0.00	1	F	F	F
JP Morgan USA Gov't Bond	0.00	0.01	6.3	F	F	F
Fed Trade-Weighted Dollar index	0.00	0.03	6.3	F	F	F
Goldman Sachs Commodity index	0.01	0.02	31.5	F	F	T
Fama-French SMB	0.13	0.03	100	T	T	T
Fama-French HML	0.03	0.03	55.4	T	F	T
SPCa	0.00	0.00	8.6	F	F	F
SPCo	0.00	0.00	6.2	F	F	F
SPPa	0.00	0.00	14.7	F	F	F
SPPo	-0.01	0.00	93.7	T	T	T
R^2%				53.05	51.35	54.39
PMP%				16.00	15.00	11.00

Table 14b: Event Driven / 1990-1991

Posterior parameter estimates, standard deviations and probabilities that the coefficients are non-zero.

	Mean	St. Dev	$\Pr(\beta \neq 0 \mid D)$	1st Best Model/Stepwise Selected Model	2nd Best Model	3rd Best Model
Intercept	1.03	0.34				
S&P 500	0.00	0.02	5.4	F	F	F
MSCI World ex-US	0.00	0.01	3.9	F	F	F
MSCI Emerging	0.01	0.03	30.2	F	F	F
JP Morgan Global Gov't Bond	-0.03	0.10	16.7	F	F	F
JP Morgan USA Gov't Bond	-0.13	0.21	38.7	F	T	T
Fed Trade-Weighted Dollar index	0.00	0.05	3.7	F	F	F
Goldman Sachs Commodity index	0.01	0.03	29.8	F	F	F
Fama-French SMB	0.17	0.14	73.6	T	T	F
Fama-French HML	0.00	0.03	2.6	F	F	F
SPCa	0.00	0.01	2.2	F	F	F
SPCo	0.00	0.01	2.2	F	F	F
SPPa	0.00	0.01	18.7	F	F	F
SPPo	-0.01	0.00	91.5	T	T	T
R^2%				62.73	66.87	61.93
PMP%				9.00	7.00	7.00

Table 14c: Event Driven / 1992-1993

Posterior parameter estimates, standard deviations and probabilities that the coefficients are non-zero.

	Mean	St. Dev	$\Pr(\beta \neq 0 \mid D)$	1st Best Model/Stepwise Selected Model	2nd Best Model	3rd Best Model
Intercept	1.07	0.26				
S&P 500	0.03	0.07	12.8	F	F	T
MSCI World ex-US	0.01	0.02	19.2	F	F	F
MSCI Emerging	0.00	0.01	7.1	F	F	F
JP Morgan Global Gov't Bond	0.00	0.00	0	F	F	F
JP Morgan USA Gov't Bond	0.00	0.02	3.2	F	F	F
Fed Trade-Weighted Dollar index	0.02	0.07	12.2	F	F	F
Goldman Sachs Commodity index	-0.02	0.06	22.5	F	F	F
Fama-French SMB	0.32	0.06	100	T	T	T
Fama-French HML	0.32	0.07	100	T	T	T
SPCa	0.00	0.00	30.2	T	F	F
SPCo	0.00	0.00	37.9	F	T	F
SPPa	0.00	0.00	8.8	F	F	F
SPPo	0.00	0.00	11.2	F	F	F
$R^2\%$				70.75	70.74	70.07
PMP%				11.00	11.00	8.00

Table 14d: Event Driven / 1994-1995

Posterior parameter estimates, standard deviations and probabilities that the coefficients are non-zero.

	Mean	St. Dev	$\Pr(\beta \neq 0 \mid D)$	1st Best Model	2nd Best Model	3rd Best Model	Stepwise Selected Model
Intercept	0.26	0.17					
S&P 500	0.12	0.17	40.8	T	T	F	F
MSCI World ex-US	-0.01	0.03	12.8	F	F	F	F
MSCI Emerging	0.01	0.02	23.2	F	F	F	F
JP Morgan Global Gov't Bond	-0.08	0.10	51.4	F	F	T	F
JP Morgan USA Gov't Bond	0.14	0.10	80.4	T	T	T	F
Fed Trade-Weighted Dollar index	0.11	0.11	63.7	T	T	F	F
Goldman Sachs Commodity index	0.10	0.04	99.2	T	T	T	T
Fama-French SMB	0.01	0.03	5.7	F	F	F	T
Fama-French HML	-0.23	0.06	100	T	T	T	T
SPCa	0.01	0.01	43.7	F	F	T	T
SPCo	0.00	0.01	37.7	F	F	F	F
SPPa	0.01	0.02	41.1	T	F	T	F
SPPo	0.00	0.02	29.6	F	T	F	F
R^2%				84.52	84.24	84.06	75.78
PMP%				6.00	5.00	4.00	

Table 14e: Event Driven / 1996-1997

Posterior parameter estimates, standard deviations and probabilities that the coefficients are non-zero.

	Mean	St. Dev	$Pr(\beta \neq 0 \mid D)$	1st Best Model/Stepwise Selected Model	2nd Best Model	3rd Best Model
Intercept	1.09	0.13				
S&P 500	0.00	0.02	9.7	F	F	F
MSCI World ex-US	0.00	0.02	8.6	F	F	F
MSCI Emerging	0.08	0.03	100	T	T	T
JP Morgan Global Gov't Bond	-0.14	0.16	61.5	F	T	T
JP Morgan USA Gov't Bond	0.28	0.09	100	T	T	T
Fed Trade-Weighted Dollar index	-0.06	0.13	29.9	F	F	T
Goldman Sachs Commodity index	0.00	0.01	4	F	F	F
Fama-French SMB	0.18	0.04	100	T	T	T
Fama-French HML	0.00	0.02	7.6	F	F	F
SPCa	0.00	0.01	35.2	F	F	T
SPCo	0.00	0.01	28.2	F	F	F
SPPa	0.00	0.02	13	F	F	F
SPPo	0.00	0.02	13.2	F	F	F
R^2%				70.15	72.93	79.1
PMP%				8.00	6.00	5.00

Table 14f: Event Driven / 1998-1999

Posterior parameter estimates, standard deviations and probabilities that the coefficients are non-zero.

	Mean	St. Dev	$\Pr(\beta \neq 0 \mid D)$	1st Best Model/Stepwise Selected Model	2nd Best Model	3rd Best Model
Intercept	0.85	0.12				
S&P 500	0.00	0.01	4.7	F	F	F
MSCI World ex-US	0.00	0.01	7.9	F	F	F
MSCI Emerging	0.00	0.00	4.7	F	F	F
JP Morgan Global Gov't Bond	-0.03	0.08	24.9	F	F	F
JP Morgan USA Gov't Bond	-0.11	0.06	86.7	T	T	T
Fed Trade-Weighted Dollar index	-0.02	0.06	16.5	F	F	F
Goldman Sachs Commodity index	0.00	0.01	10	F	F	T
Fama-French SMB	0.24	0.03	100	T	T	T
Fama-French HML	0.11	0.03	100	T	T	T
SPCa	0.00	0.00	6.4	F	F	F
SPCo	0.00	0.00	7.7	F	F	F
SPPa	0.00	0.01	18.8	F	T	F
SPPo	-0.01	0.01	90.3	T	F	T
R^2%				94.52	94.11	94.62
PMP%				23.00	10.00	6.00

Table 14g: Event Driven / 2000-2001

Posterior parameter estimates, standard deviations and probabilities that the coefficients are non-zero.

	Mean	St. Dev	$\Pr(\beta \neq 0 \mid D)$	1st Best Model	2nd Best Model	3rd Best Model	Stepwise Selected Model
Intercept	0.20	0.25					
S&P 500	0.45	0.14	100	T	T	T	T
MSCI World ex-US	-0.02	0.06	27.7	F	F	F	F
MSCI Emerging	0.01	0.03	18.4	F	F	F	F
JP Morgan Global Gov't Bond	-0.11	0.12	60.4	T	T	T	F
JP Morgan USA Gov't Bond	0.07	0.06	77.8	T	T	T	F
Fed Trade-Weighted Dollar index	-0.09	0.15	39.7	T	F	T	F
Goldman Sachs Commodity index	0.06	0.02	99.6	T	T	T	T
Fama-French SMB	0.13	0.05	98.4	T	T	T	T
Fama-French HML	0.03	0.03	73.6	T	T	T	F
SPCa	-0.01	0.01	99.6	T	T	T	T
SPCo	0.00	0.00	31.4	F	F	T	F
SPPa	0.01	0.01	58.8	T	F	T	F
SPPo	0.00	0.01	43.8	F	T	F	T
R^2%				86.48	84.21	87.76	74.81
PMP%				7.00	6.00	5.00	

Table 16: Summary Statistics and BMA Estimates for the Event Driven - Distressed Securities Index

The following table shows the BMA estimates along with the stepwise estimates for the sample period Jan. 1990 to Dec. 2001. The table contains the posterior means, standard deviations and posterior effect probabilities, Pr ($\beta \neq 0 \mid D$), for the coefficient associated with each variable. Posterior effect probabilities are obtained by summing the posterior model probabilities across models for each predictor. In addition, p-value of the coefficients of the variables that are chosen by the stepwise models is given. PMP denotes the posterior model probability. Only the 3 models with the highest PMP values are shown. T indicates that the variable is included, while F indicates that it is not, for each of the models.

	Mean	St. Dev	Pr($\beta \neq 0 \mid D$)	*p*-value	1st Best Model	2nd Best Model/Stepwise Selected Model	3rd Best Model
Intercept	0.99	0.14					
Fama-French SMB	0.16	0.04	100	<0.0001	T	T	T
SPPa	-0.03	0.01	98.1	0.0003	T	T	T
MSCI Emerging	0.07	0.03	94.3	0.0044	T	T	T
SPPo	0.02	0.01	78.6	0.0041	T	T	F
Fama-French HML	0.02	0.04	33.9	0.0477	F	T	F
Goldman Sachs Commodity index	0.00	0.01	6.3	-	F	F	F
Fed Trade-Weighted Dollar index	0.01	0.04	5.9	-	F	F	F
SPCo	0.00	0.00	5.7	-	F	F	F
S&P 500	0.00	0.03	5.4	-	F	F	F
SPCa	0.00	0.00	4.9	-	F	F	F
MSCI World ex-US	0.00	0.01	4.8	-	F	F	F
JP Morgan USA Gov't Bond	0.00	0.01	3.9	-	F	F	F
JP Morgan Global Gov't Bond	0.00	0.01	3.4	-	F	F	F
R-square%					46.28	47.80	43.76
PMP%					25.00	16.00	11.00

Table 17: Summary Statistics and BMA Estimates for the Event Driven Risk - Arbitrage Index

The following table shows the BMA estimates along with the stepwise estimates for the sample period Jan. 1990 to Dec. 2001. The table contains the posterior means, standard deviations and posterior effect probabilities, Pr ($\beta \neq 0 \mid D$), for the coefficient associated with each variable. Posterior effect probabilities are obtained by summing the posterior model probabilities across models for each predictor. In addition, p-value of the coefficients of the variables that are chosen by the stepwise models is given. PMP denotes the posterior model probability. Only the 3 models with the highest PMP values are shown. T indicates that the variable is included, while F indicates that it is not, for each of the models.

	Mean	St. Dev	Pr($\beta \neq 0 \mid D$)	*p*-value	1st Best Model/Stepwise Selected Model	2nd Best Model	3rd Best Model
Intercept	0.84	0.08					
Fama-French SMB	0.13	0.03	100	<0.0001	T	T	T
SPPo	-0.01	0.01	100	<0.0001	T	T	T
Fama-French HML	0.06	0.03	94.8	0.0014	T	T	T
MSCI Emerging	0.02	0.02	52.9	-	F	T	T
SPPa	0.00	0.01	37.7	-	F	T	F
JP Morgan USA Gov't Bond	0.00	0.01	7	-	F	F	F
Goldman Sachs Commodity index	0.00	0.01	6.6	-	F	F	F
S&P 500	0.00	0.01	6.2	-	F	F	F
Fed Trade-Weighted Dollar index	0.00	0.02	5.3	-	F	F	F
SPCa	0.00	0.00	5.1	-	F	F	F
SPCo	0.00	0.00	4.9	-	F	F	F
MSCI World ex-US	0.00	0.00	3.6	-	F	F	F
JP Morgan Global Gov't Bond	0.00	0.00	1.1	-	F	F	F
R-square%					46.80	50.00	48.20
PMP%					23.00	14.00	13.00

Table 18: Summary Statistics and BMA Estimates for the Global Emerging Index

The following table shows the BMA estimates along with the stepwise estimates for the sample period Jan. 1990 to Dec. 2001. The table contains the posterior means, standard deviations and posterior effect probabilities, Pr ($\beta \neq 0 \mid D$), for the coefficient associated with each variable. Posterior effect probabilities are obtained by summing the posterior model probabilities across models for each predictor. In addition, *p-value of the coefficients of the variables that are chosen by the stepwise models is given.* PMP denotes the posterior model probability. Only the 3 models with the highest PMP values are shown. T indicates that the variable is included, while F indicates that it is not, for each of the models.

