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Performance of Funds of Hedge Funds

Hung Duong
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Performance of Funds of Hedge Funds

by

Hung Duong
Old Dominion University

A Dissertation Submitted to the Faculty of
Old Dominion University in Partial Fulfillment of the
Requirement for the Degree of

DOCTOR OF PHILOSOPHY

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ABSTRACT

Performance of Funds of Hedge Funds

Hung Duong
Old Dominion University, 2008
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The studies of hedge fund performance are hindered by the lack of quality returns data and the complicated nature of hedge fund returns. This study contributes to the literature in three ways. First, I reinvestigate the performance of hedge funds from different aspects. Second, I develop a new framework to evaluate fund of hedge funds managers' skills. Finally, I exam the performance persistence of funds of hedge funds by using various performance measures.

In the first study, I find that the annual survivorship and backfilled biases for funds of hedge funds are 0.66% and 0.21%, respectively, during the period 1994-2004. I confirm that hedge funds' monthly returns tend to have low standard deviations, negative skewness and high kurtosis. Hedge funds often underperform the equity market in terms of absolute returns, but outperform the equity market in terms of traditional performance measures like the Jensen alpha, Treynor, and Sharpe ratios. However, when accounting for downside risks, the Omega and Sortino ratios both indicate that the performance of hedge funds is not as superior as the traditional performance measures suggest. I also find that hedge funds usually have low exposures to risk factors identified by Fama and French (1993), and Fung and Hsieh (2004). The subperiod analysis indicates that hedge funds tend to underperform the equity market during a bullish stock market, but outperform the equity market during a bearish stock market. I also find some evidence of stale price when returns are measured monthly, quarterly or semiannually. However, it appears that the stale price does not affect the performance rankings.

In the second study, I am able to replicate funds of funds returns by using hedge fund strategy indices. I find that fund of hedge funds managers have neither the ability of picking winning hedge funds on the net basis nor the ability of predicting winning hedge fund strategies.

In the third study, I find strong evidence of performance persistence when returns are measured monthly, quarterly or semiannually. The evidence of persistence is substantially weakened when returns are measured annually. The quintile analysis indicates that the winners based on the past alpha tend to have the highest return while the losers based on the past Sortino ratio have the lowest return.

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I am blessed with the love and support from my parents and my wife. Their support and encouragement have urged me on. I dedicate this dissertation to my daughter, Anh Minh Duong, who will have plenty of time to study Investment.

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CHAPTER 1

Motivation

A hedge fund is typically a private investment fund that is loosely regulated, professionally managed, and not widely available to the public (Lhabitant, 2004). According to an estimation of Van Hedge Fund Advisors, the hedge fund industry has been growing at an average rate of 17% per annum over the last decade and is expected to continue at this significant rate. There were about 9,000 hedge funds operating in 2006 with a total assets value of USD 1.3 trillion. The growing popularity of hedge funds has spawned research whether hedge fund managers can really produce superior performance. Evaluating hedge fund managers' skills is a challenging task for several reasons.

First, information on hedge funds is difficult to obtain. Unlike mutual funds, hedge funds are not required to report to an industry association. They voluntarily report some information to one or more databases. As a result, the data is incomplete, and the return data is subject to a number of biases.

Second, there is the lack of standard performance measures for hedge funds due to the complicated nature of hedge fund returns. Traditional linear models (CAPM, Fama-French's three-factor model, and Carhart's four-factor model) and performance measures (Jensen alpha, Treynor ratio, and Sharpe ratio) have been widely considered as the standard instruments in mutual fund literature, but have not been very helpful in evaluating hedge fund performance because hedge fund risk-exposures are dramatically different from those of mutual funds (Fung and Hsieh, 1997). Specifically, hedge funds often employ dynamic investment strategies that cannot be captured by the traditional

linear models. In addition, hedge fund returns tend to have a low correlation with the market returns (beta), low volatility (standard deviation), negative skewness and fat tail (high kurtosis). The performance measures derived from Markowitz portfolio optimization are likely to underestimate the hedge fund risk exposures because they measure risk return trade-off in terms of mean and variance, ignoring the effects of higher moments (skewness, kurtosis) in hedge fund returns.

These issues have been addressed in a number of studies. Shadwick and Keating (2002) introduce a measure called Omega, which accounts for the effects of the higher moments. Later, Kaplan and Knowles (2004) show that both the Omega ratio and the Sortino ratio, another popular performance measure, belong to the family of “downside” risk-adjusted return measures. Both the Omega and Sortino ratios penalize the downside volatility of hedge fund returns. Regarding the risk-factors inherent in hedge fund returns, Fung and Hsieh (2001, 2004, 2006), Agarwal and Naik (2000), Edwards and Caglayan (2001), Chan, Getmansky, Haas and Lo (2006) have specified various models to explain the variations in returns of hedge funds. In addition to risk-factor models, benchmarking models have also been used in the study of hedge fund performance. Early studies use simple style benchmark, which compares a hedge fund’s return to an average return of all hedge funds that follow the same style. This simple benchmark is not accurate because hedge funds are strongly heterogeneous even they follow the same style. Recently, a growing number of studies focus on replicating hedge fund returns using statistical models (see Brooks and Kat, 2002; Amin and Kat, 2003; Kat and Palaro, 2005). By trading futures on traditional assets, the authors attempt to generate returns that have similar statistical properties as the returns generated by the fund.

Another way to gain understanding on risk return profile of hedge funds is to focus on a sub set of hedge funds called “Funds of Hedge Funds” (FOF). FOFs are investment vehicles that provide investors access to hedge fund investments with some potential benefits like risk diversifications, improved liquidity, monitoring service, and higher return (if the fund managers possess ability to pick winning hedge funds). The benefits of studying FOF performance are twofold. First, the return data on FOFs are less prone to biases such as survivorship and back-filled data (Fung and Hsieh, 2000). Second, the role of FOFs in the universe of hedge funds is similar to that of mutual funds in the universe of standard assets of bonds and stocks. This suggests that standard methods studying mutual funds can be applied to FOFs.

In summary, a number of models and measures can be used to evaluate hedge fund performance. Each of them reflects certain aspects of the performance, but none of them is likely to provide a complete answer. To analyze hedge fund performance without making spurious inferences, we need to investigate different aspects of hedge funds.

In my dissertation, I use various measures to evaluate the performance of hedge funds, particularly funds of hedge funds. In the first study, I find that the annual survivorship and backfilled biases, respectively, are 0.66% and 0.21% for the FOF sample during 1994-2004. I confirm that hedge fund returns are not normally distributed. Specifically, they usually have low standard deviations, negative skewness and high kurtosis. Hedge funds usually underperform the equity market in terms of absolute return, but outperform the equity market in terms of traditional performance measures like the Jensen alpha, Treynor, and Sharpe ratios. However, it does not necessarily mean that hedge fund managers have superior skill to manage risk. Instead, the traditional

performance measures might have overlooked the volatility in higher moments. When accounting for downside risks, the Omega and Sortino ratios indicate that the performance of hedge funds is not as superior as the traditional performance measures suggest. I also find that the multifactor models like the Fama-French's extended four-factor model and the Fung and Hsieh's seven-factor models usually indicate that hedge fund managers add value (positive alpha). However, the explanatory power (R-square) of the multifactor models ranges only from 0.09 for Convertible Arbitrage to 0.77 for HFR Main Index, compared to the range from 0.89 to 0.97 for mutual funds as reported by Carhart (1997). Hedge funds usually have low exposures to risk factors identified by Fama and French (1993), and Fung and Hsieh (2004). This might result in the underestimation of the risk of the hedge funds. The subperiod analysis indicates that hedge funds tend to underperform the equity market during a bullish stock market, but outperform the equity market during a bearish stock market. Thus, adding hedge funds to a portfolio of traditional assets can reduce the portfolio volatility. I also find some evidence of stale prices when returns are measured monthly, quarterly or semiannually. However, it appears that the stale price does not affect the performance ranking.

In the second study, I find that hedge fund strategy indices can explain substantially the variation in returns of individual funds of funds. I am able to replicate funds of funds returns by using hedge fund strategy indices. I find that FOF managers neither have the ability of picking winning hedge funds on the net basis nor the ability of predicting winning hedge fund strategies.

In the third study, I find strong evidence of performance persistence when returns are measured monthly, quarterly or semiannually. However, I cannot conclude whether

the persistence is a short term nature of hedge fund performance or due to stale prices. The evidence of persistence is substantially weakened when returns are measured annually, although evidence of persistence can be found over several years. The quintile analysis indicates that the winners portfolio based on alpha outperforms the average return of all funds by 0.91% a year and the losers portfolio based on Sortino ratio underperforms the average return of all funds by 1.51% a year.

My dissertation is organized as follows. Chapter 2 provides a brief review of the hedge fund industry. Chapter 3 addresses the issues associated with bias in hedge fund returns, and the stale price, and discusses hedge fund performance using various models and measures. Chapter 4 provides a framework to replicate the returns of funds of funds, and discusses fund manager skill against style benchmarks. Chapter 5 examines the performance persistence of funds of funds by using various performance measures.

CHAPTER 2

Background of Hedge Fund Industry

2.1 History

According to Brown et al. (1999), Lhabitant (2004), Alfred Winslow Jones, a journalist, sociologist and hedge fund manager is credited with the establishment of the first hedge fund in 1949. While writing an article about the new, post-depression class of stock-market timers for Fortune, he was inspired to try his own hand. Jones established an investment fund as a general partnership with characteristics similar to those of current hedge funds. The term “hedge” refers to an investment strategy initially employed by Jones: holding long position in undervalued stocks while short selling overvalued stocks. The strategy would work if the hedge fund manager has stock picking ability, but does not know the timing of the market. He also used leverage (borrowed money) to enhance the potential return and introduced the incentive fee structure of the hedge fund industry. He operated his fund in complete secrecy until 1966. Then he revealed his highly successful investment approach in another Fortune article. Since then, many hedge funds have been established.

Nowadays, the common form of hedge funds is a limited partnership or a limited liability company, which can issue securities in "private offerings". Unlike mutual funds, hedge funds are exempted from the Investment Company Act of 1940, which regulates the structure and operation of mutual funds and requires funds to safeguard their portfolio securities, forward price their securities, and keep detailed books and records. This exemption provides hedge funds a great flexibility to select investment options. They can use short selling, leverage, derivatives, and highly concentrated investment positions to

enhance their risk/returns. Hedge funds are also exempted from Securities Exchange Act of 1934; therefore they are not required to make periodic reports to SEC. The flexibility also has its own cost. Hedge funds have to limit the number of investors to 500 to qualify for exclusion from the regulations governing public issuance of securities. In addition, hedge fund investors must meet certain requirements. For instance, a qualified investor must have a minimum net worth of US\$1,000,000 or, alternatively, a minimum income of US\$200,000 in each of the last two years and a reasonable expectation of reaching the same income level in the current year. Hedge funds are not allowed to advertise in public. Due to this restriction, hedge funds report voluntarily to database vendors so that they can distribute the information and attract investors' dollars. However, they may stop reporting if they perform poorly. Alternatively, they may also stop reporting if they perform remarkably well and thus are closed to new investors. This typically creates a survivorship bias in measuring fund performance.

Since hedge funds usually report their returns on a voluntary basis, it is not possible to accurately estimate the size of the hedge fund universe as well as to verify hedge funds' returns. Collecting reliable information on hedge funds is a challenge, but according to an estimation of Van Hedge Fund Advisors, the hedge fund industry has been growing at an average rate of over 17% per annum over the last decade and is expected to continue at this significant rate. There were about 9,000 hedge funds operating in 2006 with a total assets value of USD 1.3 trillion.

2.2 Fee Structure

Hedge funds follow a wide range of strategies, but usually share the same fee structure. This fee structure usually consists of a fixed management fee (typically 1%)

plus an incentive fee (typically 20% of the profit). The incentive structure is designed to attract the most skilled managers to the industry. However, to avoid abusing investors, most hedge funds also have a hurdle rate and a high water mark clause. The hurdle rate is a predefined minimum return (LIBOR or a fixed rate) to investors before application of any incentive fees. The “High water mark” means that the manager cannot get any incentives until the fund recovers its past loss.

2.3 Classifications and Funds of Hedge Funds

There are several ways to classify hedge funds. First, the classification can be based on the location where a hedge fund is registered. Onshore (or domestic) funds are registered in the US whereas offshore funds are typically registered in a tax haven such as British Virgin Islands, the Bahamas, Bermuda, the Cayman Islands, Dublin, and Luxembourg where tax liability to non-US investors is minimal. Second, hedge funds can be classified according to their investment style either reported by the hedge fund managers or determined by an algorithm. Since there are no broad consensus about the meaning of “investment style”, each database service vendor has its own set of definitions about hedge fund style.

Making direct investment in hedge funds is difficult and risky. The minimum investment in a single hedge fund is about US\$100,000 to US\$1,000,000 (Fung and Hsieh, 2000). In order to create a well diversified portfolio of hedge funds, an investor needs a substantial investment and a great effort to monitor the activities of the hedge funds. For this reason, a special group of hedge funds called “funds of hedge funds” (FOF, hereafter) have emerged to facilitate investing in hedge funds. FOFs are investment vehicles that are supposed to allocate investor dollars into the winning hedge

funds, diversify risk, improve liquidity, do the proper due diligence, and monitor the hedge funds they invest in. The downside of investing in FOFs is the double fee layer. FOFs often charge 1% management fee plus 10% performance fee on top of the fees charged by hedge fund managers. Despite of the double fee structure, FOFs have enjoyed an exponential growth. According to an estimate in the EurekaHedge database, the universe of FOFs had 2,600 funds with a total value of \$624 billions as of the end 2006, up 35% from the 2005 estimate, and accounts for 40% of total global hedge fund assets. Another report by Hedge Fund Research shows that 85% of new hedge fund investment in 2003 was through a fund of funds as compared to less than half in 2000.

2.4 Common Types of Investment Organizations

< Figure 1 to be inserted here >

Figure 1 shows the relation among some popular investment organizations including index funds, mutual funds, hedge funds and funds of funds. A number of distinctive characteristics can be observed. First, both index fund and mutual funds are registered with the SEC, while hedge funds are not. Some FOFs are registered, but the majority are not.

Second, the performance of both index funds and mutual funds are usually evaluated by a relative return, which compares a fund's actual return to a benchmark's return. For instance, the Vanguard 500 index fund's return should be benchmarked against the SP500 return. In contrast, hedge funds and FOFs pursue absolute returns, which aim to make positive returns regardless whether the overall market is up or down.

Third, index funds usually follow a computer generated buying/selling rules. Mutual fund managers may attempt to pick securities or time the market, but their decisions are often seriously constrained by regulations. Thus, the investment strategy of both index and mutual funds can be approximated by a Buy and Hold strategy (Fung and Hsieh, 1997). In contrast, hedge fund managers have more freedom to select investment tools and often employ dynamic trading strategies (Agarwal & Naik, 2000b). FOF managers aim to pick winning hedge funds.

Fourth, the number of securities held by these organizations varies remarkably. An index fund's portfolio usual has the same number of securities as the corresponding index. Typical mutual funds usually hold a few hundred of different securities to diversify the risk. Hedge funds usually make concentrated investments; therefore they tend to hold only a small number of securities. The number of hedge funds held in a portfolio of funds of funds is also much smaller than that in a portfolio of a mutual fund.

Finally, due to the mechanical strategy of trading securities, index funds do not have to hire expensive managers; thus, the fees are typically below 1%. Mutual funds often charge higher fees, ranging from 1.5% to 5%. Among mutual funds, loaded funds are usually more expensive than the no load ones. However, most mutual funds do not charge performance fees. Hedge fund fees are much higher and widely vary fund by fund. According to Fung and Hsieh (2006), about 80% of hedge funds charge 1 to 2% management fee plus 20% performance fee.

CHAPTER 3

Risk Adjusted Measures of Performance

3.1 Introduction

Evaluating hedge fund manager skills has important implications for the industry as well as for the academics. If hedge fund managers have superior skills in beating the market, it would jeopardize the market efficiency hypothesis. If hedge fund managers do not have the true talents, it would raise the question about the motivation of investing in hedge funds and the fee structure imposed in the industry.

The performance of portfolio managers has been extensively investigated in the finance literature. Early studies employ framework developed by Jensen (1968) and then refined by Black, Jensen, and Scholes (1972). The underlying idea is to compare a particular manager's performance to a benchmark of similar risks. The stock picking ability is often measured by Jensen's alpha in the CAPM below.

$$R_p - R_f = \alpha_p + \beta_p R_m + e_p \quad (1)$$

where $(R_p - R_f)$ and R_m are respectively excess returns (net of risk free rate) on the portfolio p , and the market portfolio, β_p measures the sensitivity of the portfolio return to the market portfolio return, e_p is a random error, which has an expected value of zero. The intercept is known as Jensen alpha, which is expected to be positive if the manager has superior stock picking ability, zero if the manager employs random buy-and-hold strategy and negative if the manager does not have stock picking ability.

An alternative measure of ranking portfolio performance is the Treynor ratio, which measures the reward-to-systematic risk as follows:

$$T = \frac{\alpha_p}{\beta_p} \quad (2)$$

where α_p , β_p are Jensen's alpha and portfolio beta, respectively.

Another popular measure is the Sharpe ratio, which measures the amount of excess return per unit of volatility as follows:

$$S = \frac{R_p - R_f}{\sqrt{\text{Var}[R_p - R_f]}} \quad (3)$$

where R_p , R_f are average return on portfolio and risk-free asset, respectively.

< Figure 2 to be inserted here >

In Figure 2, the Sharpe ratio is the slope of the line joining cash to portfolio X. A higher Sharpe ratio implies a better investment performance.

Frank Sortino argues that the most important risk is not the volatility risk, but rather the risk of not achieving a minimum acceptable return, MAR (see Sortino and Meer, 1991; Sortino and Price, 1994). He suggests using the downside volatility instead of the standard deviation in the Sharpe ratio. The Sortino ratio is defined as follows:

$$\text{Sortino_ratio} = \frac{R_p - R_f}{DD_p} \quad (4)$$

where DD_p is the downside deviation of returns of portfolio P below the minimum acceptable return (MAR).

Evaluating hedge fund performance is difficult, mainly because hedge fund returns are not normally distributed. Specifically, hedge fund returns often have a low standard deviation, but a negative skewness and a fat tail (high kurtosis). The traditional

performance measures like Jensen's alpha, Sharpe's ratio rely on mean and variance, and ignore the effects of the higher moments and underestimate the risk inherent in hedge fund returns. To address this issue, Shadwick and Keating (2002) introduce a measure called Omega, which accounts for the effects of the higher moments.

The Omega function is defined as follows:

$$\Omega(L) = \frac{\int_a^b (1 - F(r)) dr}{\int_a^L F(r) dr} \quad (5)$$

Where (a,b) is the interval of returns and $F(r)$ is the cumulative distribution of returns.

Omega is the ratio of the gain to the loss, given the return threshold L . By considering all threshold values, we can establish omega function for an asset or a portfolio. In practice, we often consider omega value at the risk-free rate or a zero threshold. The omega function has several interesting properties. First, it is a pay-off function. For each threshold, it calculates a probability adjusted ratio of gain to loss. Second, it is not affected by the sampling error because it is calculated directly from the observed distribution and requires no estimates. Consequently, it contains all information of the higher moments. According to Shadwick and Keating (2002), Omega usually shows markedly different ranking of funds from those derived by Sharpe ratios and Jensen alpha when the higher moments matter.

Different performance measures focus on different aspects of a portfolio. Both the Jensen alpha and Treynor ratio are derived from the CAPM and measure the risk as the systematic part of the volatility of the return. Jensen alpha measures the total excess

return while Treynor ratio measures the excess return per unit of systematic risk. Unlike Treynor ratio, Sharpe ratio focuses on the total risk, and Sortino ratio focuses on the downside risk. The recently introduced omega ratio extends beyond the mean and variance framework to capture risks associated with the higher moments of returns. It is important to note that these measures are explicitly described by a few variables like a fund's historical returns, the risk-free rate (or minimum acceptable return) and the market risk premium. Other important economic factors, however, are not explicitly included.

Fama and French (1993), and then Carhart (1997) suggest a multiple-factor model to improve the explanatory power of CAPM. The four-factor model has been frequently used in measuring the performance of mutual funds, but appears insufficient when applied to hedge funds. Its limitation is mainly due to the fact that hedge funds often employ dynamic investment strategies, which can not linearly be captured by traditional risk factors.