	Mean	St. Dev	Pr($\beta \neq 0 \mid D$)	*p*-value	1st Best Model/Stepwise Selected Model	2nd Best Model	3rd Best Model
Intercept	0.86	0.28					
MSCI Emerging	0.49	0.05	100	<0.0001	T	T	T
Fama-French SMB	0.02	0.06	16.4	-	F	F	T
Fama-French HML	-0.01	0.04	9.8	-	F	T	F
Fed Trade-Weighted Dollar index	0.03	0.12	9.6	-	F	F	F
MSCI World ex-US	0.01	0.04	9.4	-	F	F	F
SPCo	0.00	0.00	8.7	-	F	F	F
S&P 500	0.01	0.04	8.3	-	F	F	F
SPCa	0.00	0.00	6.5	-	F	F	F
SPPa	0.00	0.00	5.3	-	F	F	F
SPPo	0.00	0.00	5.3	-	F	F	F
JP Morgan Global Gov't Bond	0.00	0.03	2.8	-	F	F	F
JP Morgan USA Gov't Bond	0.00	0.00	0	-	F	F	F
Goldman Sachs Commodity index	0.00	0.00	0	-	F	F	F
R-square%					54.23	54.95	54.91
PMP%					30.00	8.00	7.00

Table 19: Summary Statistics and BMA Estimates for the Global International Index

The following table shows the BMA estimates along with the stepwise estimates for the sample period Jan. 1990 to Dec. 2001. The table contains the posterior means, standard deviations and posterior effect probabilities, Pr ($\beta \neq 0 | D$), for the coefficient associated with each variable. Posterior effect probabilities are obtained by summing the posterior model probabilities across models for each predictor. In addition, p-value of the coefficients of the variables that are chosen by the stepwise models is given. PMP denotes the posterior model probability. Only the 3 models with the highest PMP values are shown. T indicates that the variable is included, while F indicates that it is not, for each of the models.

	Mean	St. Dev	$Pr(\beta \neq 0 \| D)$	*p*-value	1st Best Model/Stepwise Selected Model	2nd Best Model	3rd Best Model
Intercept	0.79	0.13					
MSCI Emerging	0.14	0.02	100	<0.0001	T	T	T
Goldman Sachs Commodity index	0.07	0.03	94.4	0.0043	T	T	T
Fama-French HML	-0.05	0.05	68.3	0.0109	T	T	F
SPPa	0.00	0.00	54.4	0.0058	T	F	T
SPPo	0.00	0.00	27.1	-	F	T	F
Fama-French SMB	0.02	0.04	24.9	-	F	F	T
S&P 500	0.02	0.04	14.2	-	F	F	F
JP Morgan Global Gov't Bond	-0.01	0.03	7.8	-	F	F	F
MSCI World ex-US	0.00	0.01	6.2	-	F	F	F
Fed Trade-Weighted Dollar index	0.00	0.02	2.1	-	F	F	F
JP Morgan USA Gov't Bond	0.00	0.01	1.4	-	F	F	F
SPCa	0.00	0.00	1.2	-	F	F	F
SPCo	0.00	0.00	1	-	F	F	F
R-square%					49.86	49.50	49.30
PMP%					17.00	10.00	8.00

Table 20: Summary Statistics and BMA Estimates for the Global Established Index

The following table shows the BMA estimates along with the stepwise estimates for the sample period Jan. 1990 to Dec. 2001. The table contains the posterior means, standard deviations and posterior effect probabilities, $\Pr(\beta\neq 0 \mid D)$, for the coefficient associated with each variable. Posterior effect probabilities are obtained by summing the posterior model probabilities across models for each predictor. In addition, p-value of the coefficients of the variables that are chosen by the stepwise models is given. PMP denotes the posterior model probability. Only the 3 models with the highest PMP values are shown. T indicates that the variable is included, while F indicates that it is not, for each of the models.

	Mean	St. Dev	$\Pr(\beta\neq 0 \mid D)$	*p*-value	1st Best Model/Stepwise Selected Model	2nd Best Model	3rd Best Model
Intercept	0.74	0.10					
S&P 500	0.46	0.04	100	<0.0001	T	T	T
Fama-French SMB	0.32	0.03	100	<0.0010	T	T	T
Fama-French HML	-0.04	0.04	59	0.0200	T	F	F
MSCI World ex-US	0.01	0.03	29.8	-	F	F	T
JP Morgan USA Gov't Bond	0.00	0.02	9.2	-	F	F	F
SPPo	0.00	0.00	7.8	-	F	F	F
MSCI Emerging	0.00	0.01	7	-	F	F	F
SPPa	0.00	0.00	5.2	-	F	F	F
Fed Trade-Weighted Dollar index	0.00	0.02	5.1	-	F	F	F
SPCo	0.00	0.00	3.7	-	F	F	F
Goldman Sachs Commodity index	0.00	0.00	3.5	-	F	F	F
JP Morgan Global Gov't Bond	0.00	0.01	3	-	F	F	F
SPCa	0.00	0.00	0	-	F	F	F
R-square%					81.93	81.21	81.76
PMP%					20.00	15.00	10.00

Table 21: Summary Statistics and BMA Estimates for the Global Macro Index

The following table shows the BMA estimates along with the stepwise estimates for the sample period Jan. 1990 to Dec. 2001. The table contains the posterior means, standard deviations and posterior effect probabilities, Pr ($\beta \neq 0 \mid D$), for the coefficient associated with each variable. Posterior effect probabilities are obtained by summing the posterior model probabilities across models for each predictor. In addition, p-value of the coefficients of the variables that are chosen by the stepwise models is given. PMP denotes the posterior model probability. Only the 3 models with the highest PMP values are shown. T indicates that the variable is included, while F indicates that it is not, for each of the models.

	Mean	St. Dev	Pr($\beta \neq 0 \mid D$)	*p*-value	1st Best Model/Stepwise Selected Model	2nd Best Model	3rd Best Model
Intercept	0.52	0.16					
MSCI Emerging	0.16	0.03	100	<0.0001	T	T	T
JP Morgan USA Gov't Bond	0.24	0.06	100	<0.0001	T	T	T
Fed Trade-Weighted Dollar index	0.40	0.12	100	0.0006	T	T	T
SPPa	0.00	0.00	15.7	-	F	T	F
SPPo	0.00	0.00	15.3	-	F	F	T
S&P 500	0.01	0.03	15.2	-	F	F	F
Fama-French SMB	0.01	0.02	13.5	-	F	F	F
Fama-French HML	0.00	0.01	9.1	-	F	F	F
SPCa	0.00	0.00	7.9	-	F	F	F
SPCo	0.00	0.00	6.6	-	F	F	F
MSCI World ex-US	0.00	0.01	2.2	-	F	F	F
JP Morgan Global Gov't Bond	0.00	0.02	2.1	-	F	F	F
Goldman Sachs Commodity index	0.00	0.00	2.1	-	F	F	F
R-square%					38.19	39.69	39.66
PMP%					25.00	12.00	12.00

Table 22: Summary Statistics and BMA Estimates for the Market Neutral Index

The following table shows the BMA estimates along with the stepwise estimates for the sample period Jan. 1990 to Dec. 2001. The table contains the posterior means, standard deviations and posterior effect probabilities, Pr ($\beta \neq 0 \mid D$), for the coefficient associated with each variable. Posterior effect probabilities are obtained by summing the posterior model probabilities across models for each predictor. In addition, p-value of the coefficients of the variables that are chosen by the stepwise models is given. PMP denotes the posterior model probability. Only the 3 models with the highest PMP values are shown. T indicates that the variable is included, while F indicates that it is not, for each of the models.

	Mean	St. Dev	$Pr(\beta \neq 0 \mid D)$	*p*-value	1st Best Model/Stepwise Selected Model	2nd Best Model	3rd Best Model
Intercept	0.86	0.04					
Fama-French SMB	0.03	0.01	96.7	0.0028	T	T	T
MSCI Emerging	0.02	0.01	95.2	<0.0001	T	T	T
MSCI World ex-US	0.01	0.01	30.2	-	F	F	T
Fed Trade-Weighted Dollar index	0.01	0.03	25.5	-	F	F	F
JP Morgan USA Gov't Bond	0.01	0.01	23	-	F	T	F
Fama-French HML	0.00	0.01	18.5	-	F	F	F
S&P 500	0.00	0.01	10.5	-	F	F	F
SPCo	0.00	0.00	6.7	-	F	F	F
SPPo	0.00	0.00	3.2	-	F	F	F
SPPa	0.00	0.00	3	-	F	F	F
JP Morgan Global Gov't Bond	0.00	0.01	2.6	-	F	F	F
SPCa	0.00	0.00	2.5	-	F	F	F
Goldman Sachs Commodity index	0.00	0.00	1.5	-	F	F	F
R-square%					24.10	25.88	25.72
PMP%					17.00	8.00	7.00

Table 23: Summary Statistics and BMA Estimates for the Market Neutral-Arbitrage Index

The following table shows the BMA estimates along with the stepwise estimates for the sample period Jan. 1990 to Dec. 2001. The table contains the posterior means, standard deviations and posterior effect probabilities, Pr ($\beta \neq 0 \mid D$), for the coefficient associated with each variable. Posterior effect probabilities are obtained by summing the posterior model probabilities across models for each predictor. In addition, p-value of the coefficients of the variables that are chosen by the stepwise models is given. PMP denotes the posterior model probability. Only the 3 models with the highest PMP values are shown. T indicates that the variable is included, while F indicates that it is not, for each of the models.

	Mean	St. Dev	Pr($\beta \neq 0 \mid D$)	*p*-value	1st Best Model	2nd Best Model/Stepwise Selected Model	3rd Best Model
Intercept	1.10	0.15					
Fama-French SMB	0.19	0.04	100	<0.0001	T	T	T
Fama-French HML	-0.19	0.04	100	<0.0001	T	T	T
MSCI World ex-US	0.05	0.05	56.9	0.0035	T	T	F
JP Morgan Global Gov't Bond	-0.06	0.10	32.1	0.0322	F	T	F
MSCI Emerging	0.01	0.02	19.8	-	F	F	F
Fed Trade-Weighted Dollar index	0.01	0.05	8	-	F	F	F
SPPo	0.00	0.00	5.4	-	F	F	F
JP Morgan USA Gov't Bond	0.00	0.02	5	-	F	F	F
S&P 500	0.00	0.01	4.7	-	F	F	F
SPCa	0.00	0.00	4.2	-	F	F	F
SPCo	0.00	0.00	4.2	-	F	F	F
SPPa	0.00	0.00	3.9	-	F	F	F
Goldman Sachs Commodity index	0.00	0.00	1.3	-	F	F	F
R-square%					42.20	44.09	39.94
PMP%					16.00	15.00	12.00

Table 24: Summary Statistics and BMA Estimates for the Market Neutral-Long/Short Index

The following table shows the BMA estimates along with the stepwise estimates for the sample period Jan. 1990 to Dec. 2001. The table contains the posterior means, standard deviations and posterior effect probabilities, Pr ($\beta \neq 0 \mid D$), for the coefficient associated with each variable. Posterior effect probabilities are obtained by summing the posterior model probabilities across models for each predictor. In addition, p-value of the coefficients of the variables that are chosen by the stepwise models is given. PMP denotes the posterior model probability. Only the 3 models with the highest PMP values are shown. T indicates that the variable is included, while F indicates that it is not, for each of the models.