Fung and Hsieh (2001) show that the majority of managed futures funds employ a trend-following strategy, resulting in a return profile that is similar to that of a lookback straddle portfolio. Mitchell and Pulvino (2001) find that the merger arbitrage returns resemble those of merger arbitrage hedge funds. Fung and Hsieh (2002) show that convertible bond funds were highly correlated to the CSFB Convertible Bond Index, and the High-yield funds were highly correlated to CSFB High-Yield Bond Index. Agarwal and Naik (2004) find the strong evidence that long/short equity funds had positive exposure to the stock market and Fama French's SMB factor. Extracting the factors from prior empirical studies, Fung and Hsieh (2004, 2006) develop a seven-factor model that attempt to describe risks inherent in a well-diversified portfolio of hedge funds.

In short, hedge fund performance has been studied using different performance measures and covering different data and time horizon. Given different settings, it is not surprising to find conflicting results regarding the hedge fund performance. In this study, I reinvestigate the performance of a sample of fund of funds as well as major hedge fund strategy/main indices using various performance measures.

3.2 Data and Corrections of Data Biases

There are three commercial databases of hedge funds that have more than ten years of actual data collection experience: Center for International Securities and Derivatives Markets (CISDM), Hedge Fund Research (HFR), and CTI/TASS (TASS). Although some data is available from 1990, most of the data prior to 1994 is backfilled and subject to a number of biases. Therefore, recent studies of hedge funds often employ data from 1/1994. Hedge fund databases typically issue a main index along with subindices representing different investment strategies. Each database has its own method to construct the main index and sub indices. All indices, except CTI, are equal weighted, possibly because it is difficult to determine the assets under management of hedge funds. In this study I obtain the index data directly from the website of the databases. I also obtain monthly return data of FOFs from the CISDM database, covering the period 1990 – 2004.

< Table 1 to be inserted here >

Although I have some returns data before 1994, I do not include them in the performance analysis because most of them are backfilled. Table 1 shows that the number

of funds of funds increased more than seven times during 1994-2004, starting with 145 funds in 1994 and ending with 1113 funds at the end of 2004. Totally, 1,476 funds entered and 363 funds disappeared from the database. The last column in the table reports the attrition rate, which is the ratio of the number of dissolved funds to the number that existed at the start of the year. On average, about 6.18% of funds disappeared each year, which is slightly lower than the 8.54% estimated by Liang (2000) for hedge funds. The disappearance of hedge funds is due to various reasons: fund liquidation, merged with other funds, closed to new investments, or simply no longer interested in being listed in the database. Some types of disappearances create upward biases; others create downward biases or no bias at all. For instance, poor performing funds tend to stop reporting to the database. As a result, this creates an upward bias in the return of the surviving funds. Successful funds that are closed to new investments may also stop being listed. This creates downward survivorship bias. Following Malkiel (1995), and Fung and Hsieh (2000), I measure the survivorship bias by the difference between two portfolios of hedge funds. The observable portfolio invests equal amount in each fund in the database each month. If new funds are added to the database, the portfolio is rebalanced to reflect the equal weight investment in each fund. Similarly, the capital from defunct funds is reinvested among the remaining funds. The observable portfolio is indeed an equal weighted index comprising all funds in the database. The surviving portfolio includes all funds that are still in the database at the end of the sample. The surviving portfolio is similar to the observable portfolio except that it does not include any defunct funds. The estimation of the survivorship bias is summarized in Table 2.

< Table 2 to be inserted here >

The surviving portfolio had an average annual return of 9.32% during 1994 - 2004, while the observable portfolio had an average return of 8.66% during this time. Thus, the survivorship bias in our FOF sample is 0.67% annually.

It can be noted that the attrition rate is zero during the period before 1994. This is an evidence of the backfilled bias, which arises when a vendor adds the contemporaneous returns of new fund into a database along with its historical returns. Since the historical returns tend to be more favorable than the contemporaneous returns, adding historical return to the database is likely to result in an upward biased return. In order to calculate the backfilled bias, I delete the fund returns during the incubation period, in which the fund was in operation but not reported to the database. Park (1995) estimated the incubation period 27 months in the MAR CTA database, Brown, Goetzmann, and Park (1999, hereafter BGP) found a 15-month incubation period in the TASS hedge fund database, Fung and Hsieh (2007) used a 14-month incubation period in all databases during 1994-2004. I use a 24-month incubation period for two reasons. First, it is an average of the estimates used by other researchers. Second, I need two years of return data to run Sharpe's regressions. A two-year incubation is consistent with the literature and provides consistency through our analysis. As shown in Table 2, the return on the portfolio of both "Live" and "Defunct" funds excluding the first 24 monthly returns is 8.45%. Therefore, the backfilled bias is 0.21% per year. The total of the survivorship bias and back-filled bias is about 0.88% in our FOF sample, consistent with findings reported

by Liang (2000) and Fung and Hsieh (2000)¹. The survivorship and backfilled biases vary across different databases, hedge fund strategies or the time horizon. However, it appears that both survivorship and backfilled biases are much smaller in FOF return data than in hedge fund return data (See panel B). This result lends supports to Fung and Hsieh (2000). Specifically, they argue that FOFs' track records are often reconciled and audited to match the underlying fund's performance. In addition, FOFs' tracking records retain the performance of hedge funds that already gone out of business or stopped reporting to the database. As a result, they expect that FOF return data contain less biases.

Another potential bias is stale hedge fund prices, which arises when hedge funds hold illiquid securities that are difficult to price, and they value their own portfolio. According to Lhabitat (2004), only 30% of US onshore hedge funds use third party administrators to value their portfolio. Some hedge fund managers intentionally smooth hedge fund returns, which result in underestimated systematic risk-adjusted returns. Another source of stale price is due to the way hedge fund returns are reported. According to Brown, Goetzmann, and Ibbotson (1999), the management fee and high watermarks are determined according to the year-end asset values. Consequently, the monthly data do not correspond to the normal reporting period for hedge funds and do not reflect the actual returns experienced by the investors. To reduce the potential spurious findings, I also carry out analysis using returns data at quarterly, semiannual and annual intervals.

¹ Liang (2000) finds that survivorship bias for FOFs in HFR database is 0.03% a month during 1994-1997. Fung and Hsieh (2000) find that survivorship bias for FOFs in TASS database is 1.4% per year during 1994-1998.

3.3 Empirical Results

3.3.1 *Single Factor Model (CAPM), Sharpe, Omega and Sortino Ratios*

Table 3 shows the annual returns of different hedge fund indices and sub indices along with the returns on the equity market² and US T-bill.

< Table 3 to be inserted here >

The return on the FOF sample has been adjusted for both survivorship and backfilled biases using the estimates in previous section. The returns of hedge fund indices/subindices have been adjusted for survivorship bias³ by using Fung and Hsieh (2006)'s estimates. During 1994-2004, the average annual return on the equity market was 11.69% compared to 9.64% on HFR main index, 10.78% on equal weighted CISDM main index and 8.39% on value-weighted CTI main index. The portfolio of the FOF sample performed poorly, averaging at only 7.78% per year. Among the hedge fund strategies, only Equity Hedge was able to beat the equity market. The whole investigation period experienced a period of bull market during 1994-1999 and a period of bear market during 2000-2004. The return on the equity market was very impressive, averaging at 20.82% annually in the first subperiod (bull market), but was miserable, averaging only 0.21% annually in the second subperiod (bear market). All hedge fund strategies could not beat the equity market during the bull market, but all of them still generated decent

² Equity market is the portfolio of all funds included in the COMPUSTAT database, obtained from French's website.

³ According to HFR, funds must stay in the data base at least one month before their current returns are included in the calculation of hedge fund indices. Thus, the indices after 1994 are free of backfilled bias. However, the individual fund's return data may contain the backfilled biases.

returns when the equity market was bearish. Among the hedge fund strategies, Equity Hedge generated the highest average return (12.52%), followed by the Event-Driven (11.51%). The Equity Hedge reaped huge benefits during the bullish stock market, earning an average of 19.08% a year while reduced the exposure to the equity market during the bearish stock market, earning 4.66% annually. The portfolio of the FOF sample performed poorly compared to other hedge fund strategies. In fact, it outperformed only the Equity Market Neutral.

< Table 4 to be inserted here >

Table 4 provides further statistics on hedge funds' characteristics. Panel A1 shows selected performance measures using monthly returns. Both the beta and standard deviation of all hedge fund strategies are smaller than those of the equity market. In fact, some hedge fund strategies (Convertible Arbitrage, Equity Market Neutral) have near-zero betas and very small standard deviations, only about 3-4% annually compared to 15.67% of the equity market. However, the returns on some other hedge fund strategies (Merger Arbitrage and Relative Value Arbitrage) were strongly skewed to the left, and the returns on all hedge fund indices displayed high kurtosis, indicating evidence that hedge fund returns are not normally distributed.

Despite the poorer performance in term of average return, all hedge fund indices outperformed the equity market in terms of the Jensen alpha, Treynor or Sharpe ratio. The reason is that hedge funds have small beta and standard deviation. It should be noted that CAPM is not a good model when applied to hedge fund returns. In fact, the model's

R-Squares are relatively small, ranging from 0.09 (Convertible Arbitrage) to 0.64 (Equity Hedge).

The evidence suggests that traditional performance measures like the Jensen alpha, Treynor ratio, and Sharpe ratio tend to favor the hedge funds over the stocks. When performance is measured by the Omega and Sortino ratios, the performance ranking varies depending on the threshold. Both the Omega and Sortino ratios represent the concept of gain-to-loss, despite gains and losses are measured differently. When the threshold is set low, investment with lower chance of loss will be preferred. Similarly, when the threshold is set high, investment with higher chance of gain will be preferred. Risk avoiding investors would set threshold low so that they can avoid loss, while risk tolerant investors would set the threshold high so that they can reap more gain. When threshold is set to zero, both the Omega and Sortino ratios agree with the traditional measures. When threshold is set to the risk free rate, the performance rankings based on the Omega and Sortino are strikingly different from those based on the traditional measures. The equity market now outperformed five out of the eight hedge fund strategies. It also outperformed the CTI index and the CISDM FOF sample. Both the Omega and Sortino often yield identical performance ranking, possibly because both of them are conceptually related “downside” risk-adjusted return measures, and special cases of Kappa, a generalized risk-adjusted performance measure (see Kaplan and Knowles, 2004). The performance ranking by Omega and Sortino are different from that by Sharpe despite that Sharpe ratio is also based on the concept of gain-to-loss. The reason is that the Sharpe ratio only penalizes the volatility measured by the standard

deviation, while the Omega also penalizes volatilities in higher moments (like skewness and kurtosis).

When broken down into sub periods, Panel A2 and A3 in Table 4 show that all hedge fund indices deeply underperformed the equity market during the bullish stock market, but outperformed both the equity market and T-Bill index during the bearish stock market. Hedge fund returns become less volatile while the equity market returns become more volatile during the bearish stock market. Hedge funds' exposures to the equity market (beta) also decrease during the bearish stock market.

During the first subperiod (1994-1999), all hedge funds underperformed the equity market in term of absolute return, but only Macro shows negative Jensen alpha and Treynor ratio. However, the Sharpe, Omega and Sortino ratios indicate different rankings during this period. The Sharpe ratio indicates five out of eight HFR hedge fund strategy indices underperformed the equity market, while both the Omega (Rf) and Sortino (Rf) indicate only the Equity Hedge index would beat the equity market.

To avoid spurious results due to the potential of stale-price effect, I also carry out analysis using returns data at different intervals. If the returns are independent from each other, the actual annual standard deviations can be estimated from periodic standard deviations as follows:

$$\delta_a = \delta_m * \sqrt{N} \quad (6)$$

where δ_a is the actual standard deviation of the annual returns, δ_m is the standard deviation of periodic returns, which can be daily, weekly, monthly, etc. , N is the number of periods per year, which is 12 for monthly, 4 for quarterly, 2 for semiannual intervals. If the periodic price is smoothed, the standard deviation will be underestimated using

periodic returns. As the return interval increases, the standard deviation will be less affected by price smoothing. Therefore, in the presence of stale prices, I expect the annualized standard deviation increases when the measurement interval increases.

I select January-December period for computing annual returns, January-June and July-December for semiannual returns, January-March, April-June, July-September, and October – December for quarterly returns. The Panels B, C and D show the results using quarterly, semiannual and annual return intervals. Some interesting patterns are observed when the measurement interval increases from a month to a year as follows.

- As the return intervals increase from a month to a half-year, the annualized standard deviations do not always increase, and in some cases, they decrease. However, when the measurement interval increases to a year, all standard deviations increased significantly. This suggests the possibility that fund managers, intentionally or not, smooth periodic returns.

- The annualized returns increase slightly, possibly due to compounding effects.

- The negative skewness and fat tail (high kurtosis) characterize only the monthly return distributions. When longer intervals are used, hedge fund returns become less negatively skewed and the distribution tails become thinner (lower kurtosis). In fact, both the HFR and CISDM main indices display positive skewness and thin tail (kurtosis is lower than 3) when measured semiannually or annually.

- The beta of most hedge fund strategies or hedge fund indices remained unchanged while the R-Square dropped significantly. For instance, when the interval

increases from a quarter to a half-year, the beta for HFR main index changed from 0.41 to 0.39 while the R-Square dropped from 0.73 to 0.54.

- Traditional performance measures (Jensen alpha, Treynor, Sharpe ratio) basically remained unchanged. The Omega and Sortino ratios increase slightly, but the performance rankings remained unchanged.

In summary, the results confirm the previous findings that monthly returns of hedge funds tend to have small standard deviations, negative skewness and high kurtosis. The traditional performance measures like the Jensen alpha, Treynor and Sharpe ratios tend to favor the hedge funds over the stocks despite that most hedge fund strategies underperformed the equity market in term of absolute returns. The main reason is due to the low exposure to the market measured by beta and the low total volatility measured by the standard deviations. When adjusted for the volatility in higher moments (skewness and kurtosis in the Omega ratio) or the downside volatility (in the Sortino ratio), hedge fund returns become less favored compared to the equity market. Analysis using various measurement intervals indicates the potential stale prices in hedge funds' periodic returns. Similar evidence is also found for the equity market. The performance rankings, however, do not appear to be affected by the stale price.

3.3.2 Multifactor Models

The low R-Squares in the CAPM model when applied to hedge funds suggests that hedge fund returns are exposed to factors other than the market. I employ Fama-French's extended four-factor model to investigate the potential impacts of non-market factors on hedge fund returns. The model is specified as follows:

$$R_p - R_f = \alpha_p + \beta_p * R_m + s_p * SMB + h_p * HML + w_p * WML + e_p \quad (7)$$

where $(R_p - R_f)$ is monthly excess return of portfolio p , R_m is monthly market risk premium, SMB, “small minus big” is the monthly return on a portfolio of small stocks minus the monthly return on a portfolio of large stocks, HML, “High book value minus Low book value” is the monthly return on a portfolio of high book value stocks minus the monthly return on a portfolio of low book value stocks, and WML, “Win minus Loss” is the monthly return on a portfolio of the past year’s winners minus the monthly return on a portfolio of the past year’s losers (See Fama French, 1995, 1996). Fama-French’s four factors and the risk-free rate are obtained from French’s website.

< Table 5 to be inserted here >

Table 5 summarizes the regression results for eight strategy hedge fund indices, three main hedge fund indices (HFR, CISDM, and CTI) as well as the portfolio of the FOF sample. First, the model does not perform well when applied to hedge funds. The R-Squares for equal weighted HFR and CISDM indices are .77 and .74, respectively. The R-Square for the value-weighted CTI index and the portfolio of FOF sample are lower, only .46 and .54, compared to the range 0.89 to 0.97 reported in mutual funds (Carhart, 1997). At the strategy index level, Fama-French model works even worse: except for the Equity Hedge ($R^2=75\%$), and the Event Driven ($R^2=69\%$), other strategies have R-Squares ranging from 0.09 to 0.41. Compared to the CAPM model, the Fama-French’s four factor model makes some improvements, but is still well below its performance in mutual funds. Second, all constant terms are positive, indicating that all hedge fund strategies, main indices, and the sample of FOF outperformed the equity market during

the whole investigation period (1994-2004). This is consistent with the findings based on the CAPM model. Third, the market factor is always significant. Other factors are all significant for the main indices and the portfolio of the FOF sample, but not for all hedge fund strategies. In particular, the size factor (SMB) is significantly positive for all strategies except Convertible Arbitrage. This indicates that hedge funds are strongly exposed to small stocks. The HML factor is significantly positive for five out eight strategies, suggesting hedge funds are also strongly exposed to stocks with high book-to-market value ratio. The momentum factor is significantly positive for only three strategies.

The subperiod analysis reveals similar results to those obtained from CAPM. First, the market betas remained significant across all strategies during both subperiods. There is also evidence that hedge funds reduced the exposure to the market, size (SMB) and financial distress (HML) factors during the bear market. For instant, the betas for all hedge fund strategies and main indices were higher during the bull market and lower during the bear market. The SMB and HML became not significant during the second subperiod. Second, the constant terms are significantly positive in all cases, except for the Macro strategy, CTI index and the portfolio of FOF sample during the period 1994-1999. Finally, the R-Squares improved in both subperiods. The changes in the factor exposure coefficients, along with the improved R-Squares suggest that hedge funds shifted their investment styles depending on the state of the market.

I also carry out analysis using the Fung and Hsieh's seven-factor model (Fung and Hsieh, 2001, 2004,2006). The model is specified as follows:

$$R_p - R_f = \alpha_p + \beta_1 * SPMRF + \beta_2 * SCMLC + \beta_3 * BDI0RET + \beta_4 * BAAMTSA + \beta_5 * PTFSBD + \beta_6 * PTFSFX + \beta_7 * PTFSOM \quad (8)$$

where SPMRF is the excess return of the S&P 500, SCMLC Small Cap minus Large Cap, BD10YRET the return of ten-year Treasury bond above the risk-free return, BAAMTSY the return of Baa bonds above the return of ten-year Treasury bond. The last three factors, PTFSD, PTFSE, and PTFSCOM are the return of a portfolio of lookback straddles on bonds futures, currency future and commodity futures, respectively. SPMRF and SCMLC are the equity factor most important for long/short equity funds; BD10RET and BAAMTSY are the bond factor most important for fixed-income hedge funds; the three lookback portfolios are most important for trend followers or managed futures (see Fung and Hsieh, 2001, 2004, 2006). The Fung and Hsieh's seven factors can be thought as the proxies for three types of investment strategies: "Buy-and-Hold", "Dynamic Trading", and "Leverage" strategies (Fung and Hsieh, 1997). The first four risk factors are for capturing returns generated by "Buy-and-Hold" strategies, while the lookback straddles factors for capturing the returns generated by strategies of dynamic trading or using leverage.

< Table 6 to be inserted here >

Table 6 summarizes the regression results for the Fung and Hsieh's seven factor model. Panel A provides the results for the whole period. In term of the R-Square, the seven-factor model does not perform better than the Fama-French's four-factor model. Specifically, it improves the R-Squares for equal-weighted HFR and CISDM indices by only 2-3%, but decreases the R-Squares for value-weighted CTI and the portfolio of the FOF sample by the same amount. The constant terms remain significantly positive for all

hedge fund strategies, main indices and the FOF sample. The first two factors in the seven factor model are similar to the market and size factors in Fama-French's. Thus, they are significant like their counterparts in the Fama-French's model. The next two factors, BD10RET and BAAMTSY are significant for some hedge fund strategies, CTI index and the FOF sample, but not for equal-weighted main indices. The last three factors, PTFSBD, PTFSFX, and PTFSKOM are designed to capture the dynamic trading strategies employed by hedge funds. However, only PTFSBD can be found significant in all main hedge fund indices and the portfolio of FOF sample. The PTFSFX are not significant for any main indices. The PTFSKOM is slightly better than the PTFSFX, being significant for CTI index. At the strategy level, PTFSBD is found significant for four strategies; the other lookback straddles factors are only significant for one or two strategies.

The subperiod analysis reveals similar results. The R-Squares have been improved slightly. For instance, the R-Squares for the HFR, CISDM main indices increased from 0.77 - 0.79 for the whole period to 0.81-0.86 for the subperiods. However, the three lookback straddle factors are not significant for all the main indices during 1994-1999. Interestingly, the PTFSBD is no longer significant for the three main indices and portfolio of the FOF sample. Like the Fama-French model, the seven-factor model also indicates that all strategies and main indices except the value-weighted CTI main index and the portfolio of the FOF sample outperformed the market during the period 1994-1994.

In summary, the three dynamic trading factors in the Fung and Hsieh's model do not appear to add significant explanatory power over the Fama-French's extended four-

factor model. Both models indicate that all hedge fund strategies and main indices outperformed the market during 1994-2004, and all hedge fund indices except the value-weighted CTI index and the portfolio of the FOF sample outperform the market even during the period 1994-1999, when the average annual return on the equity market was 20.82%, compared to only 13.24% of HFR main index, and 14.45% of CISDM index.