	Mean	St. Dev	$Pr(\beta \neq 0 \mid D)$	*p*-value	1st Best Model/Stepwise Selected Model	2nd Best Model	3rd Best Model
Intercept	0.73	0.04					
S&P 500	0.07	0.02	100	<0.0001	T	T	T
JP Morgan USA Gov't Bond	0.06	0.01	100	<0.0001	T	T	T
Fama-French SMB	0.05	0.01	100	<0.0001	T	T	T
SPPa	0.00	0.00	67.9	0.0065	T	F	T
SPPo	0.00	0.00	24.5	-	F	T	F
Goldman Sachs Commodity Index	0.00	0.01	18.5	-	F	F	T
SPCa	0.00	0.00	4	-	F	F	F
SPCo	0.00	0.00	3.7	-	F	F	F
MSCI World ex-US	0.00	0.00	3.4	-	F	F	F
MSCI Emerging	0.00	0.00	2.9	-	F	F	F
JP Morgan Global Gov't Bond	0.00	0.00	2.7	-	F	F	F
Fed Trade-Weighted Dollar Index	0.00	0.01	2.7	-	F	F	F
Fama-French HML	0.00	0.00	2.7	-	F	F	F
R-square%					28.21	27.57	29.64
PMP%					32.00	17.00	11.00

Table 25: Summary Statistics and BMA Estimates for the Short Index

The following table shows the BMA estimates along with the stepwise estimates for the sample period Jan. 1990 to Dec. 2001. The table contains the posterior means, standard deviations and posterior effect probabilities, Pr ($\beta \neq 0 \mid D$), for the coefficient associated with each variable. Posterior effect probabilities are obtained by summing the posterior model probabilities across models for each predictor. In addition, p-value of the coefficients of the variables that are chosen by the stepwise models is given. PMP denotes the posterior model probability. Only the 3 models with the highest PMP values are shown. T indicates that the variable is included, while F indicates that it is not, for each of the models.

	Mean	St. Dev	Pr($\beta \neq 0 \mid D$)	*p*-value	1st Best Model/Stepwise Selected Model	2nd Best Model	3rd Best Model
Intercept	1.29	0.25					
S&P 500	-0.89	0.07	100	<0.0001	T	T	T
Fama-French SMB	-0.65	0.07	100	<0.0001	T	T	T
Fama-French HML	0.01	0.04	14.4	-	F	F	T
JP Morgan USA Gov't Bond	0.02	0.06	12.4	-	F	T	F
MSCI Emerging	-0.01	0.02	9.7	-	F	F	F
MSCI World ex-US	-0.01	0.03	8.8	-	F	F	F
JP Morgan Global Gov't Bond	0.01	0.06	7.5	-	F	F	F
SPCa	0.00	0.00	4	-	F	F	F
Goldman Sachs Commodity index	0.00	0.01	3.8	-	F	F	F
SPCo	0.00	0.00	3.3	-	F	F	F
Fed Trade-Weighted Dollar index	0.00	0.04	3.1	-	F	F	F
SPPo	0.00	0.00	3.1	-	F	F	F
SPPa	0.00	0.00	0	-	F	F	F
R-square%					72.99	73.42	73.40
PMP%					37.00	10.00	9.00

Table 26: Summary Statistics and BMA Estimates for the Fund of Funds Index

The following table shows the BMA estimates along with the stepwise estimates for the sample period Jan. 1990 to Dec. 2001. The table contains the posterior means, standard deviations and posterior effect probabilities, Pr ($\beta \neq 0 \mid D$), for the coefficient associated with each variable. Posterior effect probabilities are obtained by summing the posterior model probabilities across models for each predictor. In addition, p-value of the coefficients of the variables that are chosen by the stepwise models is given. PMP denotes the posterior model probability. Only the 3 models with the highest PMP values are shown. T indicates that the variable is included, while F indicates that it is not, for each of the models.

	Mean	St. Dev	$Pr(\beta \neq 0 \mid D)$	*p*-value	1st Best Model/Stepwise Selected Model	2nd Best Model	3rd Best Model
Intercept	0.63	0.09					
MSCI Emerging	0.07	0.02	100	<0.0001	T	T	T
Fama-French SMB	0.09	0.02	100	<0.0001	T	T	T
Goldman Sachs Commodity index	0.04	0.02	86.7	0.0060	T	T	T
JP Morgan USA Gov't Bond	0.06	0.05	71.2	0.0178	T	T	F
SPPo	0.00	0.00	57.9	<0.0001	T	F	T
SPPa	0.00	0.00	37.8	-	F	T	F
JP Morgan Global Gov't Bond	-0.03	0.06	25	-	F	F	F
Fama-French HML	0.00	0.01	8.8	-	F	F	F
S&P 500	0.00	0.02	8	-	F	F	F
Fed Trade-Weighted Dollar index	0.00	0.02	4.4	-	F	F	F
MSCI World ex-US	0.00	0.01	3.5	-	F	F	F
SPCa	0.00	0.00	1.3	-	F	F	F
SPCo	0.00	0.00	1.3	-	F	F	F
R-square%					54.04	53.83	52.12
PMP%					15.00	11.00	10.00

APPENDIX 3

Figures

Figure 1: Share of the Largest Ten Funds as a Percent of Total Assets under Management

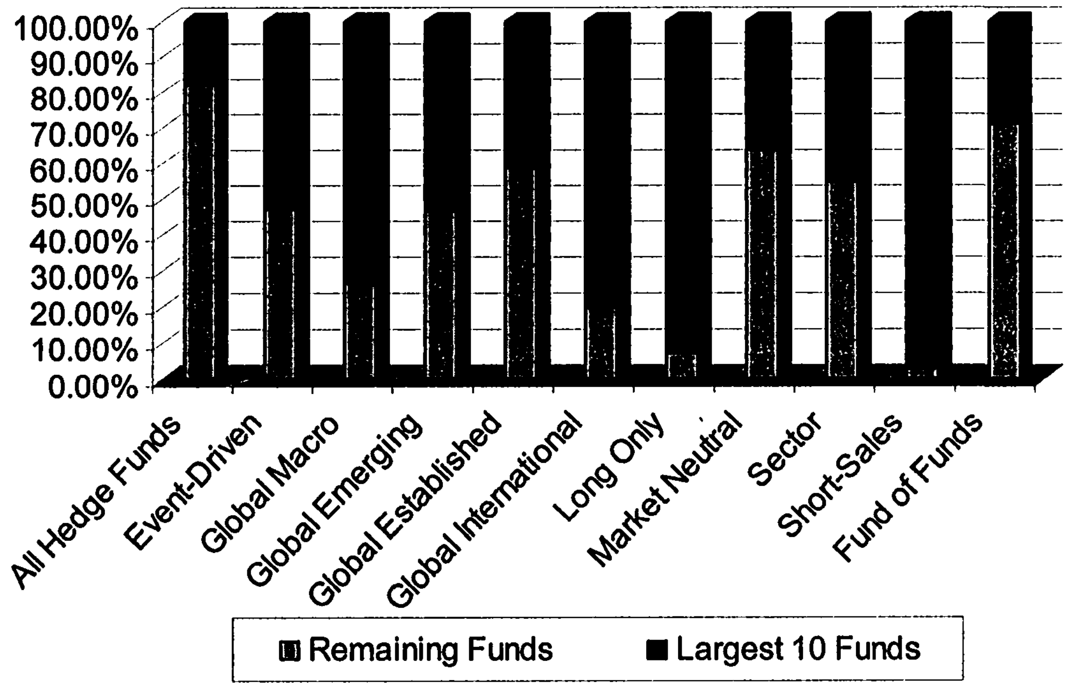


Figure 2: Distribution of the Administrative Fees

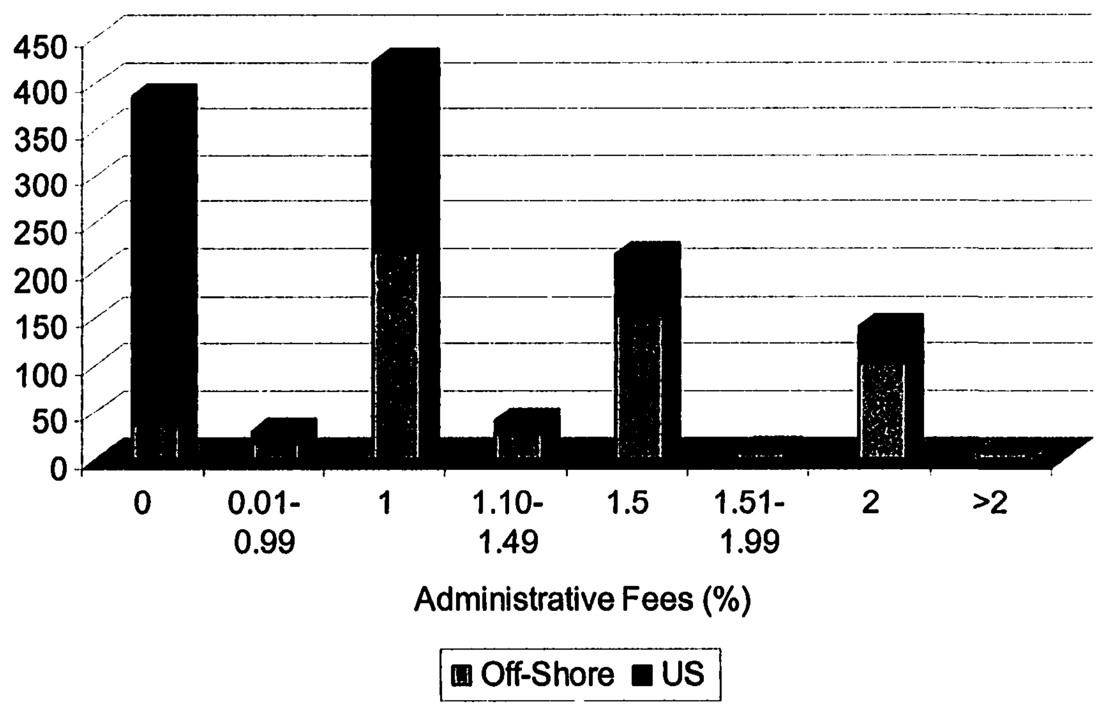


Figure 3: Distribution of Performance Fees

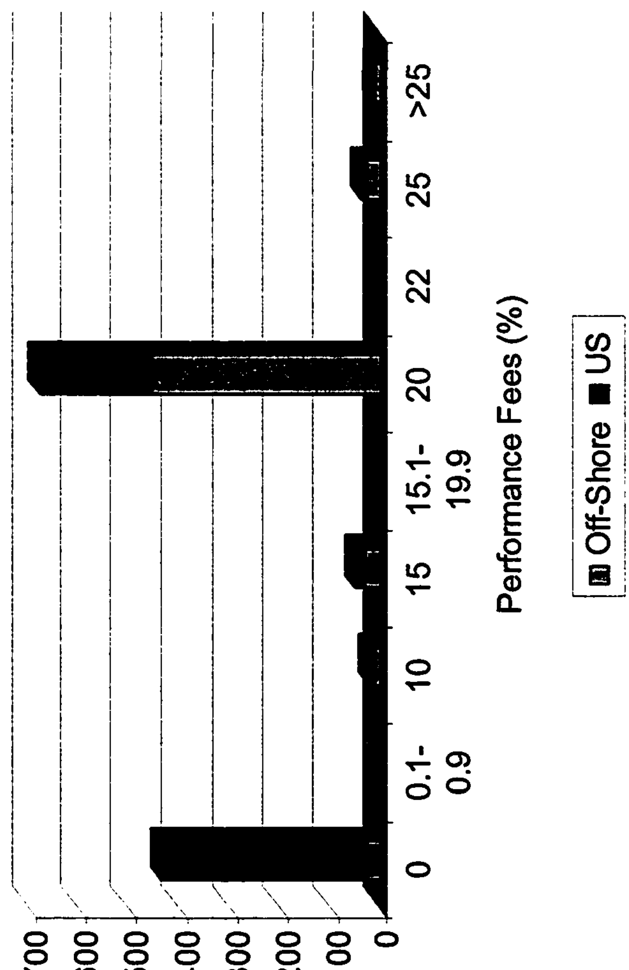


Figure 4: Distribution of Redemption Frequency

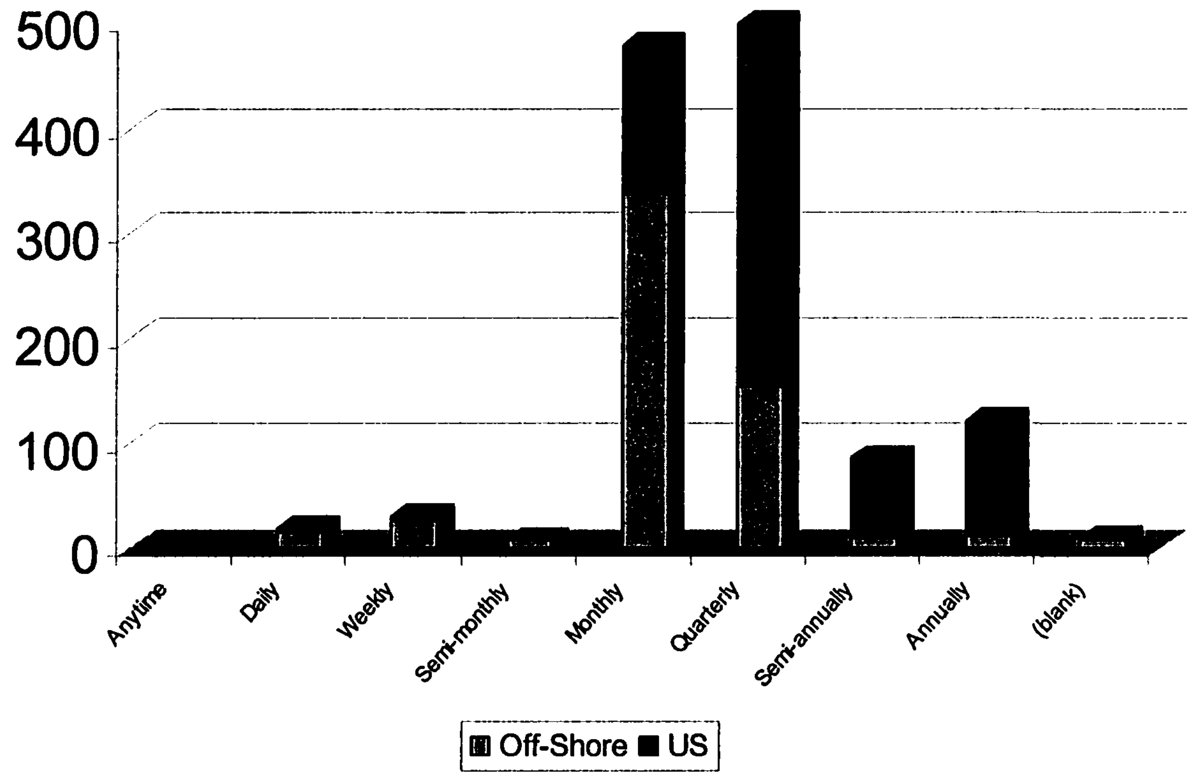


Figure 5: Distribution of the Number Days Required Before Redemption

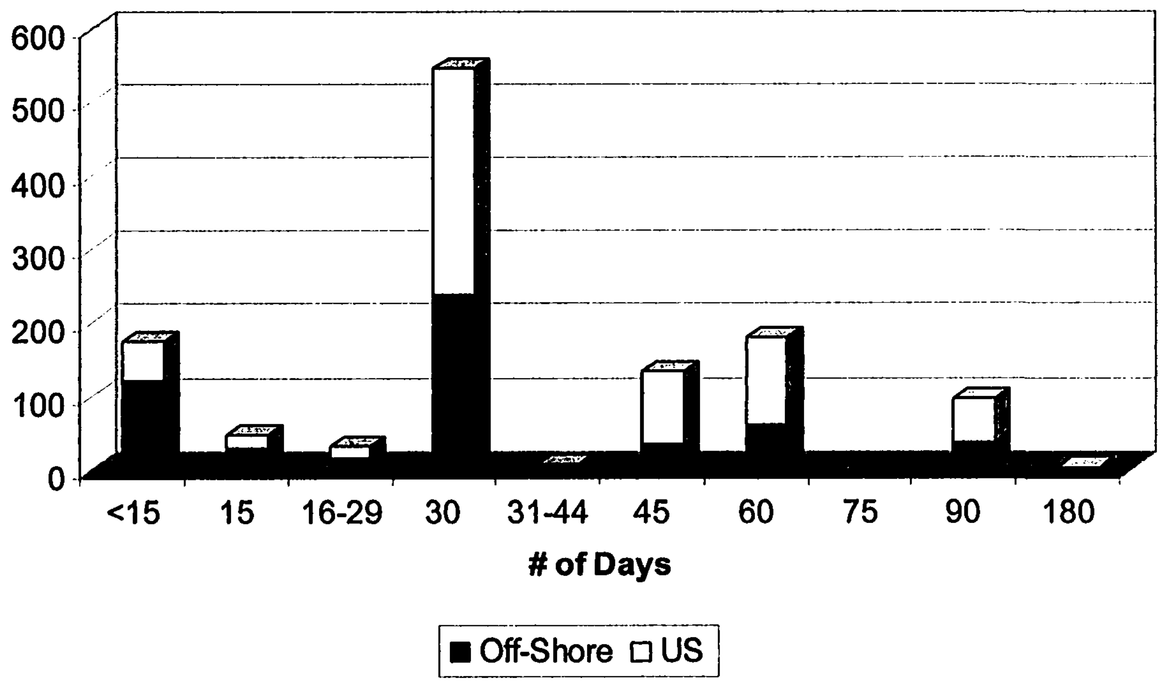


Figure 6a

Average Monthly Returns (%) of Hedge Funds