3.4 Conclusion

In this chapter, I analyze the performance of eight hedge fund strategies classified by the HFR database, along with three popular equal-weighted HFR, CISDM and value-weighted CTI main hedge fund indices, as well as the portfolio of a FOF sample obtained from CISDM databases. The study of monthly returns on the portfolio of the FOF sample reveals survivorship and backfilled biases. The average annual survivorship and backfilled biases in our FOF sample, respectively, are 0.67% and 0.21%, consistent with those reported by Liang (2000), and Fung and Hsieh (2000). The survivorship and backfilled biases in FOF return data are much smaller than those in hedge fund return data. This result lends the supports to Fung and Hsieh (2000) arguments that FOF return data contain less biases. I confirm that hedge fund returns have smaller standard deviation, but negative skewness and strong kurtosis when measured monthly. However, the negative skewness and strong kurtosis disappeared when measured at a longer interval. I also find evidence of stale price in all the periodic except annual returns. However, it appears that the performance rankings are not influenced by the presence of a stale price. Both the single factor (CAPM) and multifactor models (Fama-French's extended four-factor and Fung and Hsieh's seven-factor) suggest that the returns of all hedge fund strategies are exposed to the market and size factors. Other factors including

three lookback straddles factors are found significant for only a few hedge fund strategies during certain periods. It appears that the lookback straddle factors could not capture the dynamic trading risk for many hedge fund strategies and even for hedge fund main indices. The seven-factor model does not perform better than Fama-French's model during the whole period or during the first subperiod, but performs much better in the second subperiod. A possible explanation is that during a bearish stock market, hedge funds switch the investment style to reduce exposure to the Fama-French's factors, but not to the factors in the seven-factor model. Regardless of the models used (the CAPM, Fama-French's or Fung and Hsieh's), hedge funds' exposure to the equity market is higher during a bullish stock market, and lower during a bearish stock market. For instance, the exposure of HFR main index to the equity market was about 0.43-.45 during the first period, and only about 0.31 to 0.38 during the second period. Other hedge fund indices exhibit similar exposure patterns during the two subperiods. Performance measures based on the factor models appear to favor hedge funds over stocks even during a bullish period when hedge funds' performance was far behind that of the equity market. However, this result should be accepted with criticism because the R Squares of all the factor models were not high across the major hedge fund strategies, and hedge fund main indices. Further research need to identify more relevant factors underlying hedge fund returns. I also find that the performance ranking of the Omega and Sortino ratios usually agree with each other. When the threshold is set at zero (less risk tolerance) both the Omega and Sortino ratios tend to emphasize more on downside volatility than on the potential return; thus, they generally agree with the traditional performance measures like the Jensen alpha, Treynor, Sharpe ratio. When the threshold is set at risk-free rate (more

risk tolerance), both the Omega and Sortino break away from the traditional measures; many hedge fund strategies become less preferable over the equity market.

CHAPTER 4

Performance Benchmarks of Funds of Hedge Funds

4.1 Introduction

4.1.1 *Benchmarking Methods*

Risk factor models like the CAPM, Fama-French (1993)'s three-factor, Carhart (1997)'s four-factor models have gained popularity in mutual fund research, but not in hedge fund research. A number of factors and techniques have been proposed to better understand the nonlinear relationship between the returns of hedge funds and those of traditional assets. Fung and Hsieh (2004, 2006) use option based factors while Chan, Getmansky, Haas and Lo (2006) use squared and cubed SP500 terms to describe this nonlinear relationship. Agarwal and Naik (2000b) use the stepwise regression involving a high number of variables. These attempts improve our insight into the return behavior of hedge funds. However, it remains a challenge to uncover all the relevant factors underlying hedge fund returns because hedge funds employ a wide range of strategies.

The lack of understanding of the systematic risk factors inherent in hedge fund returns is probably a reason that some early studies measure performance as the difference between a hedge fund's return and the average return of all hedge funds following the same style. The "style" benchmark, however, is flawed because hedge fund strategies are heterogeneous even the hedge funds follow the same style.

Sharpe (1994) proposes a model to determine a fund's exposure to the twelve asset classes using only realized fund returns. Based on the exposures to the twelve asset classes, a benchmark portfolio can be established for each individual fund. The Sharpe model has gained wide acceptance in research of mutual fund performance because it

provides an insight into fund performance with using minimal information. However, its application to hedge funds has not been fruitful. Fung and Hsieh (1997) show that hedge funds follow strategies that are dramatically different from mutual funds. By running the Sharpe style analysis (without imposing constraints on the coefficient) on 3,327 open-ended mutual funds in the Morning star database, they find that half of the mutual funds have R squares above 75%, and 92% have R squares above 50%. However, when they run the Sharpe style regression on hedge funds, nearly half of the hedge fund sample has R squares below 25%. In addition, a quarter of the hedge funds are negatively correlated with the asset classes.

When applied to hedge funds, Sharpe's style analysis yields low R square because of the dynamic trading and leverage employed by hedge fund managers. A hedge fund can change its market exposure quickly. In such a case, the regression coefficients will no longer represent the fund's true investment style, resulting in a large tracking error and low R square.

Recently, some researchers attempt to build synthetic hedge funds by focusing on the statistical properties of hedge fund returns. If a hedge fund's returns can be replicated by a synthetic hedge fund at a lower cost, it would indicate that the hedge fund's performance is not superior. Kat and Palaro (2005) develop a procedure aimed at replicating the statistical properties (standard deviation, kurtosis, skewness) of hedge fund returns by trading futures on traditional assets. By investigating 485 hedge funds, they find that the majority of them did not add value because their return could have been generated by trading SP500, T-Bonds and Eurodollar futures (Kat and Palaro, 2006). However, Fung and Hsieh (2006) argue that the statistical technique does not explicitly

recognize the changing risk factors and are unlikely to determine where the next risk is coming from.

4.1.2 Focus on Funds of Hedge Funds

Methods frequently used in assessing mutual fund performance appear handicapped when applied to hedge funds. This problem is summarized by Dwyer (2006) that a direct comparison between mutual funds and hedge funds is “not a useful way of thinking about hedge funds”. Given the challenge facing researchers on hedge fund managers’ skills, some recent studies turn their focuses to Funds of Hedge Funds (FOF). Fung and Hsieh (2000) propose that FOF be a proxy of the market portfolio of hedge funds because FOFs contain less measurement biases than individual hedge funds for two reasons. First, the track records of majority of FOFs can be reconciled and audited. Second, individual track records of FOFs do not contain survivorship, selection and backfilled biases. The portfolio of FOFs, however, contains both survivorship and backfilled biases. They estimate that both survivorship and backfilled biases in the portfolio of FOFs are less than half of those in the portfolio of hedge funds, which are confirmed by my finding in the previous section.

Another important, but not widely discussed benefit of focusing on FOFs is the similarity between the role of FOFs in the hedge fund universe and that of mutual funds in the traditional capital market. Table 7 provides comparisons among the hedge funds, funds of hedge funds, and the mutual funds.

< Table 7 to be inserted here >

A mutual fund holds a portfolio of financial securities like stocks, bonds, etc, while a FOF holds a portfolio of equities of hedge funds. Unlike hedge funds, both mutual funds and FOFs face constraints in taking short positions in their assets. Fung and Hsieh (1997) show that mutual fund returns are similar to those generated by a Buy and Hold strategy. The dominating strategy of FOFs also resembles “Buy and Hold” because they cannot trade their equity freely due to the lockup period imposed by the hedge funds. On one hand, assets of mutual funds can be clearly defined as stocks, bonds, or money; assets of funds of funds can be grouped into “market neutral”, “macro”, “event driven”, etc. On the other hand, the underlying assets of hedge funds are usually not well defined because hedge funds can engage in all kinds of trading and change their portfolio mix quickly. According to Fung and Hsieh (2000), FOFs are also more transparent than hedge funds.

FOFs are similar to mutual funds in many important aspects. Therefore, I expect that standard methods applied to mutual funds can also be applied to FOFs. This observation is important because we have known a great deal about mutual funds, but not much about the hedge funds and funds of funds. Viewing from this perspective, it is natural to use “hedge fund indices” as “asset classes” when analyzing the returns of funds of funds in Sharpe’s framework.

Amence and Vaissie (AV, 2006) attempt to measure individual FOFs’ performance by regressing FOF returns on EDHEC indices, subject to Sharpe’s constraints:

$$R_{FOF,t} = \sum_{k=1}^N \beta_k R_{k,t} + (\alpha + \varepsilon_t) \quad \text{for } t = 1, \dots, T \quad (9)$$

where R_{FOF_t} is the return of FOF at time t , β_k is the exposure of the FOF to style factor k , $R_{Ik,t}$ is the return of the style factor (EDHEC index) k at time t , α is the intercept term, and ε_t is white noise. They find that the hedge fund indices on average explain about 56.7% of the variations in *individual* FOFs' returns. Only a quarter of FOFs display an R square of 43% or less. In addition, when decomposing FOF returns into two components: strategic allocation ($\sum_{k=1}^N \beta_k R_{Ik,t}$) and active management (α), they find that on average FOF managers generate an excess return of 0.89% annually. Of this total excess return, 1.55% is due to the manager's strategic allocation skills, and -0.65% is due to the manager's active management. They also find that while 88.66% of hedge fund managers display positive strategic allocation skills, only 30.91% of them display active management skills. This study, however, has some limitations. First, it assumes that FOF managers do not change their style exposures during the investigation period (1/1994 – 12/2003). This assumption may lead to a downward biased estimate of active management⁴. Second, they select only a small sample of 97 FOFs that have full records during the study period. This selection procedure is likely to increase the survivorship bias, resulting in upward bias of estimating FOF performance.

Figure 3 summarizes a few directions in research of hedge funds and FOFs. The majority of studies attempt to uncover the factors underlying portfolios/ indices of hedge funds. Representative studies include Fung and Hsieh (1997, 2004, 2006), Chan, Getmansky, Haas and Lo (2005). Another research area targeting at the return behavior of individual hedge funds is represented by Agarwal Naik (2000), Edward and Caglayan

⁴ Grantt (1977) demonstrates that market timing ability will cause down-ward biased estimate of active management performance.

(2001). Fung and Hsieh (2000) discuss various biases related to individual FOFs as well as the portfolio of FOFs. Amence and Vaissie (2006) analyze the performance of FOFs using Sharpe's style analysis involving hedge fund strategy indices.

< Figure 3 to be inserted here >

In this study, I will also implement the Sharpe style analysis on FOFs. However, my study differs from Amenc and Vaissie (2006) in several important aspects. First, their objective is to determine "ex post" excess returns based on a multivariate regression. My objective is to build an appropriate benchmark portfolio for each FOF so that I can calculate "ex ante" excess returns. Second, AV (2006) assume the style exposures to remain constant during the study period while I update them every month. Therefore, my estimate of fund performance is not biased. Third, I do not impose the condition that funds must have continuous track record during the whole investigation period. As a result, I can work with a much larger sample with both living and defunct funds

4.2 Data Descriptions

From the FOF sample described in the previous study, I select funds of funds that have at least three years of returns data during 1/1992-12/2004. The hedge fund strategies are represented by the eight HFR sub indices.

< Table 8 to be inserted here >

Table 8 provides the correlation coefficients between the FOF portfolio and the hedge fund strategies. During the whole period, 1994-2004 (Panel A), the correlation coefficients between the FOF sample and the hedge fund strategy indices are moderate, ranging from 0.33 to 0.85. In addition, there is no high correlation among the hedge fund strategy indices. Panel B and C show the correlation coefficients during subperiods. In general, some coefficients changed slightly from a period to the next, but the patterns are similar to those observed for the whole period.

< Table 9 to be inserted here >

Table 9 shows results of regressions of FOF portfolio returns on eight HFR strategy indices. The regression coefficients were constrained to non-negativity and their sum was constrained to be one (100%). During the whole period, the R-square was about 0.87 and the constant term was about -11 basis points a month, or -1.32% per year. The FOF portfolio was exposed strongly to the Macro, Equity Hedge and Distressed Securities and negligibly to the other indices. When broken down into subperiods, the alpha was negative during the first subperiod, but slightly positive during the second period. The R square was also improved slightly, from 0.87 to 0.91. FOFs changed the style exposures even though the three strategies, Macro, Equity Hedge and Distressed Securities remained the most important factors in both subperiods. It can be concluded that eight HFR strategy indices can explain a significant portion of variations in the returns of the FOF portfolio. The result is robust through time. Overall, FOFs as a group

underperformed the style benchmark portfolio of hedge fund indices on the net basis. However, the underperformance of 1.32% per year was well within the fee schedules.

4.3 Empirical Results

I run Sharpe's style regression for each FOF using a rolling window of 24 months to determine its exposure to the major hedge fund strategies:

$$R_{i,w} = \beta_{1i,t}F_{1,w} + \beta_{2i,t}F_{2,w} + \dots + \beta_{8i,t}F_{8,w} + e_w \quad (10)$$

where $R_{i,w}$ is the monthly returns of fund i during the past two years, $F_{k,w}$ is the monthly returns on strategy index k during the past two years, e_w is error term with expected value of zero. The constant term is suppressed to zero. The regression coefficients are subject to a non-negativity constraints and their sum must equal 100%.

< Figure 4 to be inserted here >

Figure 4 shows that the about half of the FOFs have an average R square above 50%, which is much better than the average R-square obtained from regressing individual hedge fund return on various asset classes⁵. However, there is also one-fifth of FOFs that have an average R-square below 25%. Figure 5 and 6 show the average R-square distribution in subperiods. Only 45% of FOFs in the first subperiod have an average R-square above 0.5 compared to 56% of funds in the second subperiod. Overall, the result suggests that the eight HFR strategy indices are capable of explaining the major variation in returns of a significant portion of FOFs. The reasonably high average R- square raises

⁵ Fung and Hsieh find that half of the mutual funds have R square above 75%, and 92% have R squares above 50%. However, when they run Sharpe style regression on hedge funds, nearly half of the hedge fund sample has R square below 25%.

the prospect of replicating the funds' returns by using the portfolios of the eight HFR strategy indices.

< Figure 5 to be inserted here >

< Figure 6 to be inserted here >

Based on the regression coefficients obtained from equation (10), I construct benchmark portfolios for each individual fund as follows:

$$BP_{i,t} = b_{1i,t}F_{1,t} + b_{2i,t}F_{2,t} + \dots + b_{8i,t}F_{8,t} \quad (11)$$

where $b_{k,t}$ is the style exposure to the hedge fund strategy k during the past two years, and $F_{k,t}$ is returns on the strategy k during period t .

To investigate the fund managers' skills, I create three portfolios. The "FOF" portfolio is an equal-weighted portfolio of all funds of funds in the sample. The "FOF" portfolio gives the actual returns to the investors, net of all fees. The "Style Benchmark" portfolio is equal-weighted portfolio of individual benchmarks, which are calculated by equation (11). The "Style Benchmark" portfolio represents fund managers' investment styles, or strategic capital allocation. The "market" portfolio is equal weighted portfolio of eight HFR strategy indices. The "market" portfolio represents an investment strategy that requires no skills at all. If the fund manager possesses ability to pick winning funds, I expect the "FOF" portfolio outperform the "Style Benchmark" portfolio. If the manager has ability to forecast the winning strategies, I would expect the "Style Benchmark" portfolio outperform the "market" portfolio.

< Table 10 to be inserted here >

Table 10 reports the performance of the three portfolios. Panel A1 shows the results involving 802 qualified funds for the whole period. The qualified funds are those which have returns data for at least three consecutive years. The Style Benchmark portfolio displays the statistic characteristics (standard deviation, skewness, and kurtosis, beta) that are close to those of the FOF portfolio, indicating that the overall replication is successful. The annualized returns on the FOF portfolio is only 7.90%, compared to 8.63% on the Style Benchmark. Thus, fund managers do not outperform the style benchmarks on the net return basis. However, the difference between the annual return on the FOF portfolio and that on the Style benchmark portfolio is only 0.73%, apparently smaller than typical management and incentive fees⁶. This suggests that FOFs might outperform the style benchmark on the pre-fee basis. In other words, fund managers might have some fund-picking skills, but they do not pass on any gain to the investors. This view is consistent with market efficiency with costly information. The return on the style benchmark portfolio is smaller than that on the market portfolio. This indicates that following hedge fund investment style would not add value. Thus, the hypothesis that managers have ability to predict winning hedge fund strategies is not supported.

Since the results can be affected by the funds that have low R squares, I repeat the analysis by imposing different conditions on the R-squares. Panel A2 and A3 report the analysis with minimum R-square above zero and the average R-square above 0.5,

⁶ Fung and Hsieh (2006) show that for FOF, the median management fee was 1% and the median incentive fee was 10%. Given these estimates, the total fees would be 1.88% for the net return of 7.90%.

respectively. When more condition is imposed on R-square, the sample size is shrunk, but the findings are largely the same.

< Figure 7 to be inserted here >

Figure 7 shows cumulative return differences among the three portfolios. Holding FOF portfolio for the whole period (1994-2004) would earn less than holding style benchmark and the market portfolios by about -0.74% and -1.16% a year. However, the difference cannot be rejected at any meaningful significance. The return on the style benchmark portfolio minus that on the market portfolio declined sharply after 1999. Figures 8 and 9 show similar results when different conditions on R-square are imposed. All the three figures indicate a potential break point around the end of 1999, coincident with the disruption of the internet bubbles.

< Figure 8 to be inserted here >

< Figure 9 to be inserted here >

I then carry out the subperiod investigation. Panels B2 and B3 (Table 10) show the performance of the three portfolios during the two subperiods, 1994-1999 and 2000-2004, respectively. It can be seen that FOF portfolio underperformed the market portfolio in both subperiods, but slightly outperformed the style benchmark portfolio during the second subperiod. This is consistent with the previous finding in Table 9. The style

benchmark portfolio generated the highest returns during a bullish stock market, but gained the lowest return during a bearish stock market. Again, the style benchmark portfolio characteristics (standard deviation, skewness, kurtosis, beta) resembled those of the FOF portfolio in both subperiods, indicating the success of replicating FOF returns, at least at the portfolio level.

To gain insight into the performance of individual funds, I carry out the analysis of tracking errors. A fund's tracking error is the difference between its return and that on the style benchmark portfolio during a period. A high average tracking error can indicate either exceptional performance of a fund (too bad or too good) or a poor benchmark or both.

< Figure 10 to be inserted here >

< Figure 11 to be inserted here >

< Figure 12 to be inserted here >

Figure 10 shows the distribution of average tracking errors for individual funds. When no restriction is imposed on R-square, the total cases with extreme returns account for less than 4% of the sample. About 86% of the sample has moderate average tracking errors, which are between -0.5% and 0.5% a month. Specifically, about 30% of funds underperformed the style benchmark slightly while 56% of funds outperformed the style benchmarks slightly. When I select only funds that have all R squares above zero, the sample size is reduced from 802 to 533 funds. Figure 11 shows the cases with extreme

negative tracking errors (more than one percent a month below zero) account for less than 2% while no significant cases exhibiting extreme positive tracking error (more than one percent a month above zero). The central distribution is similar to that in Figure 10: 26% of funds slightly underperformed the style benchmarks, while 62% slightly outperformed the style benchmarks. Figure 12 show the distribution of tracking errors using the most stringent conditions on R-square. The number of funds now is reduced to 407, and there is no case with extreme returns. Again, the central distributions remain basically the same: 27% of fund exhibiting a slightly negative performance while 66% of funds exhibiting a slightly positive performance against the style benchmarks. Hence, the evidence suggests that most of the extreme cases are due to the poor style benchmark, and they will go away when a better style benchmark (higher average R square) is used. Despite the potential issues related to a small number of extreme cases, the overall distribution of tracking errors suggest about two third of funds outperform the style benchmarks, while only a third lag behind the style benchmarks.

< Figure 13 to be inserted here >

< Figure 14 to be inserted here >

To investigate whether the findings are robust to time horizon, I repeat the analysis in subperiods. Figure 13 shows that the percentage of extreme cases was relatively large in the first subperiod, accounting for 12% of the sample, which is evenly divided into two groups of positive and negative extreme tracking errors. The cases that have moderate tracking errors account for only 74% of the sample. Specifically, 41% of

the sample slightly underperformed the style benchmark, compared to 31% of the sample that slightly outperformed the style benchmark. Figure 14 shows that the distribution of the tracking errors in the second subperiod is similar to that during the whole period. The proportion of funds that outperformed the style benchmark during the whole period appears biased toward the results in the second period because the sample size in the second period is more than twice of that in the first period. The evidence suggests funds tend to underperform the style benchmark in the first subperiod and outperform the style benchmark in the second period. A possible explanation is that the style benchmarks performed well in the first half period and did poorly in the next half period.