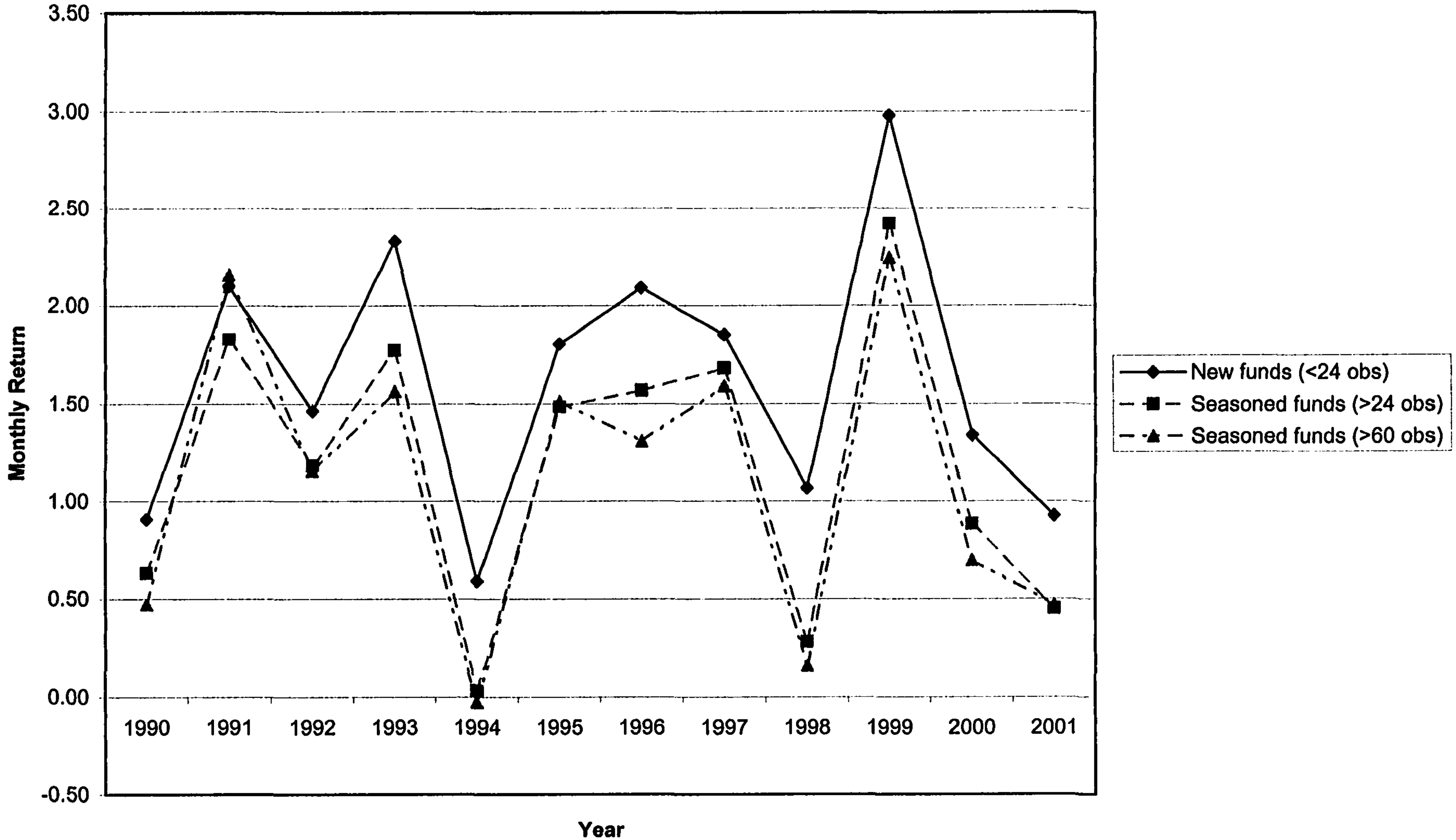


Figure 6b

Standard Deviation of the Monthly Returns of Hedge Funds

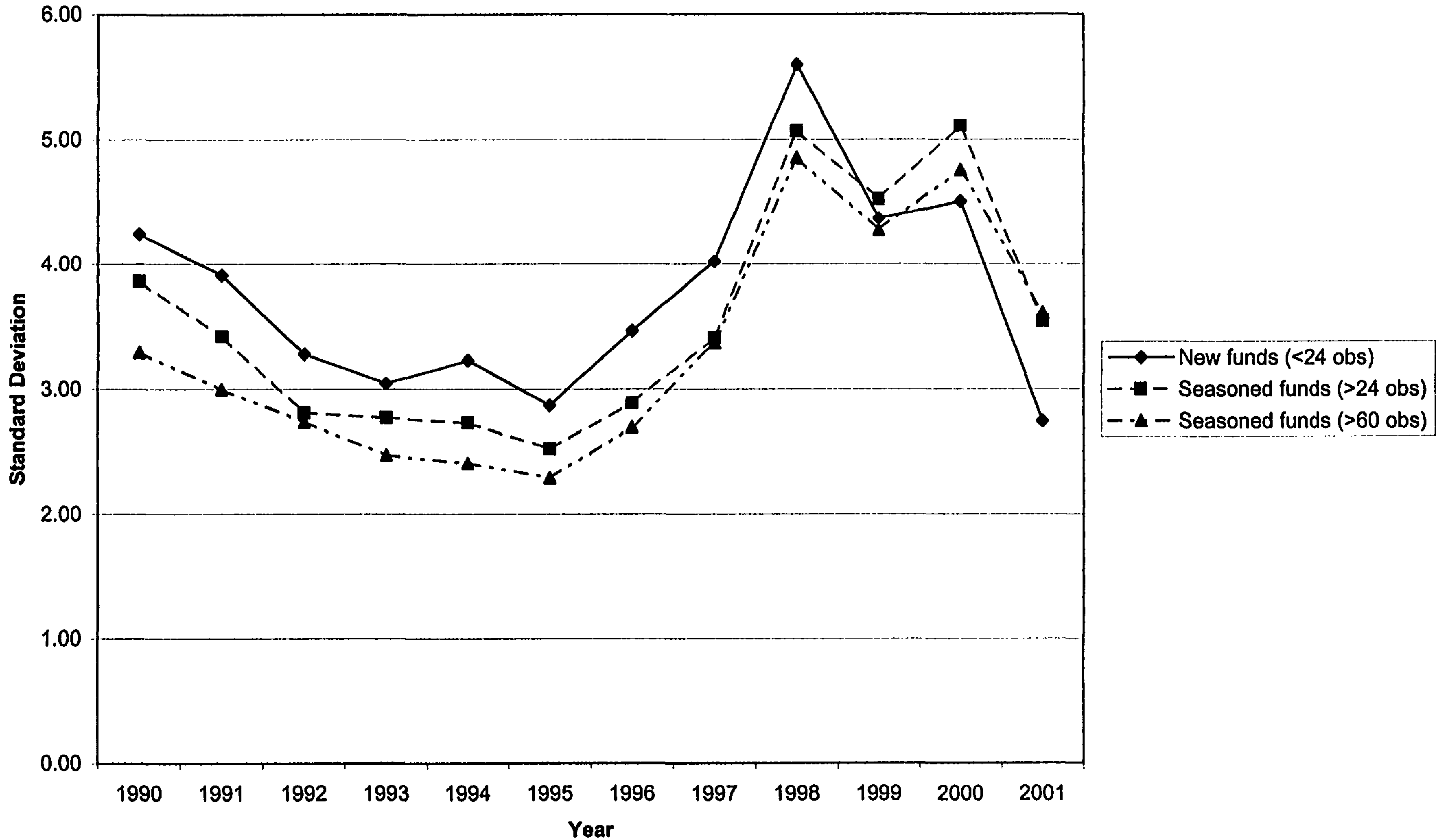


Figure 6c

Percentiles of Monthly Returns for New Funds

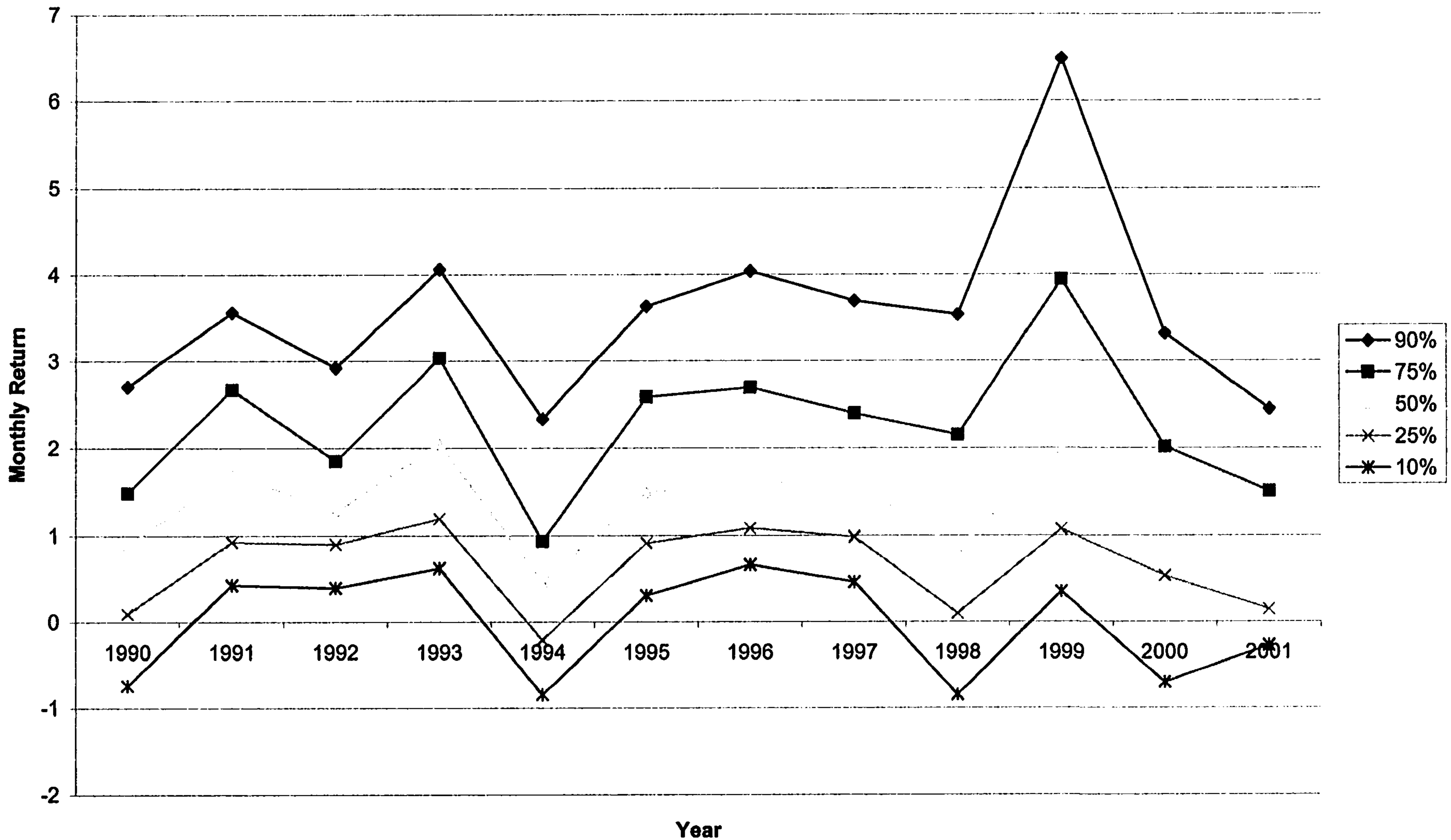


Figure 6d

Percentiles of Monthly Returns for Seasoned Funds (>2 years)

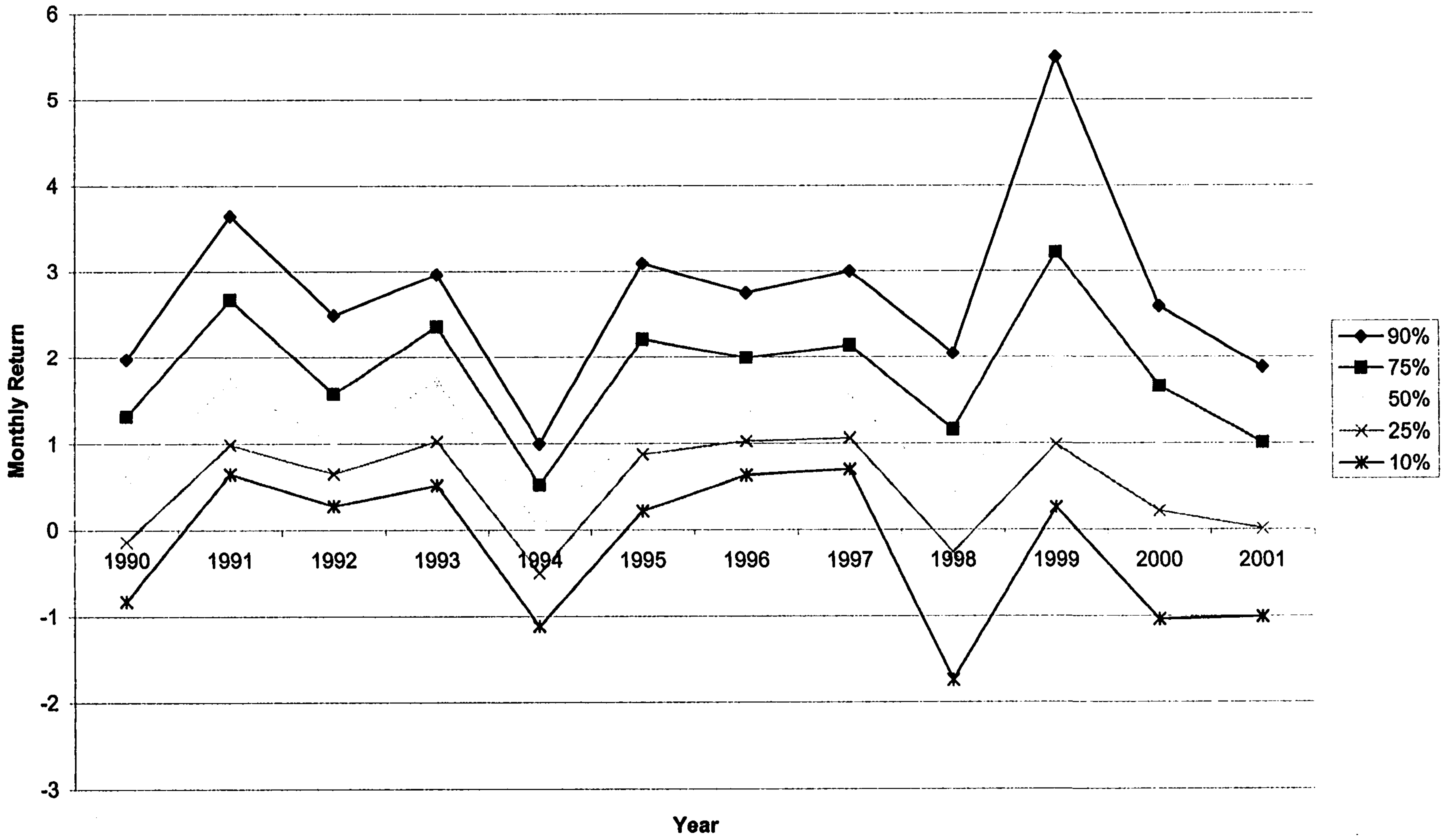


Figure 6e

Percentiles of Monthly Returns for Seasoned Funds (>5 years)