< Table 11 to be inserted here >

To further assess the performance of individual funds, I test if a fund's returns are significantly different from those of the style benchmark. Table 11 summarizes the testing results. Panel A1 shows that about 3% of the sample consistently underperformed the corresponding style benchmarks, compared to 8% of the sample consistently outperformed the style benchmarks. The results are robust whether I impose the conditions on R square or not (see Panels A2 and A3). Panel B1 shows that about 5% of the sample significantly underperformed the style benchmarks during the first period, compared to only 3% of the sample outperformed the style benchmarks. Panel B2 confirms the previous findings that funds were more likely to outperform the style benchmarks in the second subperiod.

4.4 Conclusion

In this chapter, I analyze the performance of a sample of FOFs obtained from CISDM database. As I discussed in the previous study, the factor models have several serious limitations when applied to hedge funds. Particularly, factors underlying hedge fund returns are not sufficiently identified in the literature. Instead of using a factor model, I rely on style benchmark portfolios as a performance measure for FOFs. I show that the hedge fund strategy indices can explain substantially the variation in returns of at least half of the FOF sample. Simple regressions of the returns of the portfolio of FOFs on the returns of the eight HFR strategy indices shows that FOFs as a group underperformed the eight hedge fund strategy indices during the period 1994-1999, but slightly outperformed the indices during 2000-2004. However, the simple regressions also reveal that FOFs changed their exposure to the indices. Thus, the average exposures determined from the simple regression might not correctly describe the movement of the FOF portfolio. I refine the analysis by developing a style benchmark portfolio for each individual fund. A style benchmark portfolio is formed from the hedge fund strategy indices with the weights (style exposure) determined from the Sharpe's style regression using rolling windows of 24 months. To evaluate the fund manager skill, I construct three portfolios. The FOF portfolio is an equal weighted portfolio of FOFs. The aggregate style benchmark portfolio (hereafter Style Benchmark portfolio) is an equal weighted portfolio of all individual style benchmark portfolios. Finally, the market portfolio is an equal weighted portfolio of the eight hedge fund indices. Then, I decompose the funds' excess return above the market into two components. The first component, the fund-picking skill, is the return difference between FOF portfolio and the style benchmark

portfolio. The second component, the trend forecasting skill, is the return difference between the style benchmark portfolio and the hedge fund market portfolio. I find that the style benchmark portfolio replicates the FOF portfolio remarkably well. The results are robust in subperiods as well as under different criteria of replication measured by R-squares. Overall, I find that FOFs as a group underperformed the hedge fund market by 1.16% a year. The major part of the underperformance is due to the negative fund-picking skill on the net basis, about -0.74% a year. However, this amount is significantly smaller than typical management and incentive fees charged by the fund managers. Thus, fund managers on average may have ability to pick winning funds on the gross basis. Unfortunately, I do not have information to estimate the gross return directly. The second part of the underperformance is due to the managers' strategic allocation of capitals, about -0.42% a year. This amount is reduced, but remains negative when I impose more stringent conditions on R squares. Thus, managers appear to have no ability to predict the winning hedge fund strategies.

The fund level analysis reveals that about 8% of funds consistently outperformed the style benchmarks while about 2% of funds consistently underperformed the style benchmarks. Funds were more likely to underperform the style benchmarks in a bullish stock market than in a bearish stock market. The results are robust to conditions imposed on R-squares.

CHAPTER 5

Performance Persistence of Funds of Hedge Funds

5.1 Introduction

A direct test of the managerial skill of fund managers is the test of performance persistence. If success were due primarily to luck rather than skill, we would not expect to see a high degree of performance persistence among successful managers (Edwards and Caglayan, 2001). The studies of hedge fund performance persistence, however, yield mixed results.

Brown et al. (1999) study the performance of offshore hedge funds over the period 1989 through 1995. They measure the performance by both raw and market risk adjusted annual returns. They find no evidence of performance persistence regardless whether using raw or market risk adjusted returns.

Agarwal and Naik (2000) exam the quarterly, half yearly and annually performance persistence using HFR data that cover the period between 1/1982 and 12/1998. They measure fund performance by the alpha and appraisal ratio. They find that the performance persistence decreases as the length of return measurement intervals increases. They also extend analysis to the series of wins and losses for more than two consecutive periods. In the multi period framework, the level of performance persistence is significantly smaller than that observed in the two-period framework, and is due mainly to repeat-losers rather than repeat-winners.

Edwards and Caglayan (2001) employ a multi factor model to measure the Jensen alphas for individual hedge funds during the period 01/1990 through 08/1998. They find

evidence of significant performance persistence over one- and two-year horizons among both winners and losers.

In past studies, alpha and Sharpe ratio are the two most popular performance measures for hedge funds. In general, alpha measures the excess return above a benchmark of similar risk while the Sharpe or information ratio scales the excess return to a unit of return volatility. In practice, there are several ways to measure alpha because risk can be estimated differently. For instance, alpha is defined as a constant term in a CAPM (Brown et al 1999) or in a multiple factor model (Edwards and Caglayan, 2000). Alpha can also be defined as the return of a hedge fund using a particular strategy less the average return for all hedge funds following the same strategy (Agarwal Naik, 2000). The main issue with alpha is that we do not have a good risk-factor model for hedge funds (see discussion in the first essay). As a result, alpha is unlikely to represent a true risk-adjusted excess return. In addition, both alpha and Sharpe ratio are designed for the mean-variance framework. Thus, they are not capable of capturing the effects of the higher moments in hedge fund returns.

In this study, I address the issue of performance measures by using Sortino ratio and style benchmark in addition to traditional measures like alpha and Sharpe ratio. As shown in the previous section, the Omega ratio is capable of capturing all moments in returns while the Sortino can capture the downside volatility. When the threshold is set at risk-free rate, the Omega and Sortino ratio often produce performance ranking that are strikingly different from those produced by traditional measures. Since the Omega and Sortino often generate similar performance ranking⁷ I will use Sortino as a performance

⁷ Kaplan and Knowles (2004) show that both Omega and Sortino are conceptually related “downside” risk-adjusted return measures, and special cases of Kappa, a generalized risk-adjusted performance measure.

measure in this study. I also use the excess return above the style benchmark as another performance measure. Unlike alpha, the excess return above the style benchmark will exclude the effects of investment style and provides clearer evidence on managers' fund-picking skills.

In order to avoid the potential effects of stale price, I carry out the analysis using returns data at different frequencies. To avoid potential returns biases, I focus on the FOF because FOF return data tend to contain the least bias (Fung and Hsieh, 2000).

5.2 Empirical Results

5.2.1 Test of Two Period Performance

I follow Agarwal and Naik (2000) and use the two way winner-and-loser contingency table method. The winner/ losers are defined as funds that performed above/ below the median using a particular performance measure. Persistence is determined by whether a fund is a winner (or loser) in two consecutive periods. Consistent winners and losers are labeled as WW and LL. Similarly, winner (or loser) in the first period and loser (or winner) in the second period is labeled as WL (or LW). I employ cross-product ratio (CPR) to detect persistence. The CPR is calculated as follows:

$$\text{CPR} = (\text{WW} * \text{LL}) / (\text{WL} * \text{LW}) \quad (12)$$

According to Christensen (1990), the natural logarithm of the CPR follows normal distribution and has a standard error as follows:

$$\sigma_{\ln(\text{CPR})} = \sqrt{\frac{1}{\text{WW}} + \frac{1}{\text{WL}} + \frac{1}{\text{LW}} + \frac{1}{\text{LL}}} \quad (13)$$

If wins and losses are random, we expect CPR to be one. The null hypothesis of no persistence or trend reversal is rejected if Z statistic is significantly different from zero (two-tail test). Z statistic of CPR is calculated as follows:

$$Z = \frac{\ln(CPR)}{\sigma} \quad (14)$$

A Z-statistic value of 1.96 (-1.96) corresponds to significance at the 5% level, and indicates performance persistence (trend reversal).

< Table 12 to be inserted here >

As shown in the first essay, there is some evidence of stale pricing when returns are measured monthly, quarterly or semiannually. To avoid potential impacts of stale price, I use the annual returns data. To be included in the sample, funds must have at least three calendar years of returns data. Table 12 reports the findings over the period 1994-2004. The returns data in 1994 is used to determined the first past winners. It is shown on the table 12 that the null hypothesis is strongly rejected for the whole period, regardless of the use of performance measures. However, the results of overall persistence are biased toward the trend in recent years. Indeed, as the sample size increased about ten folds during the ten-year period, from 49 in 1995 to 445 in 2004, the CPR ratios in recent years would have more weight in the calculation of the overall CPR. As seen on Table 12, there is overwhelming evidence of persistence during 2001-2004: fifteen out of sixteen cases have been found positively significant. The only case that did not indicate the persistence occurred in 2003 when performance is measured by alpha.

The evidence of persistence, however, is less significant during 1995-2000. Specifically, when performance is measured by the Style Benchmark, Sharpe and Sortino ratios, the Z statistics are positive in seventeen out of eighteen cases, but significant only in four cases during the period. All the four significant cases occurred in 1997 and 1999. When performance is measured by alpha, no evidence of performance can be found. Eventually, three out of the six cases have negative Z statistics, and one of them is significantly negative (in 2000). The mixed results during 1995-2000 are due to the ways I measure the performance. Alpha measures a fund's relative performance to the average of all funds. Alpha often produces the least evidence of persistence. When adjusting for the investment style, the evidence of persistence becomes much stronger. Specifically, the style benchmark indicates that the CPR ratios in every year are greater than one, and the null hypothesis is rejected in five out of ten years. Style benchmark also focuses on the fund's return but adjusts for the style difference. Sharpe and Sortino ratios generally agree with style benchmark.

< Table 13 to be inserted here >

The downside of using annual data is the reduced number of investigation periods. To investigate the potential impact of the measurement interval, I count the percentage of periods that experience persistence or trend reversal. Table 13 reports the percentage of significant cases for each performance measure. In general, more than half of the periods experienced performance persistence, regardless the measures or return interval used. The only exception occurred when the annual performance is measured by

alpha. In this case, only 30% of the periods experienced persistence. The degree of trend reversal is much weaker than that of the persistence. When measurement intervals are monthly or quarterly, about 5-13% of periods experienced trend reversal. When semiannual or annual return intervals are used, no trend reversal could be observed if performance is measured by the Sharpe or Sortino ratios.

In summary, the two period performance persistence tests indicates strong evidence of persistence during the period 2001-2004, but only marginal evidence of persistence during 1995-2000. The evidence of persistence during 1995-2000 is largely consistent with Edwards and Cagayan's (2000). Generally, the degree of persistence does not decrease when the measurement interval increases as documented by Agarwal & Naik (2000). However, when performance is measured by alpha, the degree of persistence decreases significantly at the annual interval. The trend reversals are only occasionally observed, particularly if the semiannual or annual intervals are used. The degree of performance persistence is usually lowest when performance ranking is based on alpha. When adjusting for the investment style or scaling excess return to a unit of volatility, I often find stronger evidence of persistence.

5.2.2 Quintile Analysis

In the previous section, I have found some evidence that the past performance positively influences the future performance, particularly when performance is measured by the Style benchmark, Sharpe or Sortino ratios. In this section, I will investigate how the past performance influences the future return. At the end of each period, FOFs are sorted into quintiles according to a particular performance measure. Funds in the bottom quintile have the poorest performance while funds in top quintile have the highest ones.

Then, I form three portfolios. The “past winners” is equal weighted portfolio of all funds in the top quintile. The “past losers” is an equal weighted portfolio of all funds in the bottom quintile. Both the “past winners” and the “past losers” portfolios are rebalanced at the end of the next period. The “All Funds” is an equal weighted portfolio of all funds in the sample. In addition, I also set up three zero investment portfolios. The “past winners minus past losers”, or WML portfolio is an equal weighted, zero investment portfolio with a long position in the past winners and a short position in the past losers. The “past winners minus all funds”, or WMA is an equal weighted zero investment portfolio with a long position in the past winners and a short position in all funds in the sample. The “past losers minus all funds”, or LMA is an equal weighted zero investment portfolio with a long position in the past losers and a short position in all funds in the sample. The three zero investment portfolios are also rebalanced at the end of the next period. Although it is unrealistic to keep short position in a portfolio of FOFs, the analysis of zero investment portfolios can shed light into the relative performance of different groups of funds. In each period, I test whether the return on zero investment portfolio is significantly positive for WML and WMA (winners continue to win), or significantly negative for LMA (losers continue to lose).

< Table 14 to be inserted here >

Table 14 show average annual returns for the three portfolios. Panel A shows the return differences between the past winners and the past losers. The null hypothesis of no performance persistence is rejected if the return on zero investment WML is significantly

positive at 5% significant level. On average, annual returns on WML are positive, ranging from 0.16% (measured by style benchmark) to 1.77% (measured by Sortino), but not significant for the whole period 1994-2004. The evidence of persistence, however, is found in several years, particularly in 2001-2002, and 2004 when the returns on WML portfolio are all positive, and eleven out of twelve cases are significantly positive. There is also some evidence of persistence during 1996-1997 when returns on WML are all positive and two out of eight cases were significant. In many cases, the return on WML is quite large, but the null hypothesis cannot be rejected, possibly because of the small sample size during this period. Overall, performance persistence is evidenced at least in four out of ten years, consistent with results in previous section.

I further investigate whether the persistence is due to the past winners or to the past losers. Panel B reports the returns on WMA, "Winners Minus All Funds" portfolio. The average annual returns on WMA are usually positive, but not statistically different from zero for the whole period 1994-2004. Indeed, the returns on WMA are positive in 25 out of 40 cases, and ten of them are significant. Similarly, Panel C reports returns on LMA, "Losers Minus All funds" portfolio. The average annual returns on LMA are usually negative, but not statistically different from zero for the whole period 1994-2004. The returns on LMA portfolio are negative in 24 out of 40 cases, and nine of them are significant. Overall, the degree of persistence is equally found among the past winners and the past losers, particularly in 2001, 2002 and 2004. The WMA portfolio has the highest return (0.95%/year) if performance is measured by alpha. Similarly, the LMA portfolio has the lowest return (1.47%/year) if the performance is measured by Sortino

ratio. This suggests investors could have used alpha to select past winner and used Sortino ratio to avoid past losers.

< Table 15 to be inserted here >

I also investigate the persistence using shorter time intervals. As indicated in the previous sections, there is some evidence of stale price in monthly, quarterly and also semiannual returns. Thus, I expect a higher degree of persistence when the shorter measurement intervals are used. Table 15 shows the summary findings. Panel A shows the annual return on portfolio WML. As the measurement intervals increase, the returns on zero investment decline, regardless how to measure the performance. Specifically, the return on the portfolio WML is ranging from 11% to 13% in the case of monthly interval, from 7% to 8.5% in the case of quarterly or semiannual interval, and from 0.16% to 1.77% in the case of annual interval. Interestingly, the percentage of significant cases (column Pos. Sig. %) changes only slightly while the return on the portfolio WML drops sharply when the measurement interval increases. Panels B and C report the returns on portfolio WMA (Winners minus All funds) and LMA (Losers minus All funds). The results are similar to those reported in Panel A: the degree of persistence decreases when the interval increases. It also appears that the persistence is due to both past winners and past losers, which is consistent with Edwards and Caglayan (2000). Panel D provides the summary of test statistics for Panels A, B and C. The null hypothesis of no persistence for the period 1994-2004 is always rejected if monthly, quarterly or semiannual interval is used. The hypothesis cannot be rejected if annual interval is used.

5.3 Conclusions

In this study I investigate the performance persistence of funds of hedge funds for the period 1994-2004 by using the two-period framework (see Brown et. al, 1999) and quintile analysis. Using funds of funds data minimizes potential data biases as argued by Fung and Hsieh (2000). Fund performance is evaluated by four different measures: alpha, style benchmark, the Sharpe and Sortino ratios. Alpha measures a fund's excess return above the average return of all funds. Style benchmark adjusts the excess return for a fund's investment style. The Sharpe ratio scales the excess return to a unit of total volatility while the Sortino ratio scales the excess return to a unit of down-side volatility . The investigation uses different measurement intervals: monthly, quarterly, semiannual and annual interval.

When using measurement intervals from a month to a half year, I find strong evidence of persistence. The two-period framework suggests that about 47% to 67% of the periods experienced the persistence. The quintile analysis also indicates similar degree of persistence. In addition, the quintile analysis shows that the persistence is due to both past winners and past losers, although the degree of persistence is more profound among the losers. The return on zero investment portfolio WML is impressive, ranging from 7.20% to 13.62% per year, and usually decreases as the measurement interval increases. However, short-term persistence can be inflated by the stale fund price. In addition, most funds have a significant lock-up period, making it difficult for investors to take advantages of short term persistence.

When using annual interval, I obtain mixed results. The two-period framework continues to reject the null hypothesis of no persistence for the whole period 1994-2004,

but the result is biased toward the patterns in recent years. The quintile analysis shows positive returns on the WML zero investment portfolio, but none of them is significant, possibly due to the short period of the investigation.

The choice of performance measures does not affect the results if measurement interval is a half year or less. In this case, all four measures indicate significant persistence during the period 1994-2004. When the annual return is used, the two-period framework shows that alpha produces the least evidence for persistence while the other three measures tend to agree with each other. The quintile analysis, however, shows that the past winners portfolio based on alpha tend to do the best, outperforming the equal weighted index of FOF by 0.95% per year. In contrast, the past losers portfolio based on the Sortino ratio tend to suffer the most, underperforming the equal weighted index of FOF by 1.57% per year. This implies that the investors should consider funds that have the highest returns in the past and avoid funds that have the lowest Sortino ratio in the past.

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Table 1: Number of Funds of Hedge Funds (FOFs) in CISDM during 1/1990 – 12/2004

Funds must report at least one monthly return

Most of the return data before 1994 are backfilled

Attrition is the ratio the number of dissolved funds to the number that existed at the start of the year

Year	Start	Entry	Exit	End	Attrition rate
1990	27	22	0	49	
1991	49	22	0	71	
1992	71	30	0	101	
1993	101	44	0	145	1.38%
1994	145	79	2	222	
1995	222	68	18	272	8.11%
1996	272	74	9	337	3.31%
1997	337	89	17	409	5.04%
1998	409	75	32	452	7.82%
1999	452	107	32	527	7.08%
2000	527	95	41	581	7.78%
2001	581	150	51	680	8.78%
2002	680	176	29	827	4.26%
2003	827	187	43	971	5.20%
2004	971	231	89	1113	9.17%
Average					6.18%
Total	1476	363			24.59%

Table 2: FOF Annual Return, Survivorship Bias and Backfilled Bias, 1990-2004

“Defunct” funds are the funds stop reporting at the end of 2004. “Live” are the funds still on operation at the end of 2004. Survivorship bias is the difference between the returns on portfolio of “Live” and that on the portfolio of both “Live” and “Defunct”. The backfilled bias is the difference between the return on the portfolio of both “Live” and “Defunct” and that on the portfolio of “Live” and “Defunct” excluding the first 24 monthly returns.