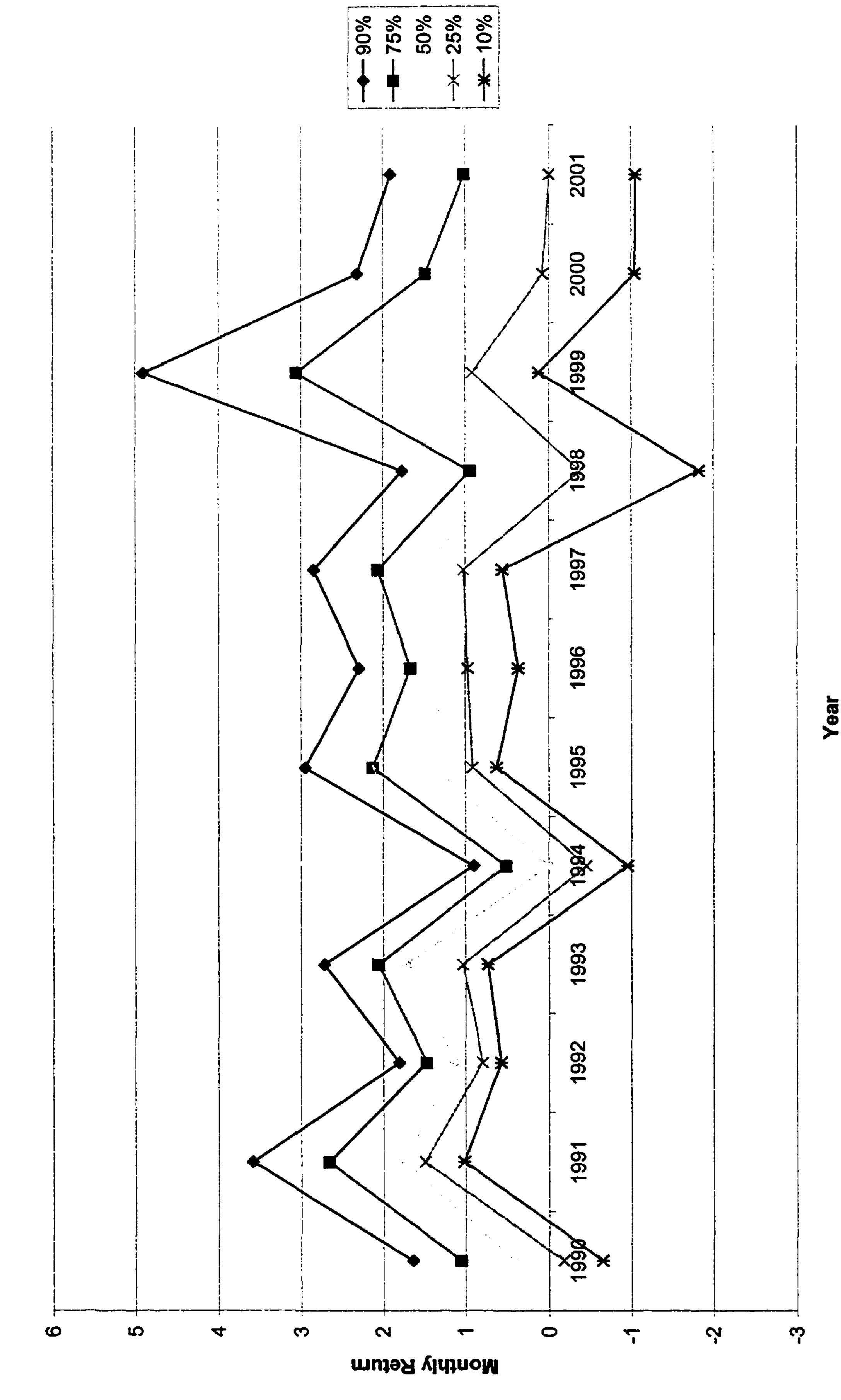


Figure 6f

Percentiles of Standard Deviation of Monthly Returns for New Funds

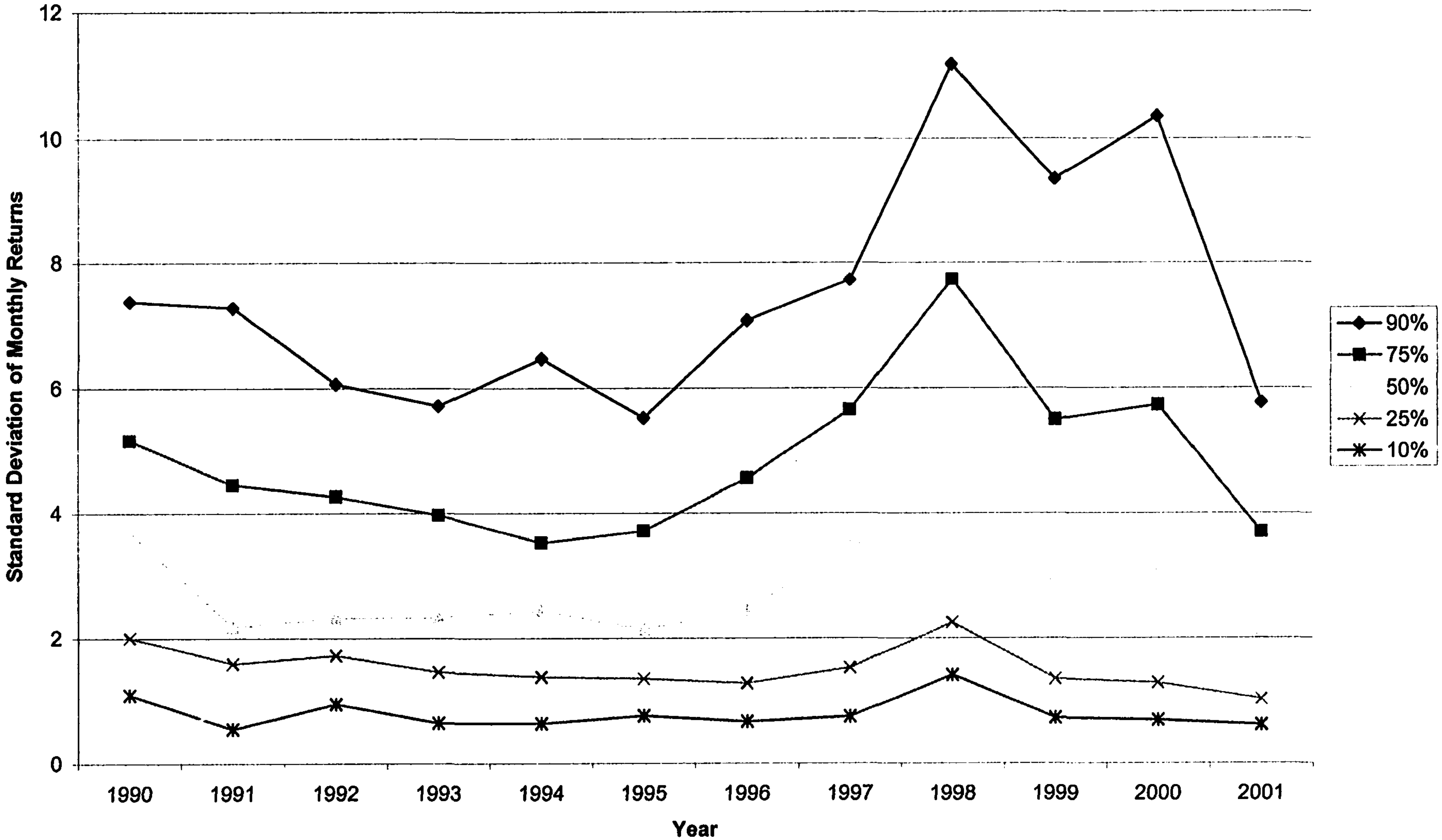


Figure 6g

Percentiles of Standard Deviation of Monthly Returns for Seasoned Funds (>2 years)

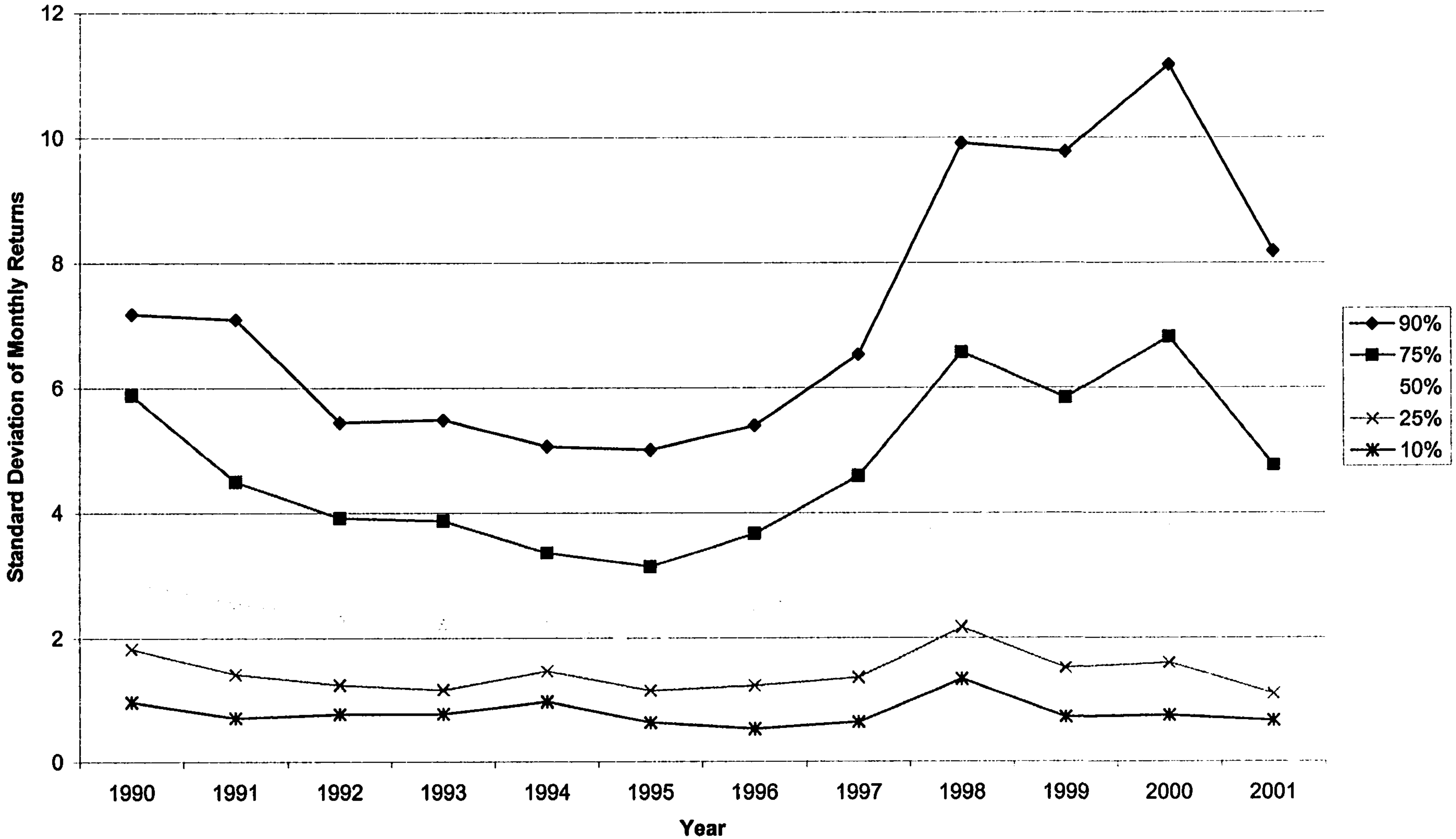


Figure 6h

Percentiles of Standard Deviation of Monthly Returns for Seasoned Funds (<5 years)

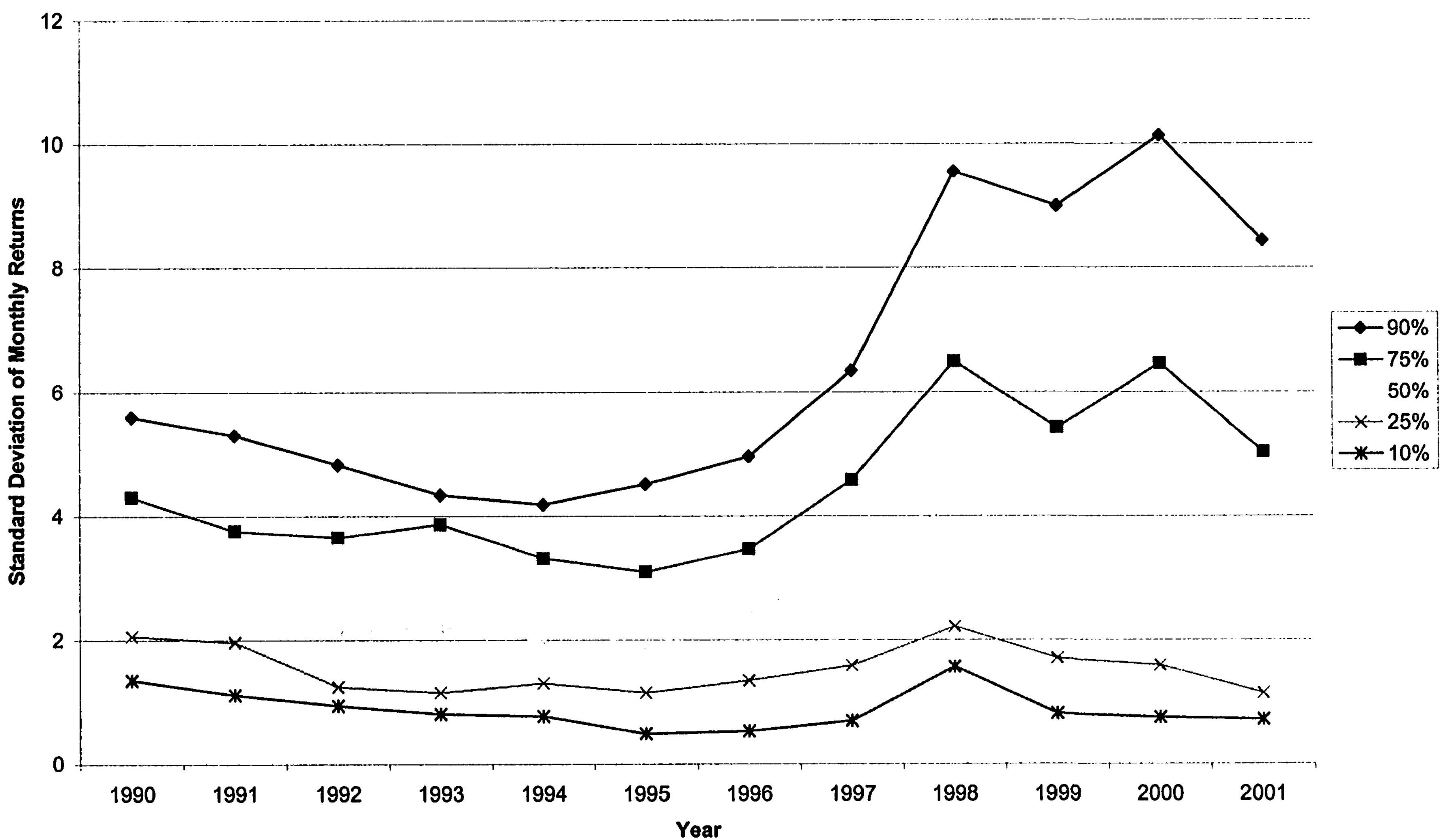


FIGURE 7
Kernel Fit (Normal, h= 3.8841, degree = 2)