Year (1)	Defunct (2)	Live (3)	Live+Defunct exc.			Survivorship Bias (6)=(3)-(4)	BackFilled Bias (7)=(4)-(5)
			Live+Defunct (4)	first 24 months (5)	Survivorship Bias (6)=(3)-(4)		
1994	(3.33)	(3.63)	(3.51)	(3.12)	(0.12)	(0.39)	
1995	9.59	11.45	10.54	10.38	0.92	0.16	
1996	14.43	16.37	15.48	15.27	0.89	0.21	
1997	15.94	16.90	16.48	16.31	0.43	0.16	
1998	(1.69)	0.77	(0.21)	(1.01)	0.98	0.80	
1999	23.31	22.79	22.93	24.06	(0.14)	(1.13)	
2000	3.11	10.50	8.36	6.63	2.14	1.73	
2001	1.33	6.14	5.01	4.55	1.13	0.46	
2002	(1.79)	2.10	1.45	1.36	0.65	0.09	
2003	8.12	11.98	11.56	11.12	0.43	0.43	
2004	5.03	7.17	7.13	7.39	0.04	(0.26)	
Average	6.73	9.32	8.66	8.45	0.67	0.21	

Table 3: Annual Return of Major Indices, 1994 -2004

The numbers are reported in percentage

Year	HFR Sub Indices										Main Hedge fund Indices			CISDM FOF Sample		Traditional Indices		
	Convertible Arbitrage	Distressed Securities	Equity Hedge	Equity Market Neutral	Event-Driven	Macro	Merger Arbitrage	Relative Value Arbitrage	HFR1	CISDM	CTI	CISDM FOF sample	Merrill Lynch Bond Index	Equity Market	US T-Bill			
1994	(5.51)	2.08	0.86	0.84	4.14	(5.83)	6.78	2.16	2.32	1.21	(6.60)	(3.79)	(3.28)	(0.28)	3.84			
1995	16.46	16.37	25.70	13.44	20.89	24.38	14.76	12.85	17.90	17.01	17.62	9.71	19.75	31.03	5.46			
1996	11.89	17.25	18.28	11.57	20.67	7.56	13.67	11.84	17.63	18.81	18.38	14.60	3.47	19.87	5.08			
1997	10.25	12.66	19.72	11.06	17.75	15.90	13.56	13.10	14.08	17.74	21.27	15.64	10.03	27.79	5.13			
1998	5.86	(5.59)	13.83	6.29	0.49	4.49	5.48	1.22	1.43	2.19	(2.05)	(1.68)	8.45	22.84	4.75			
1999	11.77	14.09	36.06	5.14	20.33	14.85	11.70	12.06	26.09	29.72	19.25	23.39	(1.84)	23.68	4.59			
2000	11.86	1.11	7.94	11.96	4.94	0.48	14.90	10.88	3.56	6.60	2.84	5.96	8.84	(10.01)	5.73			
2001	10.85	10.82	(1.13)	4.77	9.94	4.94	1.00	6.79	2.94	3.38	1.95	3.88	10.29	(9.75)	3.79			
2002	6.94	3.48	(6.42)	(0.81)	(5.93)	5.51	(2.63)	3.52	(3.14)	(1.87)	0.64	0.69	9.84	(21.35)	1.62			
2003	7.76	24.43	17.13	0.63	21.05	17.97	5.44	7.52	16.25	16.55	12.09	10.45	8.25	29.54	1.02			
2004	(0.60)	15.71	5.76	2.30	12.39	2.85	2.24	3.66	6.97	7.22	6.89	6.72	5.40	12.62	1.18			
1994 -1999	8.45	9.48	19.08	8.06	14.05	10.23	10.99	8.87	13.24	14.45	11.31	9.65	6.10	20.82	4.81			
2000-2004	7.36	11.11	4.66	3.77	8.48	6.35	4.19	6.47	5.31	6.38	4.88	5.54	8.52	0.21	2.67			
Overall	7.96	10.22	12.52	6.11	11.51	8.46	7.90	7.78	9.64	10.78	8.39	7.78	7.20	11.45	3.84			

* The returns of hedge fund indices have been adjusted for the survivorship bias estimated by Fung & Hsieh (2007) as follows: 1.8% for HFR main index and sub indices, 2.4% for CISDM and CTI indices.

** The returns of our FOF sample have been adjusted for survivorship and backfilled biases

Table 4: Descriptive Statistics of Various Hedge Fund Categories, 1994 -2004

The return and standard deviation are annualized. Skewness and Kurtosis are standardized. Jensen Alpha and Beta are estimated from the CAPM model:

$$R_p - R_f = \alpha_p + \beta_p R_m + e_p$$

where $R_p - R_f$ is the excess return of the portfolio p , R_m is the market risk premium obtained from French's website. Treynor ratio is the ratio of Jensen alpha to beta. Sharpe ratio is the annualized excess return divided by its annualized standard deviation. Omega is calculated following Keating & Shadwick (2002)

$$\Omega(L) = \frac{\int_a^b (1 - F(r)) dr}{\int_a^L F(r) dr}$$

Where (a,b) is the interval of returns and $F(r)$ is the cumulative distribution of returns. The threshold is set at zero $[\Omega(0)]$, and the risk-free rate $[\Omega(Rf)]$. Sortino is the monthly excess return divided by the downside deviation of monthly excess return. The minimum acceptable return is set at zero $[\text{Sortino}(0)]$ and at the risk-free rate $[\text{Sortino}(Rf)]$.

Table 5: Fama French Model

The extension of Fama French model is specified as follows:

$$R_p - R_f = \alpha_p + \beta_p * R_m + s_p * SMB + h_p * HML + w_p * WML + e_p$$

where $(R_p - R_f)$ is monthly excess return of portfolio p , R_m is monthly market risk premium, SMB, "small minus big" is the monthly return on a portfolio of small stocks minus the monthly return on a portfolio of large stocks, HML, "High book value minus Low book value" is the monthly return on a portfolio of high book value stocks minus the monthly return on a portfolio of low book value stocks, and WML, "Win minus Loss" is the monthly return on a portfolio of the past year's winners minus the monthly return on a portfolio of the past year's losers (See Fama French, 1995, 1996). Data on R_m , SMB, HML and WML are obtained from French's website.

Panel A: Whole Period, 1994-2004

Index Type	Constant	Market	SMB	HML	MOM	Adj. R-Square
HFR Sub Indices						
Convertible Arbitrage	0.0041	0.0856	0.0329	0.0466	0.0041	0.0912
	4.7024	3.9654	1.4079	1.6001	0.2610	
Distressed Securities	0.0042	0.2585	0.1545	0.1725	0.0264	0.4131
	3.6420	9.0497	4.9965	4.4714	1.2640	
Equity Hedge	0.0043	0.5164	0.1477	0.0602	0.1433	0.7426
	3.5005	16.9690	4.4846	1.4648	6.4538	
Equity Market Neutral	0.0017	0.0814	0.0409	0.0736	0.0915	0.3683
	2.6797	5.0949	2.3633	3.4100	7.8481	
Event-Driven	0.0047	0.3737	0.1914	0.1828	0.0163	0.6923
	4.8406	15.6350	7.3970	5.6624	0.9347	
Macro	0.0025	0.2691	0.1521	0.0918	0.1159	0.3068
	1.5278	6.5896	3.4405	1.6637	3.8886	
Merger Arbitrage	0.0034	0.1589	0.0710	0.1080	-0.0008	0.3835
	4.5433	8.7810	3.6277	4.4214	-0.0635	
Relative Value Arbitrage	0.0036	0.1288	0.0617	0.0769	0.0089	0.3143
	5.1211	7.5628	3.3504	3.3468	0.7128	
Major Indices						
HFR1	0.0029	0.4189	0.1462	0.0730	0.0856	0.7688
	3.1556	18.3720	5.9255	2.3701	5.1458	
CISDM	0.0042	0.4328	0.1273	0.0715	0.0956	0.7382
	4.0416	17.1290	4.6536	2.0949	5.1842	
CTI	0.0018	0.3614	0.1084	0.0935	0.1714	0.4586
	1.1223	9.2158	2.5539	1.7651	5.9872	
CISDM FOF sample	0.0010	0.2763	0.1110	0.0862	0.0970	0.5498
	1.0627	11.4080	4.2352	2.6353	5.4905	

Panel B: Subperiod 1994-1999

Index Type	Constant	Market	SMB	HML	MOM	Adj. R-Square
HFR Sub Indices						
Convertible Arbitrage	0.0030	0.1591	0.1080	0.0806	0.0018	0.3035
	2.4689	4.7695	2.7136	1.4125	0.0472	
Distressed Securities	0.0028	0.3333	0.2466	0.2737	-0.0121	0.5537
	1.8670	8.0802	5.0124	3.8759	-0.2549	
Equity Hedge	0.0071	0.4660	0.3941	0.0053	0.1029	0.8537
	5.3562	12.7560	9.0446	0.0845	2.4435	
Equity Market Neutral	0.0015	0.1208	0.1113	0.1649	0.1822	0.4865
	1.7273	5.1483	3.9762	4.1049	6.7339	
Event-Driven	0.0057	0.4077	0.2734	0.2112	-0.0302	0.7211
	4.2177	11.0690	6.2241	3.3500	-0.7110	
Macro	-0.0007	0.4487	0.1841	0.3208	0.2166	0.4303
	-0.2823	6.7635	2.3259	2.8253	2.8323	
Merger Arbitrage	0.0052	0.1890	0.1280	0.0825	-0.0385	0.5079
	5.1944	6.8328	3.8814	1.7440	-1.2087	
Relative Value Arbitrage	0.0032	0.2043	0.1591	0.1282	-0.0127	0.5407
	3.2292	7.4378	4.8544	2.7260	-0.3998	
Major Indices						
HFR	0.0033	0.4378	0.3116	0.0674	0.0471	0.8540
	2.9556	14.3760	8.5770	1.2926	1.3413	
CISDM	0.0043	0.4606	0.3019	0.0575	0.0578	0.8431
	3.5581	13.9030	7.6408	1.0150	1.5127	
CTI	-0.0017	0.5394	0.2310	0.4158	0.3676	0.5196
	-0.6544	7.5870	2.7239	3.4173	4.4853	
CISDM FOF sample	-0.0003	0.3511	0.2491	0.1868	0.1442	0.6251
	-0.2112	8.5650	5.0942	2.6629	3.0512	

Panel C: Subperiod 2000 -2004

Index Type	Constant	Market	SMB	HML	MOM	Adj. R-Square
HFR Sub Indices						
Convertible Arbitrage	0.0051	0.0176	-0.0165	0.0182	-0.0141	-0.0321
	3.9378	0.6695	-0.6169	0.4988	-0.7794	
Distressed Securities	0.0081	0.2124	0.0789	0.0458	0.0519	0.3413
	4.3195	5.5505	2.0240	0.8611	1.9792	
Equity Hedge	0.0023	0.5078	0.0322	0.0726	0.1197	0.7605
	1.2574	13.4130	0.8348	1.3808	4.6136	
Equity Market Neutral	0.0006	0.0464	0.0182	0.0882	0.0577	0.4188
	0.5731	2.3451	0.9036	3.2102	4.2543	
Event-Driven	0.0045	0.3400	0.1441	0.1487	0.0189	0.6863
	2.8981	10.7510	4.4780	3.3864	0.8726	
Macro	0.0047	0.1537	0.1231	0.0138	0.0920	0.2035
	1.9503	3.1603	2.4870	0.2038	2.7587	
Merger Arbitrage	0.0002	0.1124	0.0521	0.1528	-0.0264	0.4528
	0.2456	5.7108	2.6009	5.5890	-1.9596	
Relative Value Arbitrage	0.0041	0.0602	0.0017	0.0359	-0.0029	0.2001
	5.5605	4.0149	0.1143	1.7260	-0.2790	
Major Indices						
HFR1	0.0036	0.3765	0.0527	0.0360	0.0752	0.7700
	2.6404	13.5350	1.8518	0.9261	3.9228	
CISDM	0.0048	0.3809	0.0282	0.0400	0.0784	0.7198
	3.0957	11.9830	0.8720	0.9053	3.5998	
CTI	0.0038	0.2475	0.0445	0.0055	0.1291	0.5596
	2.4770	7.8317	1.3840	0.1257	5.9591	
CISDM FOF sample	0.0025	0.2102	0.0327	0.0338	0.0745	0.5779
	2.1375	8.8241	1.3477	1.0231	4.5654	

Table 6: Regression on Fung-Hsieh's seven factors

The model is specified as follows:

$$R_p - R_f = \alpha_p + \beta_1 * SPMRF + \beta_2 * SCMLC + \beta_3 * BD10RET + \beta_4 * BAAMTSY + \beta_5 * PTFSD + \beta_6 * PTFSEFX + \beta_7 * PTFSCOM$$

where SPMRF is the excess return of the S&P 500, SCMLC Small Cap minus Large Cap, BD10RET the return of ten-year Treasury bond above the risk-free return, BAAMTSY the return of Baa bonds above the return of ten-year Treasury bond. The last three factors, PTFSD, PTFSEFX, and PTFSCOM are the return of a portfolio of lookback straddles on bonds futures, currency future and commodity futures, respectively. The data on the last three factors are obtained from David Hsieh's website <http://faculty.fuqua.duke.edu/~dah7/DataLibrary/TF-FAC.xls>

Panel A: Whole Period, 1994 -2004

Index Type	Constant	SPMRF	SCMLC	BD10RET	BAAMTSY	PTFSD	PTFSEFX	PTFSCOM	Adj. R-Square
HFR Sub Indices									
Convertible Arbitrage	0.0044	0.0572	0.0505	-0.0118	-0.0119	-0.0154	0.0017	0.0017	0.1754
	5.5570	3.0773	2.0550	-2.6890	-1.3770	-2.9269	0.3982	0.2594	0.5596
Distressed Securities	0.0056	0.1518	0.1472	-0.0154	-0.0529	-0.0355	0.0043	0.0037	0.5596
	5.8708	6.7810	4.9796	-2.9157	-5.0897	-5.6143	0.8260	0.4734	0.7543
Equity Hedge	0.0056	0.4407	0.4271	-0.0011	0.0046	-0.0038	0.0048	0.0126	0.7543
	4.8094	16.3810	12.0230	-0.1770	0.3684	-0.5051	0.7710	1.3367	0.1635
Equity Market Neutral	0.0031	0.0343	0.0637	-0.0068	0.0093	-0.0096	0.0083	0.0034	0.1635
	4.3499	2.0649	2.8991	-1.7269	1.2061	-2.0440	2.1364	0.5743	0.7229
Event-Driven	0.0057	0.2828	0.2481	-0.0106	-0.0317	-0.0188	0.0040	-0.0005	0.7229
	6.5314	13.7820	9.1552	-2.1788	-3.3285	-3.2399	0.8335	-0.0646	0.3532
Macro	0.0038	0.1981	0.1533	-0.0315	-0.0530	-0.0120	0.0181	0.0299	0.3532
	2.5072	5.5512	3.2522	-3.7413	-3.2002	-1.1936	2.1721	2.3813	0.3914
Merger Arbitrage	0.0040	0.1161	0.0999	-0.0031	-0.0039	-0.0083	0.0050	-0.0099	0.3914
	5.6843	7.1371	4.6535	-0.8119	-0.5103	-1.7985	1.3065	-1.7322	0.3478
Relative Value Arbitrage	0.0041	0.0858	0.0655	-0.0064	-0.0090	-0.0155	-0.0013	-0.0034	0.3478
	6.3690	5.7126	3.3032	-1.7950	-1.2847	-3.6583	-0.3608	-0.6382	0.7865
Major Indices									
HFR1	0.0038	0.3517	0.3021	-0.0061	-0.0176	-0.0109	0.0063	0.0065	0.7865
	4.4337	17.7430	11.5410	-1.3081	-1.9137	-1.9396	1.3537	0.9345	0.7648
CISDM	0.0052	0.3607	0.3118	-0.0058	-0.0169	-0.0134	0.0067	0.0085	0.7648
	5.5698	16.6430	10.8970	-1.1369	-1.6768	-2.1854	1.3261	1.1187	0.4329
CTI	0.0040	0.2516	0.1690	-0.0243	-0.0618	-0.0307	0.0151	0.0275	0.4329
	2.5802	6.9277	3.5250	-2.8388	-3.6650	-2.9961	1.7846	2.1556	0.5521
CISDM FOF sample	0.0024	0.1979	0.1820	-0.0116	-0.0331	-0.0165	0.0074	0.0136	0.5521
	2.5626	9.0567	6.3055	-2.2456	-3.2663	-2.6661	1.4558	1.7757	

Panel B: Subperiod 1, 1994 -1999

Index Type	Constant	SPMRF	SCMLC	BD10RET	BAAMTSY	PTFSBD	PTFSFX	PTFSCOM	Adj. R-Square
HFR Sub Indices									
Convertible Arbitrage	0.0039	0.1085	0.1110	-0.0154	-0.0292	-0.0172	0.0000	0.0078	0.3594
	3.3317	3.6699	2.8641	-2.3725	-2.0303	-2.4478	-0.0076	0.9583	
Distressed Securities	0.0039	0.2122	0.2062	-0.0122	-0.0657	-0.0307	-0.0004	-0.0005	0.6172
	2.8160	6.0093	4.4563	-1.5631	-3.8301	-3.6538	-0.0560	-0.0525	
Equity Hedge	0.0091	0.4898	0.5255	-0.0025	-0.0294	0.0020	0.0036	0.0037	0.7685
	5.4252	11.5330	9.4408	-0.2630	-1.4261	0.1940	0.4566	0.3112	
Equity Market Neutral	0.0036	0.0766	0.0596	-0.0100	-0.0198	-0.0039	0.0082	0.0015	0.1540
	3.3062	2.7516	1.6325	-1.6392	-1.4662	-0.5944	1.6150	0.1981	
Event-Driven	0.0065	0.3180	0.2983	-0.0113	-0.0465	-0.0188	0.0034	-0.0002	0.6930
	4.6494	8.9038	6.3711	-1.4361	-2.6784	-2.2101	0.5161	-0.0180	
Macro	0.0022	0.3488	0.1440	-0.0322	-0.0921	-0.0163	0.0117	0.0251	0.4269
	0.9159	5.6713	1.7869	-2.3753	-3.0847	-1.1131	1.0359	1.4752	
Merger Arbitrage	0.0058	0.1376	0.1593	-0.0061	-0.0024	-0.0132	0.0030	-0.0020	0.4820
	5.5871	5.2490	4.6354	-1.0501	-0.1884	-2.1130	0.6142	-0.2727	
Relative Value Arbitrage	0.0039	0.1402	0.1449	-0.0065	-0.0234	-0.0180	-0.0019	-0.0007	0.5295
	3.8525	5.4571	4.3020	-1.1426	-1.8728	-2.9454	-0.3965	-0.1020	
Major Indices									
HFR1	0.0045	0.4328	0.3908	-0.0035	-0.0496	-0.0068	0.0066	0.0025	0.8378
	3.8463	14.5910	10.0510	-0.5363	-3.4459	-0.9595	1.2088	0.3020	
CISDM	0.0056	0.4628	0.3871	-0.0033	-0.0553	-0.0084	0.0072	0.0068	0.8362
	4.5115	14.7920	9.4391	-0.4769	-3.6387	-1.1285	1.2597	0.7814	
CTI	0.0024	0.4397	0.1444	-0.0301	-0.1469	-0.0226	0.0187	0.0295	0.5445
	0.9683	6.8741	1.7222	-2.1405	-4.7295	-1.4830	1.5918	1.6687	
CISDM FOF sample	0.0015	0.3167	0.2364	-0.0127	-0.0830	-0.0092	0.0081	0.0169	0.6652
	1.0599	8.8461	5.0381	-1.6093	-4.7715	-1.0844	1.2290	1.7109	

Panel C: Subperiod 2, 2000 -2004

Index Type	Constant	SPMRF	SCMLC	BD10RET	BAAMTSY	PTFSBD	PTFSFX	PTFSCOM	Adj. R-Square
HFR Sub Indices									
Convertible Arbitrage	0.0049	0.0199	0.0124	-0.0088	-0.0086	-0.0036	0.0060	-0.0051	-0.0389
	4.1460	0.7751	0.3906	-1.4456	-0.7941	-0.4518	0.8681	-0.4718	
Distressed Securities	0.0075	0.1398	0.0858	-0.0225	-0.0577	-0.0271	0.0134	0.0243	0.5697
	5.4376	4.6363	2.2992	-3.1549	-4.5360	-2.8813	1.6543	1.9326	
Equity Hedge	0.0010	0.4011	0.4014	-0.0114	0.0061	-0.0032	0.0132	0.0281	0.8360
	0.7068	13.1360	10.6230	-1.5778	0.4696	-0.3348	1.6196	2.2061	
Equity Market Neutral	0.0013	0.0106	0.0911	-0.0063	0.0219	-0.0118	0.0104	0.0036	0.3364
	1.3950	0.5152	3.5713	-1.2806	2.5202	-1.8308	1.8928	0.4196	
Event-Driven	0.0046	0.2554	0.2259	-0.0132	-0.0310	-0.0125	0.0073	0.0011	0.7688
	3.7818	9.6531	6.9006	-2.1132	-2.7785	-1.5198	1.0340	0.0998	
Macro	0.0033	0.0996	0.1507	-0.0343	-0.0452	0.0201	0.0314	0.0480	0.5654
	2.0746	2.8468	3.4796	-4.1385	-3.0569	1.8433	3.3505	3.2915	
Merger Arbitrage	0.0018	0.0669	0.0779	0.0007	-0.0078	-0.0014	0.0088	-0.0269	0.4015
	1.9124	3.3341	3.1385	0.1388	-0.9162	-0.2167	1.6401	-3.2182	
Relative Value Arbitrage	0.0044	0.0483	0.0107	-0.0094	-0.0118	-0.0012	0.0019	-0.0005	0.2109
	6.5701	3.3296	0.5866	-2.7255	-1.9315	-0.2646	0.4936	-0.0887	
Major Indices									
HFR1	0.0022	0.3081	0.2572	-0.0169	-0.0175	-0.0008	0.0104	0.0221	0.8589
	2.2724	14.4360	9.7379	-3.3478	-1.9476	-0.1265	1.8164	2.4830	
CISDM	0.0034	0.3033	0.2806	-0.0153	-0.0127	-0.0023	0.0103	0.0197	0.8149
	2.9353	12.0450	9.0054	-2.5704	-1.1995	-0.2975	1.5268	1.8795	
CTI	0.0018	0.1402	0.2289	-0.0219	-0.0273	-0.0146	0.0135	0.0254	0.6648
	1.4601	5.2181	6.8859	-3.4423	-2.4094	-1.7434	1.8824	2.2670	
CISDM FOF sample	0.0016	0.1364	0.1674	-0.0145	-0.0190	-0.0067	0.0099	0.0145	0.6800
	1.7080	6.7468	6.6946	-3.0289	-2.2245	-1.0609	1.8279	1.7244	

Table 7: Comparisons among Hedge funds (HF), Fund of hedge Funds (FOF) and mutual fund (MF)

	Hedge Funds	Funds of Hedge Funds (FOF)	Mutual Funds (MF)
Portfolio holding	Long/ short in financial securities	Long in equity of hedge funds. Cannot hold a short position in the hedge funds	Long in financial securities. Limited use of selling short securities.
Dominating Strategies	Dynamic trading (Agarwal Naik 2000)	Buy and Hold due to lockup period	Buy and Hold (Fung and Hsieh, 1997)
Classification of underlying assets	Not well defined.	Hedge funds can be grouped into different strategies like equity market neutral, event-driven, convertible arbitrage, Distressed securities, Macro, Merger Arbitrage, etc.	Financial securities are grouped into asset classes like stocks, bonds, money market.
Leverage	Have freedom in using leverage	Have freedom in using leverage.	Limited use of leverage.
Transparency	Not transparent	Not transparent, but more transparent than hedge funds	Transparent

Table 8: Correlation Coefficients

Panel A: Whole Period, (1/1994 – 12/2004)

	1	2	3	4	5	6	7	8	9
1 FOF Sample	1.00								
2 HFRI Convertible Arbitrage Index	0.54	1.00							
3 HFRI Distressed Securities Index	0.73	0.58	1.00						
4 HFRI Equity Hedge Index	0.85	0.45	0.63	1.00					
5 HFRI Equity Market Neutral Index	0.33	0.26	0.19	0.34	1.00				
6 HFRI Event-Driven Index	0.80	0.54	0.81	0.81	0.27	1.00			
7 HFRI Macro Index	0.78	0.39	0.49	0.60	0.27	0.58	1.00		
8 HFRI Merger Arbitrage Index	0.52	0.46	0.50	0.57	0.37	0.72	0.32	1.00	
9 HFRI Relative Value Arbitrage Index	0.64	0.71	0.71	0.59	0.33	0.72	0.39	0.67	1.00

Panel B: Sub Period 1, 1/1994 – 12/1999

	1	2	3	4	5	6	7	8	9
1 FOF Sample	1.00								
2 HFRI Convertible Arbitrage Index	0.64	1.00							
3 HFRI Distressed Securities Index	0.75	0.74	1.00						
4 HFRI Equity Hedge Index	0.83	0.60	0.66	1.00					
5 HFRI Equity Market Neutral Index	0.42	0.35	0.35	0.44	1.00				
6 HFRI Event-Driven Index	0.82	0.70	0.84	0.78	0.41	1.00			
7 HFRI Macro Index	0.83	0.52	0.53	0.64	0.35	0.64	1.00		
8 HFRI Merger Arbitrage Index	0.56	0.54	0.66	0.59	0.39	0.79	0.38	1.00	
9 HFRI Relative Value Arbitrage Index	0.67	0.73	0.85	0.65	0.38	0.82	0.45	0.70	1.00

Panel C: Sub Period 2, 1/2000 – 12/2004

	1	2	3	4	5	6	7	8	9
1 FOF Sample	1.00								
2 HFRI Convertible Arbitrage Index	0.30	1.00							
3 HFRI Distressed Securities Index	0.75	0.30	1.00						
4 HFRI Equity Hedge Index	0.92	0.21	0.67	1.00					
5 HFRI Equity Market Neutral Index	0.14	0.13	(0.01)	0.14	1.00				
6 HFRI Event-Driven Index	0.82	0.29	0.80	0.84	0.04	1.00			
7 HFRI Macro Index	0.65	0.09	0.44	0.54	0.11	0.48	1.00		
8 HFRI Merger Arbitrage Index	0.44	0.33	0.34	0.48	0.27	0.62	0.16	1.00	
9 HFRI Relative Value Arbitrage Index	0.52	0.72	0.45	0.48	0.20	0.55	0.19	0.62	1.00

Table 9: Regression of the fund weighted returns of the FOF portfolio on eight HFR Strategy Indices

$$R_t = \alpha + \sum_{k=1}^8 \beta_k R_{S,k} + \varepsilon$$

where R_t are returns on the equal weighted portfolio of the FOFs, $R_{S,k}$ are returns on HFR sub index k , α is a constant term, ε is error term.

The regression coefficients (β_k) are subject to the following constraints:

$$\beta_k \geq 0$$

$$\sum_{k=1}^8 \beta_k = 1$$

Variables	Full Period 1994-2004	Subperiod 1 1994-1999	Subperiod 2 2000-2004
Constant	(0.0011)	(0.0015)	0.0004
HFR Convertible Arbitrage Index	0.0607	-	0.0929
HFR Distressed Securities Index	0.1922	0.2394	0.1550
HFR Equity Hedge Index	0.2553	0.2424	0.3092
HFR Equity Market Neutral Index	0.0292	0.0092	0.0280
HFR Event-Driven Index	0.0168	0.0737	-
HFR Macro Index	0.2788	0.3347	0.1328
HFR Merger Arbitrage Index	-	-	-
HFR Relative Value Arbitrage Index	0.0946	-	0.0388
R-Square	0.8653	0.8652	0.9064

Table 10: Portfolio Performance Analysis by various Measures

The “FOF portfolio” is an equal weighted portfolio of all *individual* FOFs. The “Style Benchmark Portfolio” is an equal weighted portfolio of *individual* style benchmark portfolios. The “Individual style benchmark portfolio i” during period t is calculated as follows:

$$SB_{i,t} = \beta_{1i,t}F_{1,t} + \beta_{2i,t}F_{2,t} + \dots + \beta_{8i,t}F_{8,t}$$

Where $F_{k,t}$ is the current monthly return of HFR sub index k during period t, $\beta_{ki,t}$ is the style exposure of fund i on the HFR sub strategy index k during the past two years, which is determined from Sharpe styles analysis using rolling windows of 24 months:

$$R_{i,w} = \beta_{1i,t}F_{1,w} + \beta_{2i,t}F_{2,w} + \dots + \beta_{8i,t}F_{8,w} + e_w$$

where $F_{k,w}$ is the monthly returns of fund i during the past two years, $F_{k,w}$ is the monthly returns on strategy index k during the past two years, e_w is error term with expected value of zero, No constant term. The R squares are determined from the above equation. The Market portfolio is an equal weighted portfolio of the eight HFR sub indices.

The return and standard deviation are annualized. Skewness and Kurtosis are standardized. The Jensen Alpha and Beta are estimated from the CAPM model:

$$R_p - R_f = \alpha_p + \beta_p R_m + e_p$$

where $R_p - R_f$ is the excess return of the portfolio p, R_m is the market risk premium obtained from French’s website.

Treynor ratio is the ratio of Jensen alpha to beta. Sharpe ratio is the annualized excess return divided by its annualized standard deviation. Omega is calculated following Keating & Shadwick (2002)

$$\Omega(L) = \frac{\int_a^b (1 - F(r)) dr}{\int_a^L F(r) dr}$$

Where (a,b) is the interval of returns and $F(r)$ is the cumulative distribution of returns. The threshold is set at the risk-free rate. Sortino is the monthly excess return divided by the downside deviation of monthly excess return. The minimum acceptable return is set at the risk-free rate.

Only 802 funds that have at least 25 consecutive monthly returns during 1/1992 – 12/2004 are qualified in this analysis. Funds’ first 24 monthly returns are employed only in Sharpe regressions to estimate the style exposures, and are not included in any performance analysis.

Panel A1: Whole Period - No restriction on R squared

All qualified funds are included (802 funds)

Portfolios	Annualized				Jensen				Sharpe			
	Return	Std	Skewness	Kurtosis	Alpha	Beta	Treynor	Ratio	Omega	Sortino		
FOF Portfolio	7.90%	5.50%	0.0412	6.5973	2.34%	0.2258	0.1037	0.7415	1.0340	0.0171		
Style Benchmark Portfolio	8.63%	4.64%	(0.1466)	5.4516	3.15%	0.2163	0.1457	1.0494	1.1753	0.0895		
Market Portfolio	9.06%	4.13%	(1.0819)	8.5688	3.78%	0.1897	0.1992	1.2776	1.3013	0.1370		

Panel A2: Whole Period, Minimum R-Square>0

Only funds that have positive R-Squares are included (533 funds)

Portfolios	Annualized				Jensen				Sharpe			
	Return	Std	Skewness	Kurtosis	Alpha	Beta	Treynor	Ratio	Omega	Sortino		
FOF Portfolio	8.46%	7.28%	0.1105	6.3988	2.24%	0.3137	0.0713	0.6377	1.0920	0.0462		
Style Benchmark Portfolio	8.99%	5.48%	0.0641	4.8386	3.17%	0.2603	0.1219	0.9508	1.2051	0.1063		
Market Portfolio	9.06%	4.13%	(1.0819)	8.5688	3.78%	0.1897	0.1992	1.2776	1.3013	0.1370		

Panel A3: Whole Period, Mean R-Square>0.5

Only funds whose average R-Squares is greater than 50% are included (407 funds)

Portfolios	Annualized				Jensen				Sharpe			
	Return	Std	Skewness	Kurtosis	Alpha	Beta	Treynor	Ratio	Omega	Sortino		
FOF Portfolio	8.33%	6.54%	(0.1082)	6.3214	2.37%	0.2797	0.0846	0.6919	1.0854	0.0424		
Style Benchmark Portfolio	8.97%	5.30%	(0.0244)	5.0689	3.23%	0.2503	0.1290	0.9799	1.2103	0.1076		
Market Portfolio	9.06%	4.13%	(1.0819)	8.5688	3.78%	0.1897	0.1992	1.2776	1.3013	0.1370		

Panel B1: Whole Period Analysis, 1994-2004 (No Restriction on R-Squares)

All qualified funds included (802 funds)

Portfolios	Annualized					Jensen					Sharpe				
	Return	Std	Skewness	Kurtosis	Alpha	Beta	Treynor	Ratio	Omega	Sortino					
FOF Portfolio	7.90%	5.50%	0.0412	6.5973	2.34%	0.2258	0.1037	0.7415	1.0340	0.0171					
Style Benchmark Portfolio	8.63%	4.64%	(0.1466)	5.4516	3.15%	0.2163	0.1457	1.0494	1.1753	0.0895					
Market Portfolio	9.06%	4.13%	(1.0819)	8.5688	3.78%	0.1897	0.1992	1.2776	1.3013	0.1370					

Panel B2: Sub Period 1 Analysis, 1994-1999 (No Restriction on R-Squares)

Only qualified funds that have at least 25 consecutive monthly returns during 1992-1999 are included. The first 24 monthly returns are employed to estimate the style exposures, but excluded in the performance analysis (345 funds)

Portfolios	Annualized					Jensen					Sharpe				
	Return	Std	Skewness	Kurtosis	Alpha	Beta	Treynor	Ratio	Omega	Sortino					
FOF Portfolio	9.79%	6.49%	(0.1888)	5.8274	-0.18%	0.3227	(0.0057)	0.7735	1.0218	0.0112					
Style Benchmark Portfolio	11.63%	5.05%	(0.6776)	6.1963	2.37%	0.2786	0.0849	1.3651	1.3576	0.1728					
Market Portfolio	11.15%	4.60%	(1.7155)	10.3150	2.21%	0.2582	0.0855	1.3922	1.3034	0.1297					

Panel B3: Sub Period 2 Analysis, 2000-2004 (No Restriction on R-Squares)

Only qualified funds that have at least 25 consecutive monthly returns during 1998-2004 are included. The first 24 monthly returns are employed to estimate the style exposures, but excluded in the performance analysis (728 funds)

Portfolios	Annualized					Jensen					Sharpe				
	Return	Std	Skewness	Kurtosis	Alpha	Beta	Treynor	Ratio	Omega	Sortino					
FOF Portfolio	5.66%	4.09%	0.6687	6.3683	3.38%	0.1566	0.2158	0.7198	1.0649	0.0331					
Style Benchmark Portfolio	5.07%	3.93%	0.7575	5.1147	2.81%	0.1667	0.1687	0.6053	0.9496	(0.0279)					
Market Portfolio	6.55%	3.40%	0.2326	3.5878	4.22%	0.1383	0.3051	1.1267	1.3012	0.1575					

Table 11: Distribution of tracking errors

A fund's tracking error is the differences between its return and that on the style benchmark portfolio during a month. A fund's monthly tracking errors are determined from Sharpe's Style analysis, using rolling windows of 24 months:

$$R_{i,w} = \beta_{1i}F_{1,w} + \beta_{2i}F_{2,w} + \dots + \beta_{8i}F_{8,w} + e_w$$

where $R_{i,w}$ is fund i return during month t , $F_{k,w}$ is the return on strategy index k during w period, $\beta_{k,i}$ is the style exposure of fund i on the HFR sub strategy index k during the past two years, e_w is error term with expected value of zero. No constant term. R-Square terms are determined from the above equations. "Negative*": funds' tracking errors are significantly negative at 1% level.

"Negative": funds' tracking errors are negative, but not significant at 1% level.

"Positive": funds' tracking errors are positive, but not significant at 1% level.

"Positive*": funds' tracking errors are significantly positive at 1% level.

Panel A1: No restriction on R square (Whole Period)

All qualified funds are included (802 funds)

Average Monthly Tracking Error	Negative*	Negative	Positive	Positive*	Total
Number of FOFs	22	286	428	66	802
Percentage	3%	36%	53%	8%	100%

* significant at 1% level

Panel A2: Minimum R-Squares >0

Only funds that have positive R-Squares are included (533 funds)

Average Monthly Tracking Error	Negative*	Negative	Positive	Positive*	Total
Number of FOFs	20	269	235	9	533
Percentage	4%	50%	44%	2%	100%

* significant at 1% level

Panel A3 Average R-Square >0.5

Only funds whose average R-Squares is greater than 50% are included (407 funds)

Average Monthly Tracking Error	Negative*	Negative	Positive	Positive*	Total
Number of FOFs	9	120	244	34	407
Percentage	2%	29%	60%	8%	100%

* significant at 1% level

Panel B1: Whole Period

All qualified funds included (802 funds)

Average Monthly Tracking Error	Negative*	Positive	Total
Number of FOFs	22	428	802
Percentage	3%	53%	100%

* significant at 1% level

Panel B2: SubPeriod 1

Only qualified funds that have at least 25 consecutive monthly returns during 1992-1999 are included. The first 24 monthly returns are employed to estimate the style exposures, but excluded in the performance analysis (345 funds)

Average Monthly Tracking Error	Negative*	Positive	Total
Number of FOFs	16	146	345
Percentage	5%	42%	100%

* significant at 1% level

Panel B3: Subperiod 2

Only qualified funds that have at least 25 consecutive monthly returns during 1998-2004 are included. The first 24 monthly returns are employed to estimate the style exposures, but excluded in the performance analysis (728 funds)

Average Monthly Tracking Error	Negative*	Positive	Total
Number of FOFs	13	418	728
Percentage	2%	57%	100%

* significant at 1% level

Table 12: Two Period Performance Persistence for Annual Returns, 1994-2004

A fund's alpha is the difference between its return and the average return of all funds during a period. Style benchmark is the method of comparing a fund's return to that on a benchmark portfolio comprising eight HFR sub indices with the weights determined from the Sharpe's style analysis. Sharpe ratio is the annualized excess return divided by its annualized standard deviation. Sortino is the monthly excess return divided by the downside deviation of monthly excess return. The minimum acceptable return is set at the risk-free rate. The winner/ losers are defined as Funds that performed above/ below the median using a particular performance measure. The funds that win/lose in both consecutive periods are WW/LL. The funds that win(lose) in the first period then lose (win) in the second period are WL (LW). The Cross Product Ratio is determined as follows:

$$CPR = (WW * LL) / (WL * LW)$$

According to Christensen (1990), the natural logarithm of the CPR follows normal distribution and has a standard error as follows:

$$\sigma_{\ln(CPR)} = \sqrt{\frac{1}{WW} + \frac{1}{WL} + \frac{1}{LW} + \frac{1}{LL}}$$

$$Z = \frac{\ln(CPR)}{\sigma}$$

WW+LL are the total funds that continue the performance from their previous year. The bold numbers indicate significance at 5% level.

Year	Number of Funds	Alpha				Style Benchmark				Sharpe ratio				Sortino Ratio			
		WW+LL	CPR	Z-stat	Z-stat	WW+LL	CPR	Z-stat	Z-stat	WW+LL	CPR	Z-stat	Z-stat	WW+LL	CPR	Z-stat	Z-stat
1995	49	19	0.40	(1.56)	27	1.50	0.71	14	0.49	(1.02)	12	0.30	(1.69)	29	2.10	1.28	2.19
1996	66	32	0.89	(0.25)	34	1.13	0.25	29	2.10	1.28	29	2.10	1.28	42	3.06	0.32	3.79
1997	87	51	2.01	1.60	57	3.61	2.84	36	1.44	0.74	45	1.15	0.32	83	4.31	1.67	5.13
1998	123	63	1.10	0.27	69	1.63	1.35	47	1.38	0.75	89	1.71	1.67	136	4.81	5.02	5.21
1999	157	85	1.39	1.04	85	1.39	1.04	77	2.80	2.76	201	3.46	5.21	269	6.69	8.23	8.23
2000	198	76	0.39	(3.24)	112	1.70	1.84	83	1.26	0.72	89	1.71	1.67	136	4.81	5.02	5.21
2001	244	152	2.73	3.80	170	5.28	5.97	142	6.43	5.90	162	3.90	5.02	201	3.46	5.21	8.23
2002	309	213	4.92	6.48	197	3.09	4.77	168	4.89	5.74	162	3.90	5.02	201	3.46	5.21	8.23
2003	373	179	0.85	(0.78)	217	1.93	3.14	187	2.35	3.67	201	3.46	5.21	269	6.69	8.23	8.23
2004	445	297	4.03	6.92	331	8.43	9.82	229	2.53	4.36	269	6.69	8.23	269	6.69	8.23	8.23
Overall	2051	1167	1.74	6.23	1,299	2.98	11.93	1,012	2.60	9.39	1,068	3.49	12.05	1,068	3.49	12.05	12.05

Table 13: Two Period Performance Persistence for different Return Measurement Interval, 1994-2004

Persistence (Trend Reversal) is the percentage of cases that show significant positive (negative) Z statistics (trend reversal) during a period. Persistence (trend reversal) is determined by alpha, Style Benchmark, Sharpe ratio and Sortino (Rf) at Monthly, quarterly, semiannual and annual intervals. A fund's alpha is the difference between its return and the average return of all funds during a period. Style benchmark is the method of comparing a fund's return to that on a benchmark portfolio comprising eight HFR sub indices with the weights determined from the Sharpe's style analysis. Sharpe ratio is the annualized excess return divided by its annualized standard deviation. Sortino(Rf) is the monthly excess return divided by the downside deviation of monthly excess return. The minimum acceptable return is set at the risk-free rate.

The winner/ losers are defined as funds that performed above/ below the median using a particular performance measure. The funds that win/lose in both consecutive periods are WW/LL. The funds that win(lose) in the first period then lose (win) in the second period are WL (LW). The Cross Product Ratio is determined as follows:

$$CPR = (WW * LL) / (WL * LW)$$

According to Christensen (1990), the natural logarithm of the CPR follows normal distribution and has a standard error as follows:

$$\sigma_{\ln(CPR)} = \sqrt{\frac{1}{WW} + \frac{1}{WL} + \frac{1}{LW} + \frac{1}{LL}}$$

$$Z = \frac{\ln(CPR)}{\sigma}$$

	Persistence				Trend Reversal			
	Monthly	Quarterly	Semiannual	Annual	Monthly	Quarterly	Semiannual	Annual
Alpha	48.09%	51.16%	61.91%	30.00%	13.74%	13.95%	0.00%	10.00%
Style Benchmark	47.33%	46.51%	47.62%	50.00%	6.11%	9.30%	4.76%	0.00%
Sharpe	51.91%	62.79%	61.91%	50.00%	6.11%	6.98%	0.00%	0.00%
Sortino	51.91%	62.79%	66.67%	60.00%	9.16%	4.65%	0.00%	0.00%

Table 14: Quintile Analysis, annual interval

Funds are sorted into quintiles according to their performance in the past year. Alpha, Style Benchmark, Sharpe and Sortino ratios are used as performance measures. The past Winners (Losers) are the funds in the top (bottom) quintile based on a particular measure. "All funds" report returns on the portfolio of all funds. "Past Losers" report returns on the portfolio of past losers. "Past Winners" report returns on the portfolio of past winners. "WML" is the returns on the portfolio of winners minus those on the portfolio of losers. "WMA" is the returns on the portfolio of winners minus those on the portfolio of all funds. "LMA" is the returns on the portfolio of losers minus those on the portfolio of all funds.