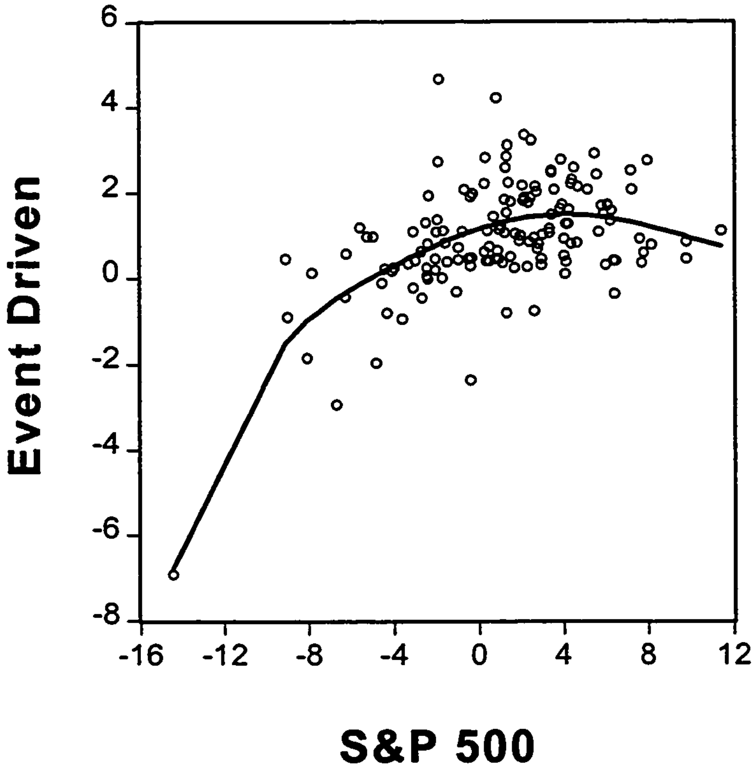


FIGURE 8

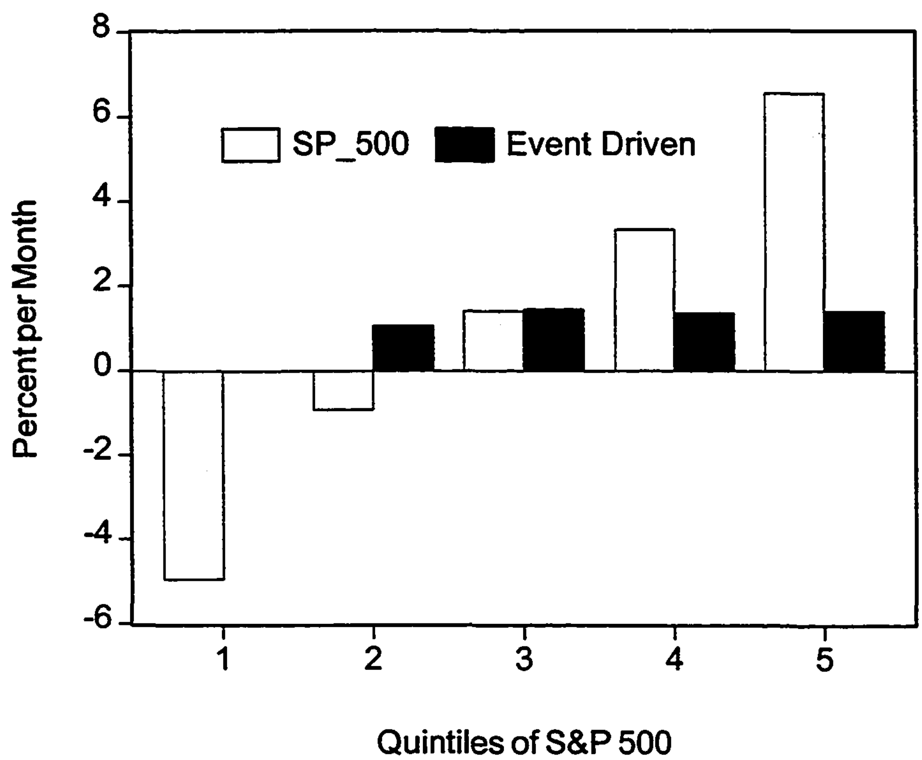

8
6
4
2
0
-2
-4
-6
Percent per Month
SP_500
Event Driven
1
2
3
4
5
Quintiles of S&P 500

FIGURE 9
Kernel Fit (Normal, h= 3.8841, degree = 3)

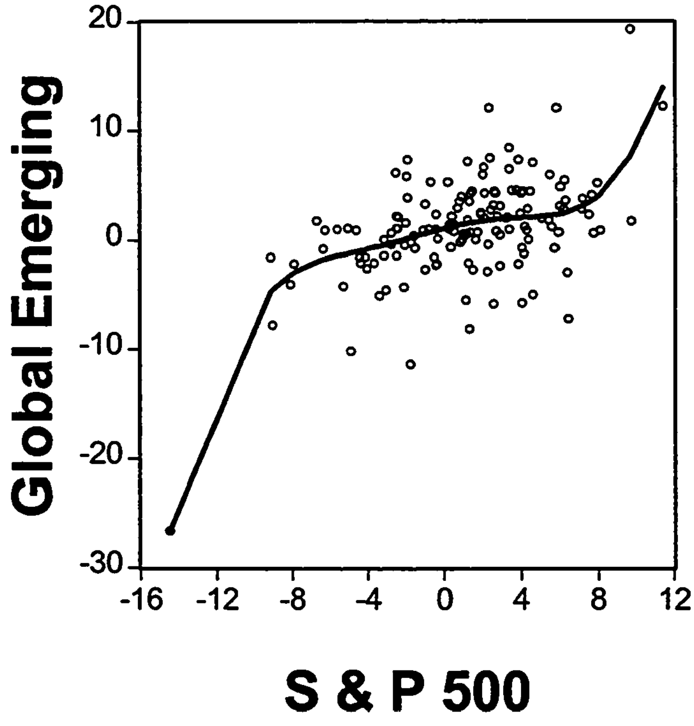
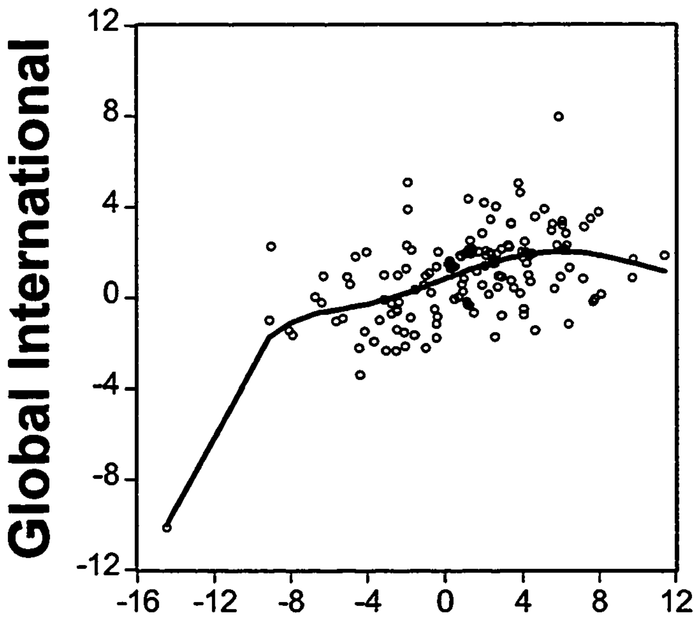


FIGURE 10
Kernel Fit (Normal, h= 3.8841, degree = 2)



S & P 500

FIGURE 11
Kernel Fit (Normal, bandwidth= 3.8841, degree = 2)

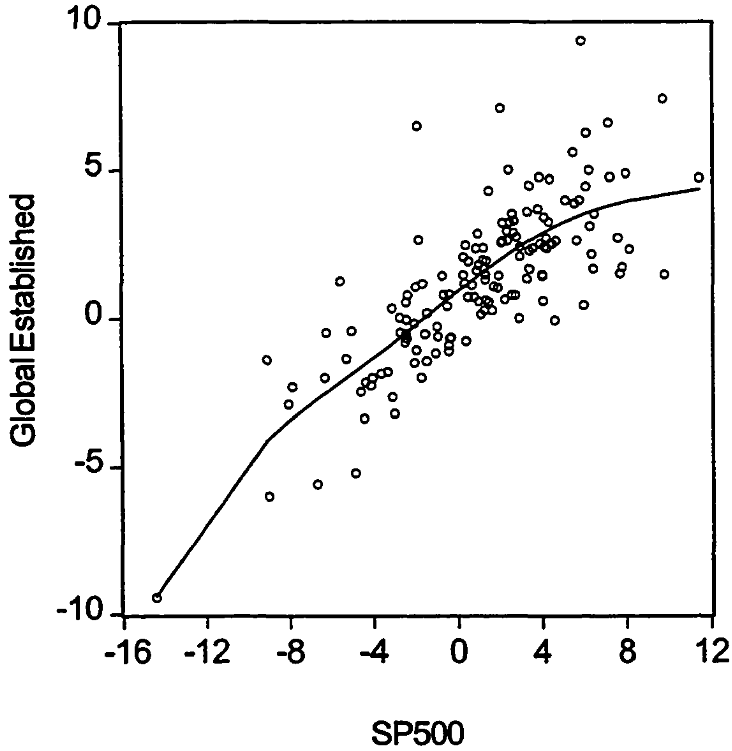


FIGURE 12
Kernel Fit (Normal, h= 3.8841, degree = 3)

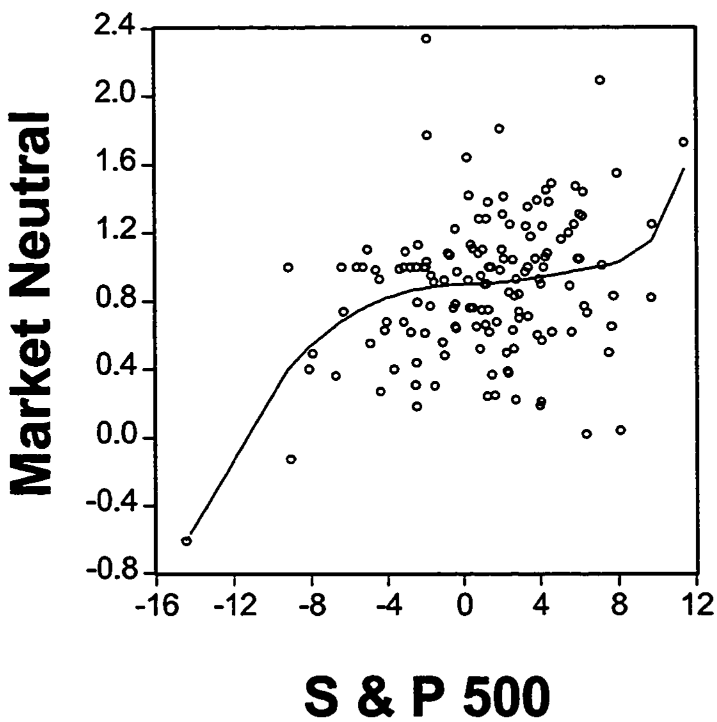


FIGURE 13
Market Neutral vs S&P 500

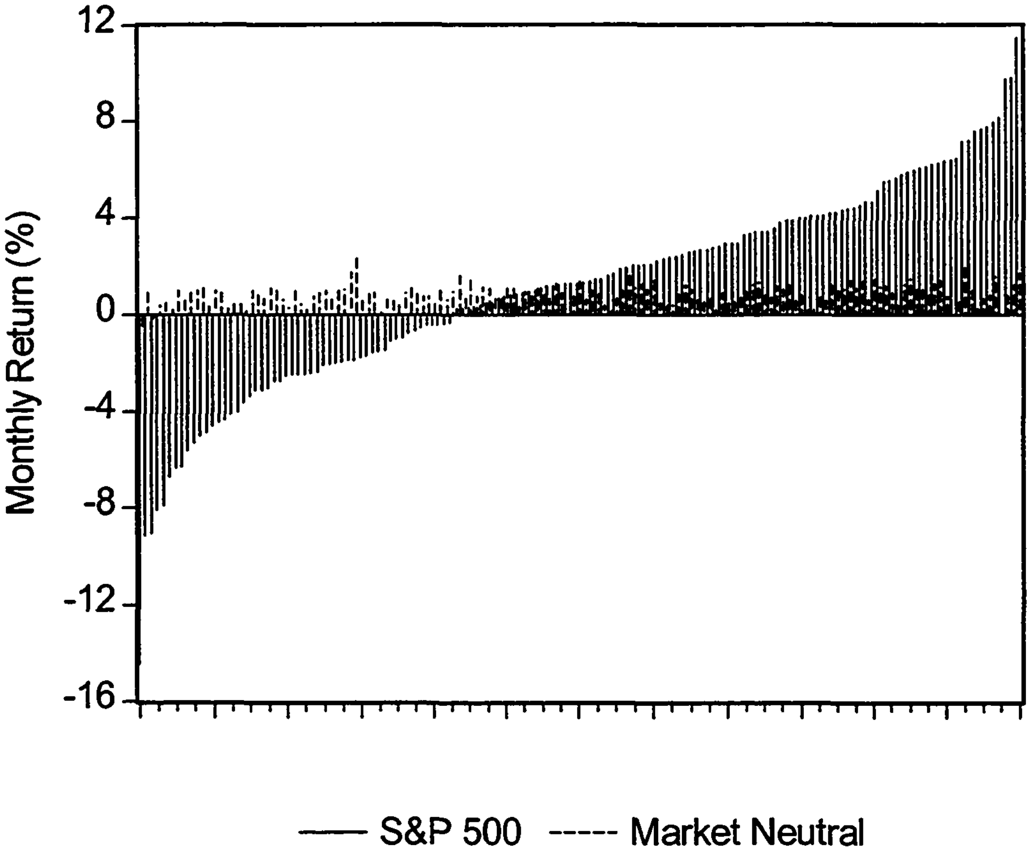


FIGURE 14
Kernel Fit (Normal, h= 3.8841, degree = 2)

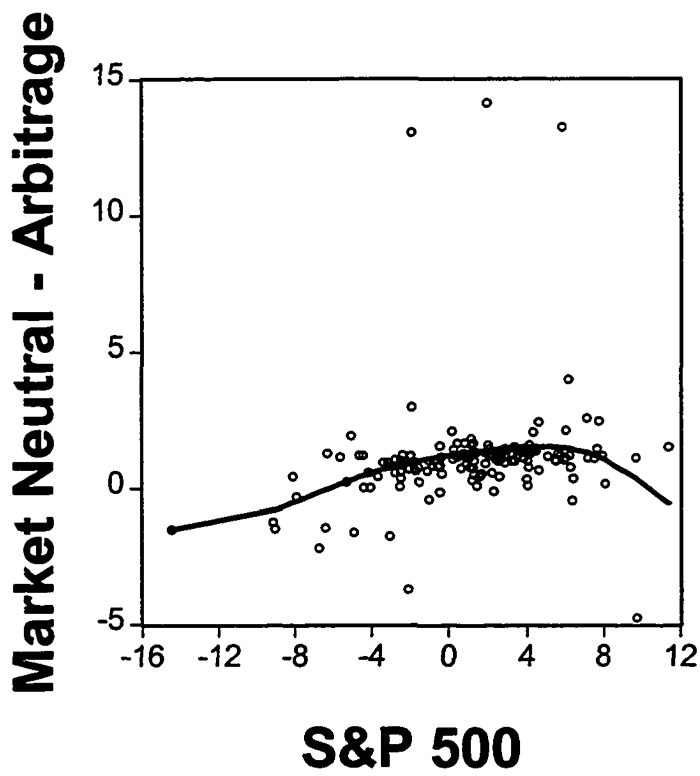


FIGURE 15
Kernel Fit (Normal, h= 3.8841)

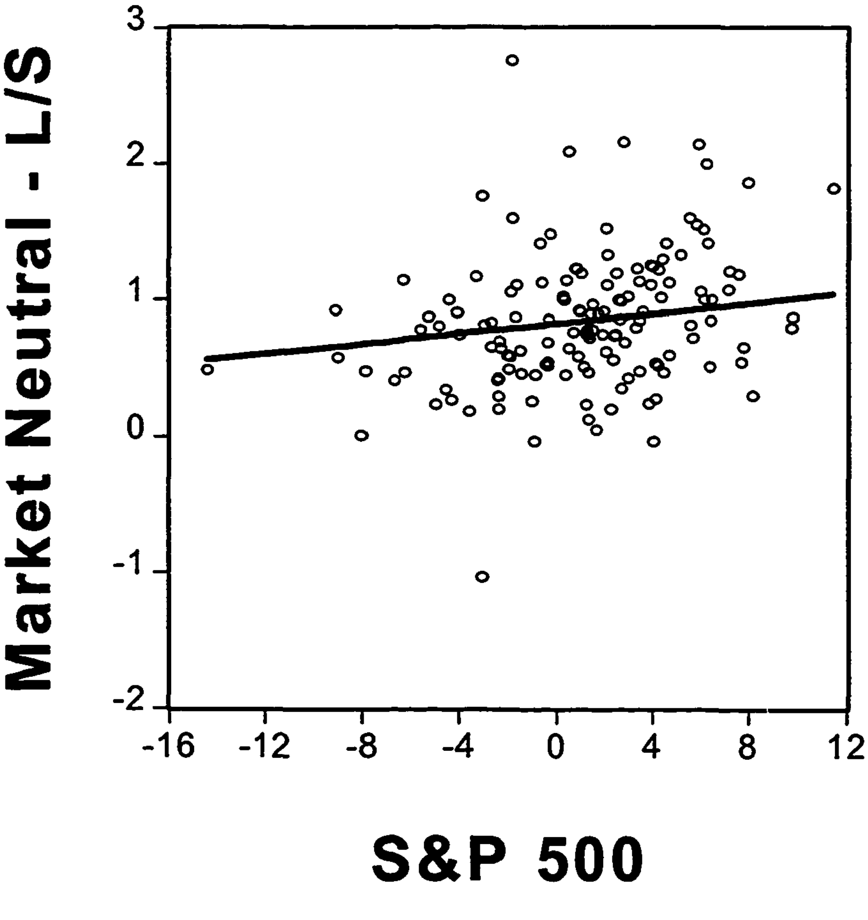


FIGURE 15

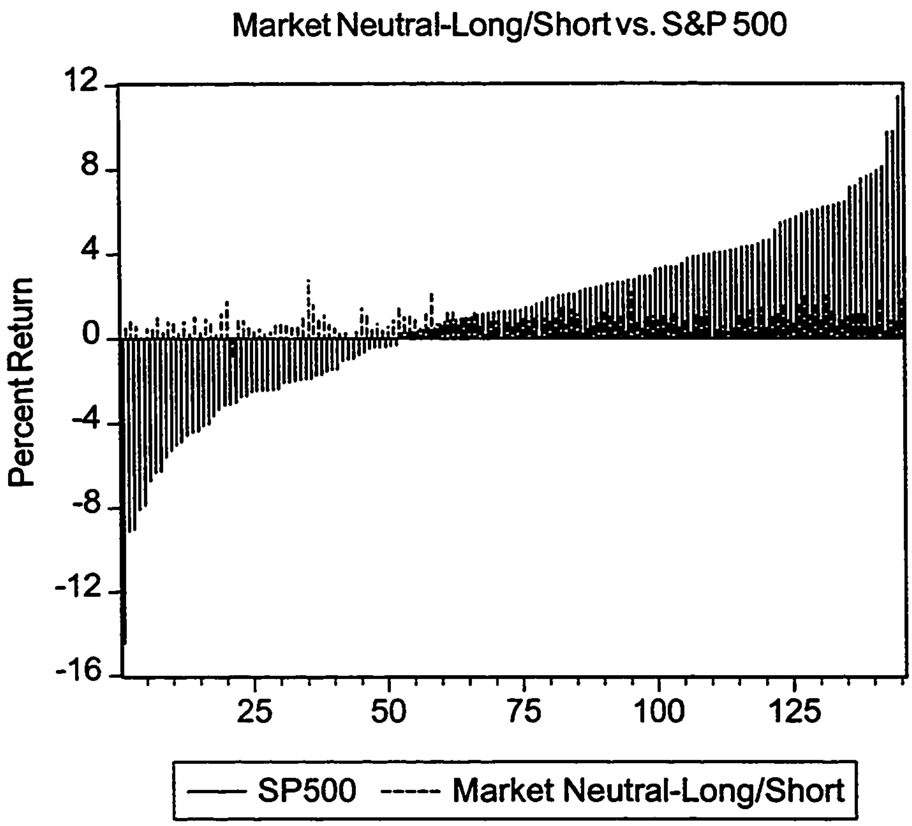

Market Neutral-Long/Short vs. S&P 500
12
8
4
0
-4
-8
-12
-16
Percent Return
25
50
75
100
125
SP500
Market Neutral-Long/Short

FIGURE 17
Kernel Fit (Normal, h= 3.8841)

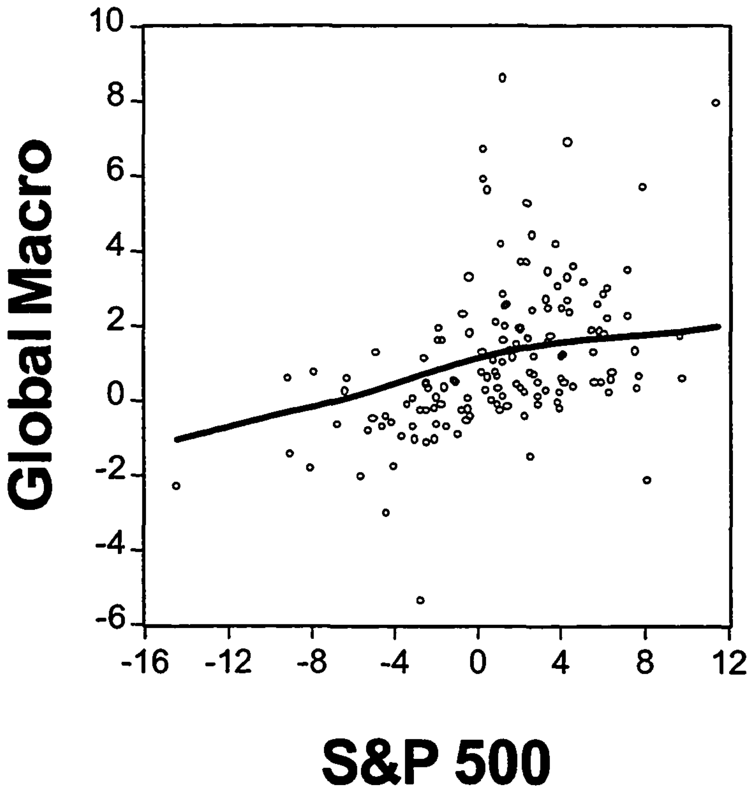


FIGURE 18
Kernel Fit (Normal, h= 3.8841, degree = 2)

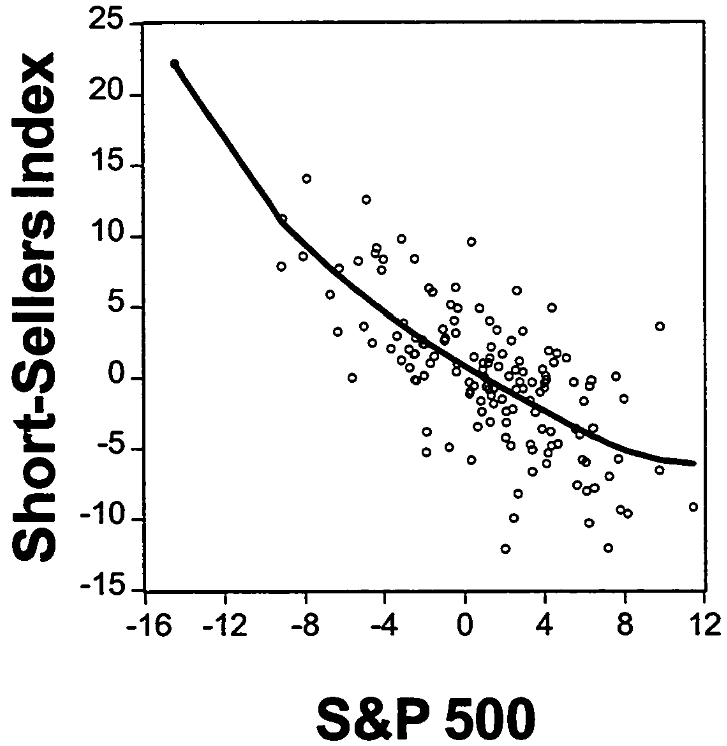
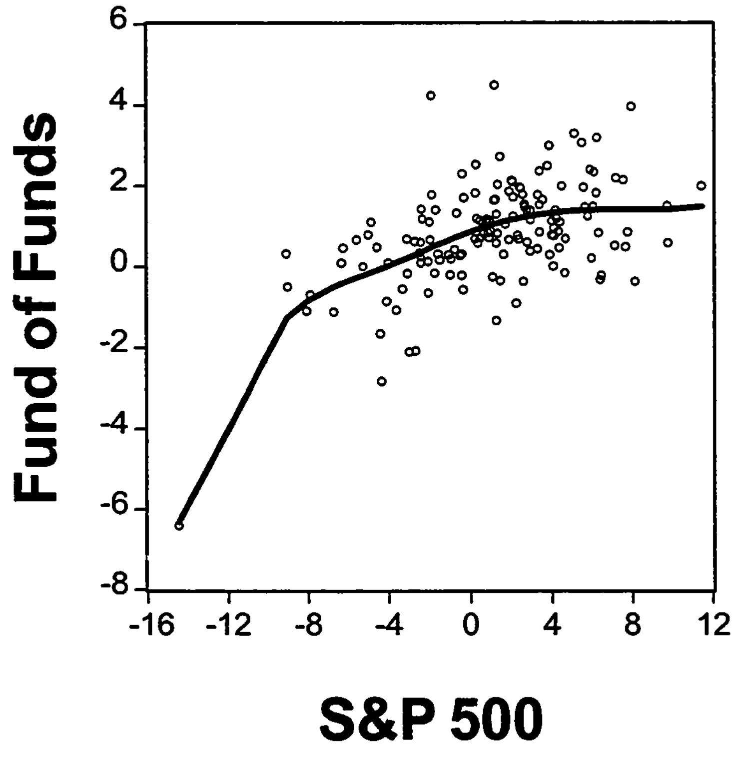


FIGURE 19
Kernel Fit (Normal, h= 3.8841, degree = 2)



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