Panels A and B test for the null hypothesis that the return on zero investment portfolio WML (WMA) is not positive. Panel C tests for the null hypothesis that the return on zero investment portfolio WMA is not negative. Bold numbers indicate that the null hypothesis is rejected at 5% significant level.

Panel A: Annual Return on Zero Investment Portfolio WML (Winners Minus Losers)

Year	Number of Funds	All Funds	Alpha		Style Benchmark		Sharpe Ratio		Sortino Ratio			
			Losers	Past	Losers	Past	Losers	Past	Losers	Past		
1995	49	13.89	15.27	10.73	15.27	11.41	17.56	4.19	(13.37)	18.07	4.19	(13.88)
1996	66	17.24	16.14	18.55	2.40	17.83	11.88	16.21	4.33	11.88	18.32	6.44
1997	87	17.75	11.20	21.88	10.67	12.19	16.16	19.03	2.87	16.34	17.64	1.30
1998	123	(1.24)	(3.69)	(4.67)	(0.98)	(2.90)	2.35	(1.00)	(3.35)	(1.66)	(0.56)	1.10
1999	157	28.57	39.61	34.91	(4.70)	40.52	28.65	32.04	3.39	23.79	32.59	8.80
2000	198	8.63	11.59	2.21	(9.38)	9.71	8.90	5.79	(3.11)	8.68	8.34	(0.34)
2001	244	5.94	3.08	7.50	4.42	5.30	3.51	8.41	4.90	3.51	8.74	5.23
2002	309	1.81	(1.67)	6.80	8.47	0.74	(1.58)	6.28	7.86	(1.61)	5.99	7.60
2003	373	12.86	15.77	14.27	(1.50)	13.77	14.66	11.78	(2.88)	14.14	12.73	(1.41)
2004	445	8.67	4.29	11.48	7.19	6.78	5.45	9.11	3.66	5.24	8.13	2.89
Annualized Return		11.41	11.16	12.36	1.21	11.92	10.76	11.18	0.43	9.84	11.61	1.77
t-stat (WML)					0.59				0.22			0.86

Panel B: Annual Return on Zero Investment Portfolio WMA (Winners Minus All funds)

Year	Number of Funds	All Funds	Alpha		Style Benchmark		Sharpe Ratio		Sortino Ratio	
			Winners	WMA	Winners	WMA	Winners	WMA	Winners	WMA
1995	49	13.89	10.73	(3.16)	11.41	(2.48)	4.19	(8.64)	4.19	(8.64)
1996	66	17.24	18.55	1.31	18.17	0.93	16.21	(0.15)	18.32	1.96
1997	87	17.75	21.88	4.12	22.03	4.28	19.03	0.74	17.64	(0.65)
1998	123	(1.24)	(4.67)	(3.43)	(4.46)	(3.22)	(1.00)	(0.61)	(0.56)	(0.17)
1999	157	28.57	34.91	6.34	32.02	3.45	32.04	2.03	32.59	2.58
2000	198	8.63	2.21	(6.42)	1.60	(7.03)	5.79	(1.98)	8.34	0.57
2001	244	5.94	7.50	1.56	7.53	1.58	8.41	2.47	8.74	2.80
2002	309	1.81	6.80	4.99	5.91	4.10	6.28	4.82	5.99	4.53
2003	373	12.86	14.27	1.41	15.56	2.70	11.78	(1.47)	12.73	(0.52)
2004	445	8.67	11.48	2.81	11.02	2.35	9.11	1.51	8.13	0.52
Annualized Return		11.41	12.36	0.95	12.08	0.67	11.18	(0.13)	11.61	0.30
t-stat (WMA)				0.74		0.57		(0.11)		0.27

Panel C: Annual Return on Zero Investment Portfolio LMA (Losers Minus All funds)

Year	Number of Funds	All Funds	Alpha		Style Benchmark		Sharpe Ratio		Sortino Ratio	
			Losers	LMA	Losers	LMA	Losers	LMA	Losers	LMA
1995	49	13.89	15.27	1.38	15.27	1.38	17.56	4.73	18.07	5.25
1996	66	17.24	16.14	(1.09)	17.83	0.60	11.88	(4.49)	11.88	(4.49)
1997	87	17.75	11.20	(6.55)	12.19	(5.56)	16.16	(2.13)	16.34	(1.95)
1998	123	(1.24)	(3.69)	(2.45)	(2.90)	(1.65)	2.35	2.75	(1.66)	(1.27)
1999	157	28.57	39.61	11.04	40.52	11.94	28.65	(1.36)	23.79	(6.22)
2000	198	8.63	11.59	2.96	9.71	1.08	8.90	1.14	8.68	0.91
2001	244	5.94	3.08	(2.86)	5.30	(0.64)	3.51	(2.43)	3.51	(2.43)
2002	309	1.81	(1.67)	(3.48)	0.74	(1.07)	(1.58)	(3.04)	(1.61)	(3.07)
2003	373	12.86	15.77	2.91	13.77	0.90	14.66	1.41	14.14	0.89
2004	445	8.67	4.29	(4.38)	6.78	(1.90)	5.45	(2.15)	5.24	(2.36)
Annualized Return		11.41	11.16	(0.25)	11.92	0.51	10.76	(0.56)	9.84	(1.47)
t-stat				(0.16)		0.36		(0.60)		(1.45)

Table 15: Summary of Returns on Zero Investment Portfolios using different interval measures, 1994-2004

Funds are sorted into quintiles according to their performance in the past period. Alpha, Style Benchmark, Sharpe and Sortino ratios are used as performance measures. The past Winners (Losers) are the funds in the top (bottom) quintile based on a particular measure. "All funds" report returns on the portfolio of all funds. "Past Losers" report returns on the portfolio of past losers. "Past Winners" report returns on the portfolio of past winners. "WML" is the return on the portfolio of winners minus those on the portfolio of losers. "WMA" is the return on the portfolio of winners minus those on the portfolio of all funds. "LMA" is the return on the portfolio of losers minus those on the portfolio of all funds.

Panels A and B test for the null hypothesis that the return on zero investment portfolio WML (WMA) is not positive. Panel C tests for the null hypothesis that the return on zero investment portfolio WMA is not negative. Bold numbers indicate that the null hypothesis is rejected at 5% significant level. Panel D provides the summary of t-statistics for the tests in panels A, B and C.

Panel A: Returns on Zero Investment Portfolio WML (Winners Minus Losers)

Interval	Alpha				Style Benchmark				Sharpe Ratio				Sortino Ratio				
	All Funds	Past Losers	Past Winners	Pos. Sig (%)	All Funds	Past Losers	Past Winners	Pos. Sig (%)	All Funds	Past Losers	Past Winners	Pos. Sig (%)	All Funds	Past Losers	Past Winners	Pos. Sig (%)	
Monthly	8.45	1.56	15.18	13.62	51.15	2.34	14.64	12.30	51.91	2.74	13.79	11.06	45.04	2.72	13.75	11.03	45.04
Quarterly	9.15	5.17	12.58	7.42	48.84	4.98	12.19	7.20	46.51	4.41	12.86	8.44	55.81	4.60	13.06	8.46	58.14
Semiannual	9.64	4.64	12.93	8.29	52.38	5.76	12.03	6.26	52.38	4.82	12.03	7.21	57.14	4.72	12.00	7.28	57.14
Annual	11.41	11.16	12.36	1.21	40.00	11.92	12.08	0.16	30.00	10.76	11.18	0.43	30.00	9.84	11.61	1.77	30.00

Panel B: Returns on Zero Investment Portfolio WMA (Winners Minus All funds)

Interval	Alpha				Style Benchmark				Sharpe Ratio				Sortino Ratio				
	All Funds	Past Losers	Past Winners	Pos. Sig (%)	All Funds	Past Losers	Past Winners	Pos. Sig (%)	All Funds	Past Losers	Past Winners	Pos. Sig (%)	All Funds	Past Losers	Past Winners	Pos. Sig (%)	
Monthly	8.45	15.18	12.58	6.74	45.04	14.64	12.19	6.19	45.80	13.79	14.64	5.35	34.35	13.75	13.75	5.30	34.35
Quarterly	9.15	12.58	12.93	3.44	48.84	12.19	12.03	3.04	44.19	12.86	12.19	3.71	46.51	13.06	13.06	3.91	39.53
Semiannual	9.64	12.93	12.36	3.29	33.33	12.03	12.08	2.39	33.33	12.03	12.03	2.39	38.10	12.00	12.00	2.36	38.10
Annual	11.41	12.36	11.16	0.95	20.00	12.08	12.08	0.67	30.00	11.18	11.18	(0.23)	30.00	11.61	11.61	0.20	20.00

Panel C: Returns on Zero Investment Portfolio LMA (Losers Minus All funds)

LMA	All		Alpha		Style Benchmark		Sharpe Ratio		Sortino Ratio	
	Funds	Past Losers	WMA	Neg. Sig (%)	Past Losers	Neg. Sig (%)	Past Losers	Neg. Sig (%)	Past Losers	Neg. Sig (%)
Monthly	8.45	1.56	(6.88)	45.80	2.34	(6.11)	2.74	(5.71)	2.72	(5.73)
Quarterly	9.15	5.17	(3.98)	48.84	4.98	(4.17)	4.41	(4.73)	4.60	(4.55)
Semmiannual	9.64	4.64	(4.99)	57.14	5.76	(3.87)	4.82	(4.82)	4.72	(4.92)
Annual	11.41	11.16	(0.25)	40.00	11.92	0.51	10.76	(0.66)	9.84	(1.57)

Panel C: T-Statistics for the returns on zero investment portfolios

Portfolio	Monthly			Quarterly			Semmiannual			Annual		
	Alpha	SB	Sharpe Sortino	Alpha	SB	Sharpe Sortino	Alpha	SB	Sharpe Sortino	Alpha	SB	Sharpe Sortino
WML	5.86	6.26	5.51	3.16	3.58	3.73	3.56	3.75	4.39	0.59	0.09	0.86
WMA	5.45	5.54	5.45	2.96	3.17	3.41	2.28	2.36	3.06	0.74	0.57	0.27
LMA	(5.45)	(5.60)	(4.91)	(2.74)	(2.96)	(3.56)	(4.59)	(3.85)	(4.80)	(0.16)	0.36	(1.45)

Figure 1: Some Types of Investment Organizations

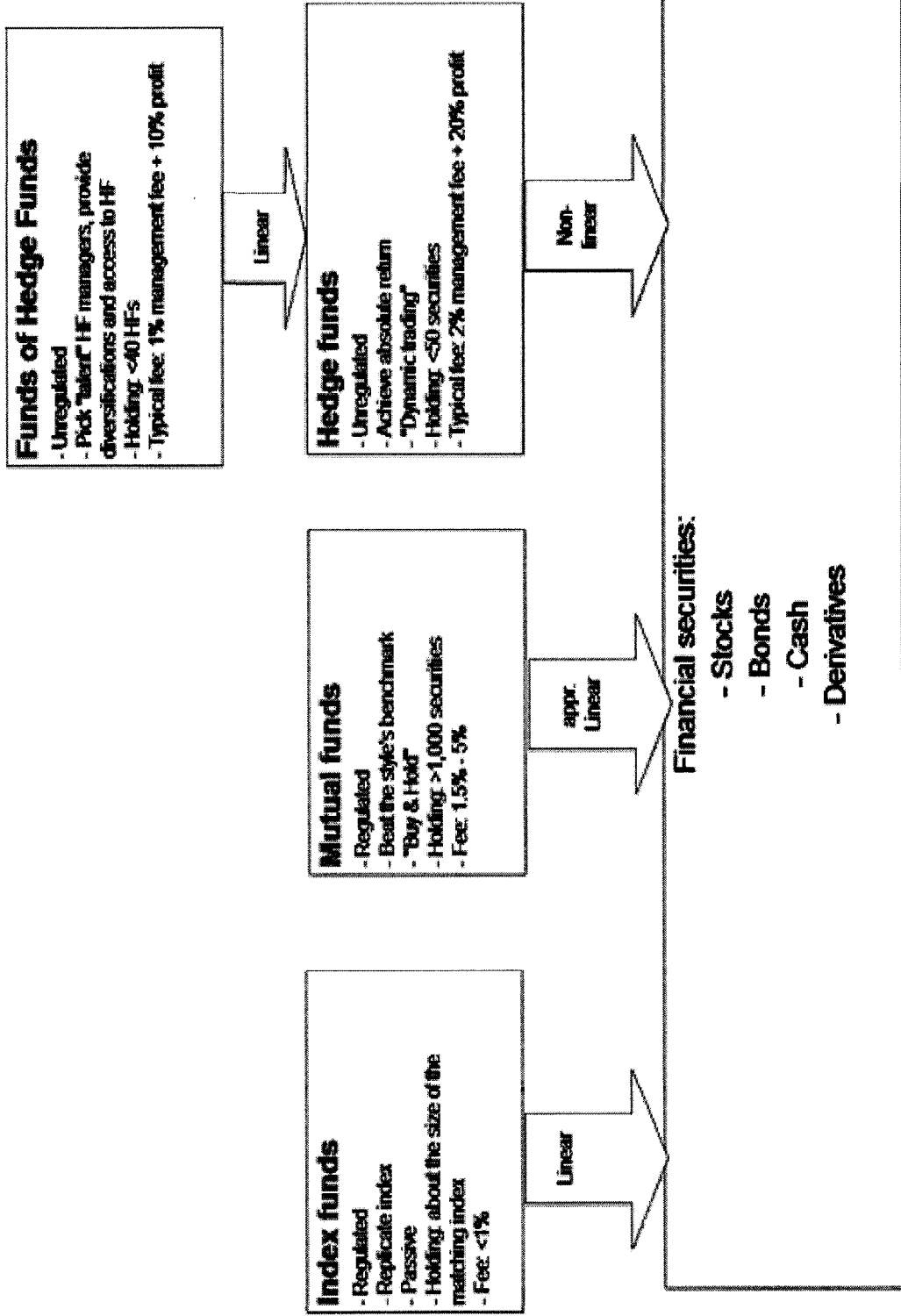


Figure 2: Sharpe ratio

$$S = \frac{R_p - R_f}{\sqrt{\text{Var}[R_p - R_f]}}$$

Sharpe ratio is the slope of the line joining cash to portfolio X. A higher Sharpe ratio implies a better investment.

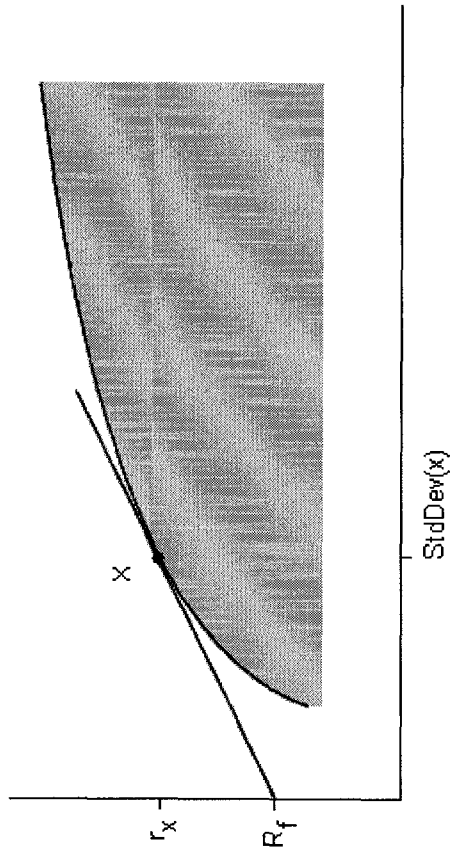


Figure 3: Review of Research in Performance of Hedge Funds and FOFs

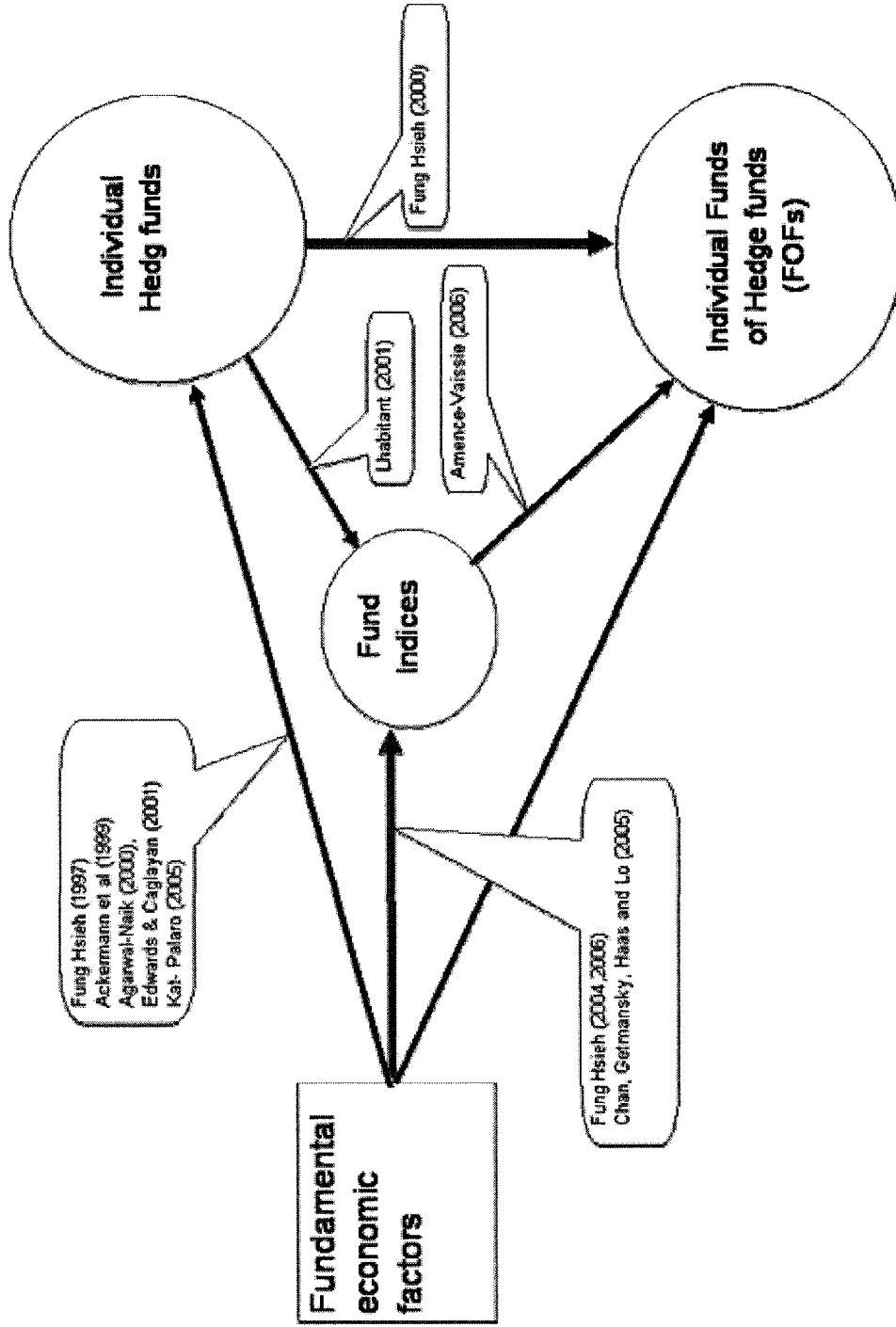
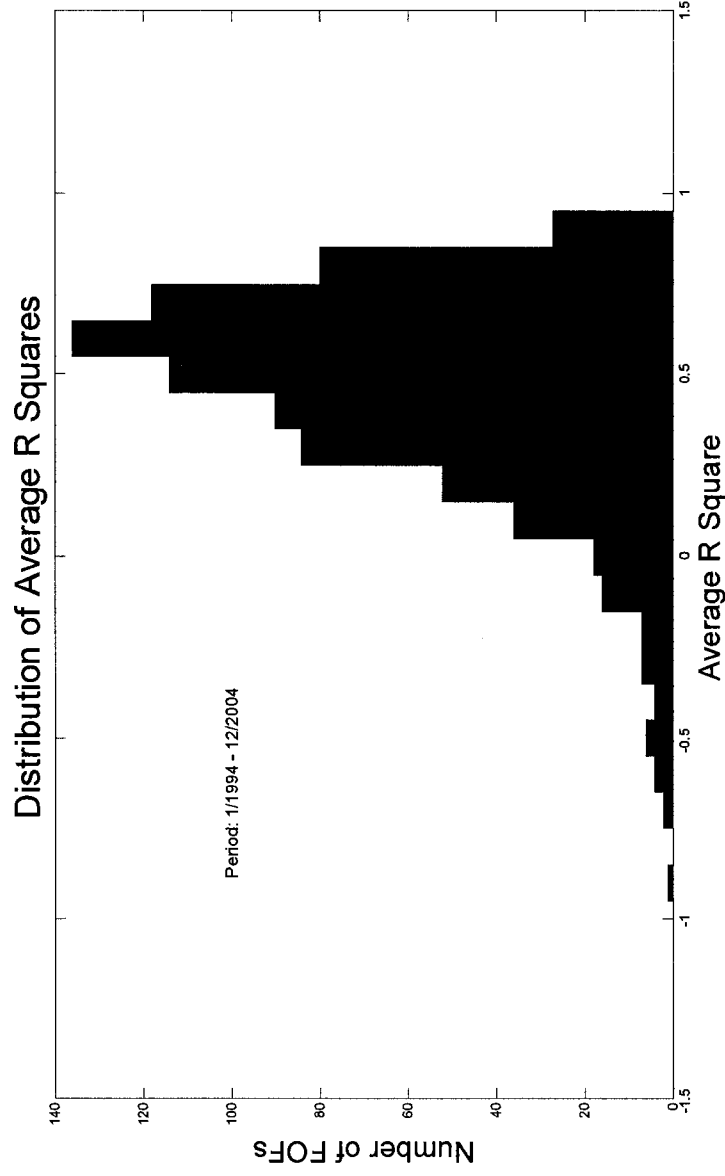


Figure 4: Sharpe Style Analysis - Distribution of R-Square (R2), full period

The figure shows the distribution of the funds' average R² during 1994-2004. Each R-square is determined from the Sharpe's style analysis with rolling windows of 24 months:

$$R_{i,w} = \alpha + \beta_{1i}F_{1,w} + \beta_{2i}F_{2,w} + \dots + \beta_{8i}F_{8,w} + e_w \quad (1)$$

where $F_{k,w}$ is the return on strategy index k during w period, $\beta_{ki,t}$ is the style exposure of fund i on the HFR sub strategy index k at time t, e_w is error term with expected value of zero, α is a constant.



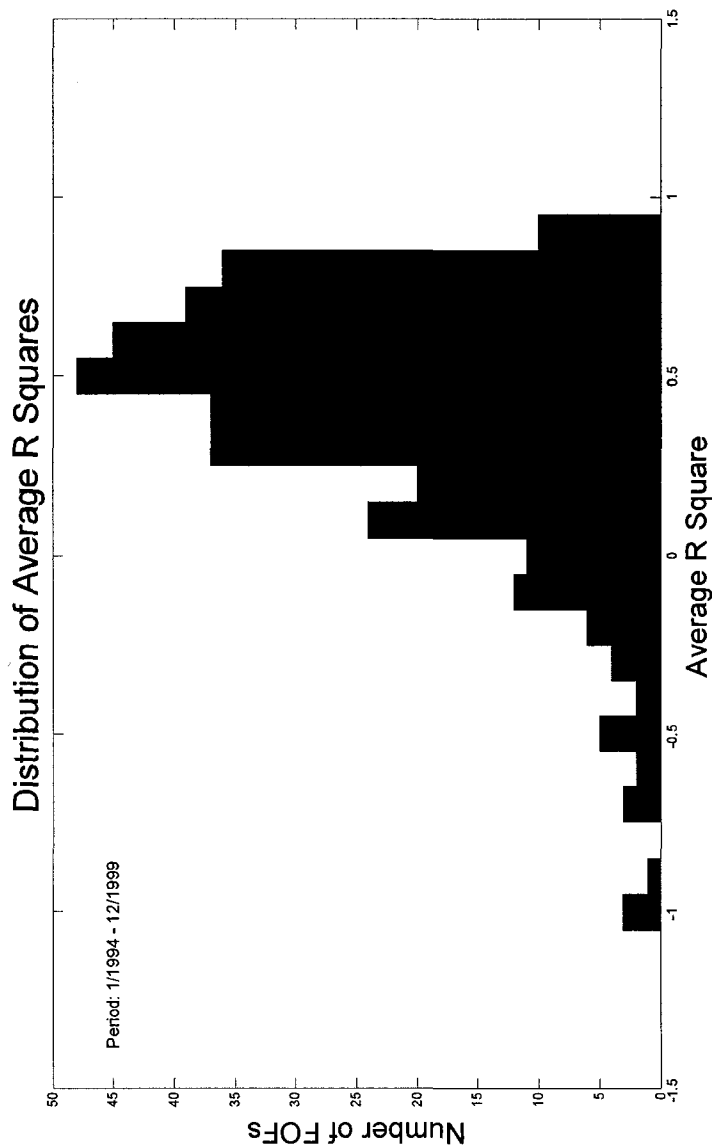
Mean R square	<0	0-25%	25%-50%	50%-75%	75%-100%	Total
Number of FOFs	55	98	242	300	107	802
Percentage	7%	12%	30%	37%	13%	100%

Figure 5: Distribution of R-Squares, sub period 1 (1994-1999)

The figure shows the distribution of the funds' average R² during 19994-2004. Each R-square is determined from the Sharpe's style analysis with rolling windows of 24 months:

$$R_{i,w} = \alpha + \beta_{1i}F_{1,w} + \beta_{2i}F_{2,w} + \dots + \beta_{8i}F_{8,w} + e_w \quad (1)$$

where F_{k,w} is the return on strategy index k during w period, β_{ki,t} is the style exposure of fund i on the HFR sub strategy index k at time t, e_w is error term with expected value of zero, α is a constant.



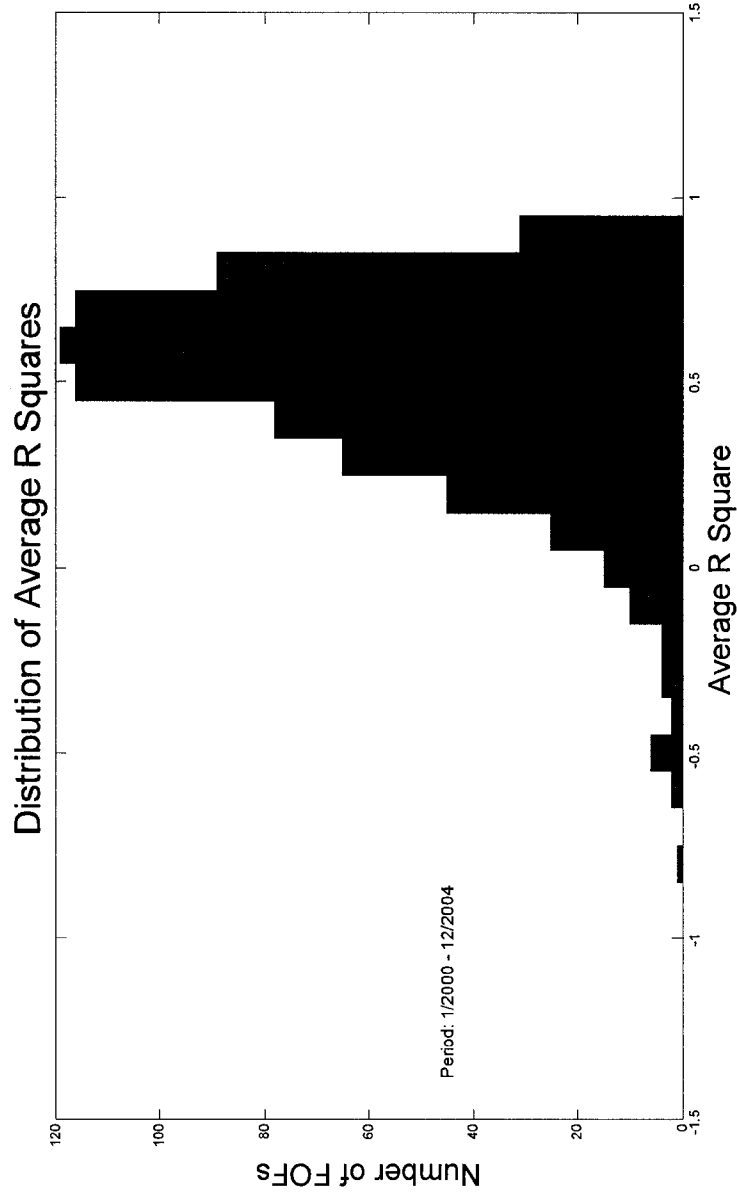
Mean R square	<0	0-25%	25%-50%	50%-75%	75%-100%	Total
Number of FOFs	43	50	95	111	46	345
Percentage	12%	14%	28%	32%	13%	100%

Figure 6: Distribution of R-Squares, Sub period 2 (2000-2004)

The figure shows the distribution of the funds' average R^2 during 19994-2004. Each R-square is determined from the Sharpe's style analysis with rolling windows of 24 months:

$$R_{i,w} = \alpha + \beta_{1,t}F_{1,w} + \beta_{2,t}F_{2,w} + \dots + \beta_{8,t}F_{8,w} + e_w \quad (1)$$

where $F_{k,w}$ is the return on strategy index k during w period, $\beta_{k,t}$ is the style exposure of fund i on the HFR sub strategy index k at time t , e_w is error term with expected value of zero, α is a constant.



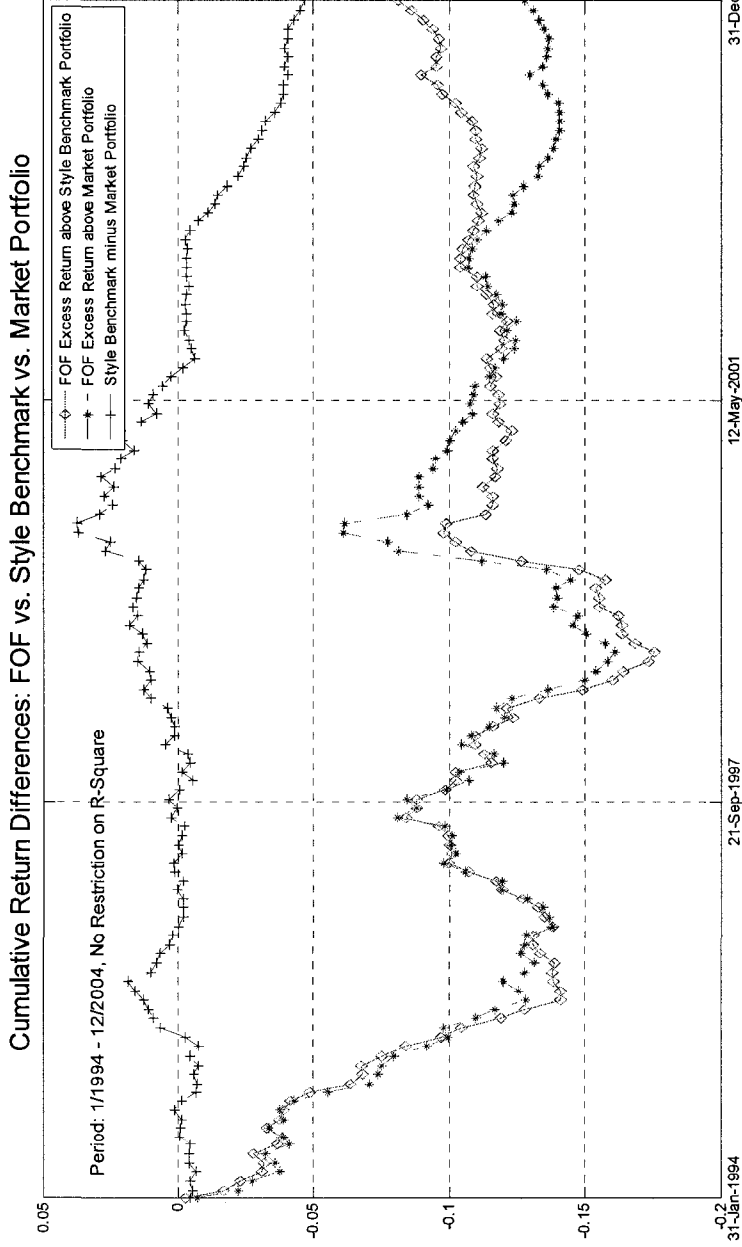
Mean R square	<0	0-25%	25%-50%	50%-75%	75% - 100%	Total
Number of FOFs	37	77	200	294	120	728
Percentage	5%	11%	27%	40%	16%	100%

Figure 7: Cumulative Return Difference, No Restriction on R2

The FOF portfolio is the equal weighted portfolio of all FOFs . The Style Benchmark Portfolios are formed from 8 HFR sub indices with the weights are determined from the Sharpe styles analysis using rolling windows of 24 months:

$$R_{i,w} = \beta_{1,i}F_{1,w} + \beta_{2,i}F_{2,w} + \dots + \beta_{8,i}F_{8,w} + e_w$$

where $F_{k,w}$ is the return on strategy index k during w period, $\beta_{k,i}$ is the style exposure of fund i on the HFR sub strategy index k at time t, e_w is error term with expected value of zero, No constant term. The R-Squares are determined from the above equation. The Market portfolio is the equal weighted portfolio of 8 HFR sub indices. Null Hypothesis is that there are no return differences between the three portfolios.



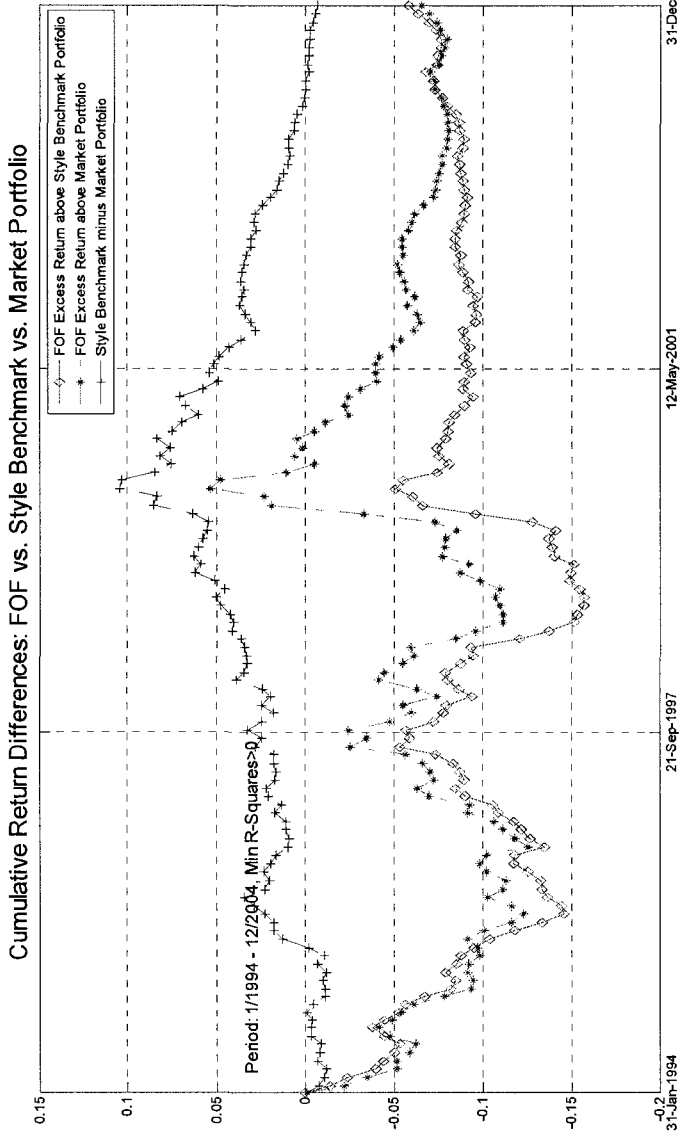
Description	Number of Months	Annualized Mean	Annualized Std	t-stat	PVal
FOFs Excess Return above the Style Benchmark Portfolio	132	-0.74%	2.12%	(1.15)	0.25
FOFs Excess Return above the Market Portfolio	132	-1.16%	2.49%	(1.54)	0.12
Style Benchmark Return minus the Market Portfolio Return	132	-0.42%	1.17%	(1.20)	0.23

Figure 8: Cumulative Return Difference, Minimum R-Square greater than zero

The FOF portfolio is the equal weighted portfolio of all FOFs. The Style Benchmark Portfolios are formed from 8 HFR sub indices with the weights are determined from the Sharpe styles analysis using rolling windows of 24 months:

$$R_{i,w} = \beta_{1,i}F_{1,w} + \beta_{2,i}F_{2,w} + \dots + \beta_{8,i}F_{8,w} + e_w$$

where $F_{k,w}$ is the return on strategy index k during w period, $\beta_{k,i}$ is the style exposure of fund i on the HFR sub strategy index k at time t, e_w is error term with expected value of zero, No constant term. The R-Squares are determined from the above equation. The Market portfolio is the equal weighted portfolio of 8 HFR sub indices. Null Hypothesis is that there are no return differences between the three portfolios.



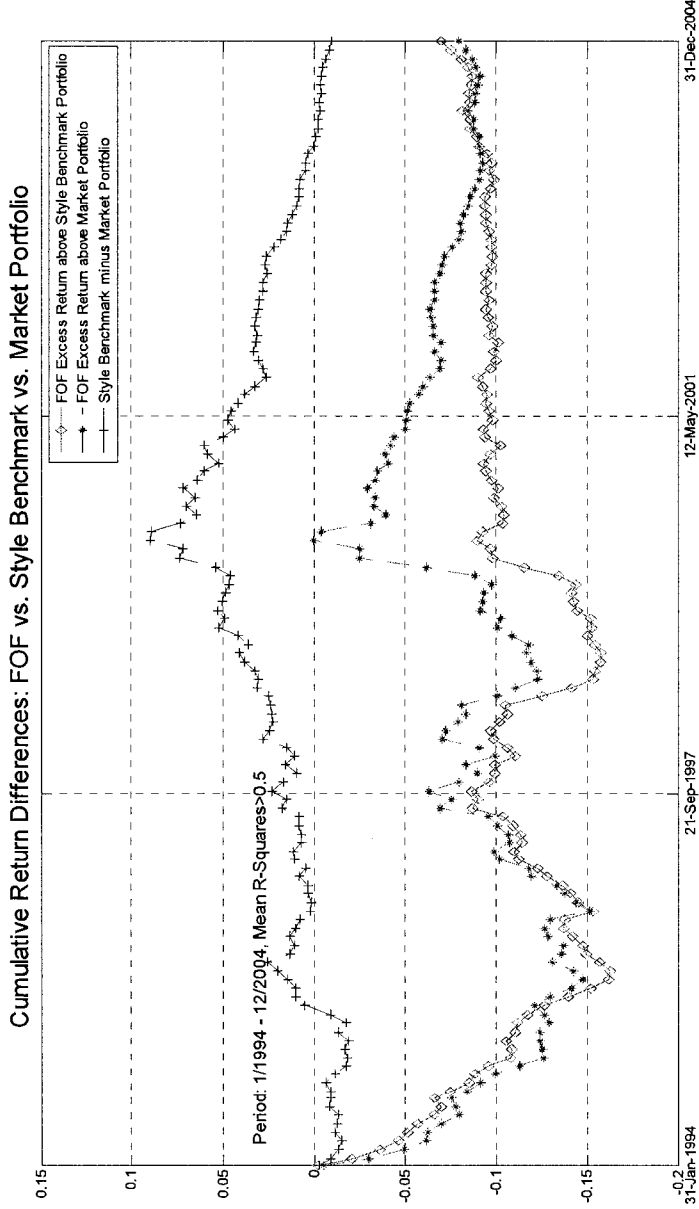
Description	Number of Months	Annualized Mean	Annualized Std	t-stat	PVal
FOFs Excess Return above the Style Benchmark Portfolio	132	-0.53%	2.83%	(0.62)	0.54
FOFs Excess Return above the Market Portfolio	132	-0.60%	3.96%	(0.50)	0.62
Style Benchmark Return minus the Market Portfolio Return	132	-0.07%	2.00%	(0.11)	0.91

Figure 9: Cumulative Return Difference, Average R-Square greater than 50%

The FOF portfolio is the equal weighted portfolio of all FOFs. The Style Benchmark Portfolios are formed from 8 HFR sub indices with the weights are determined from the Sharpe styles analysis using rolling windows of 24 months:

$$R_{i,w} = \beta_{1,i,t}F_{1,w} + \beta_{2,i,t}F_{2,w} + \dots + \beta_{8,i,t}F_{8,w} + e_w$$

where $F_{k,w}$ is the return on strategy index k during w period, $\beta_{k,i,t}$ is the style exposure of fund i on the HFR sub strategy index k at time t , e_w is error term with expected value of zero, No constant term. The R-Squares are determined from the above equation. The Market portfolio is the equal weighted portfolio of 8 HFR sub indices. Null Hypothesis is that there are no return differences between the three portfolios.



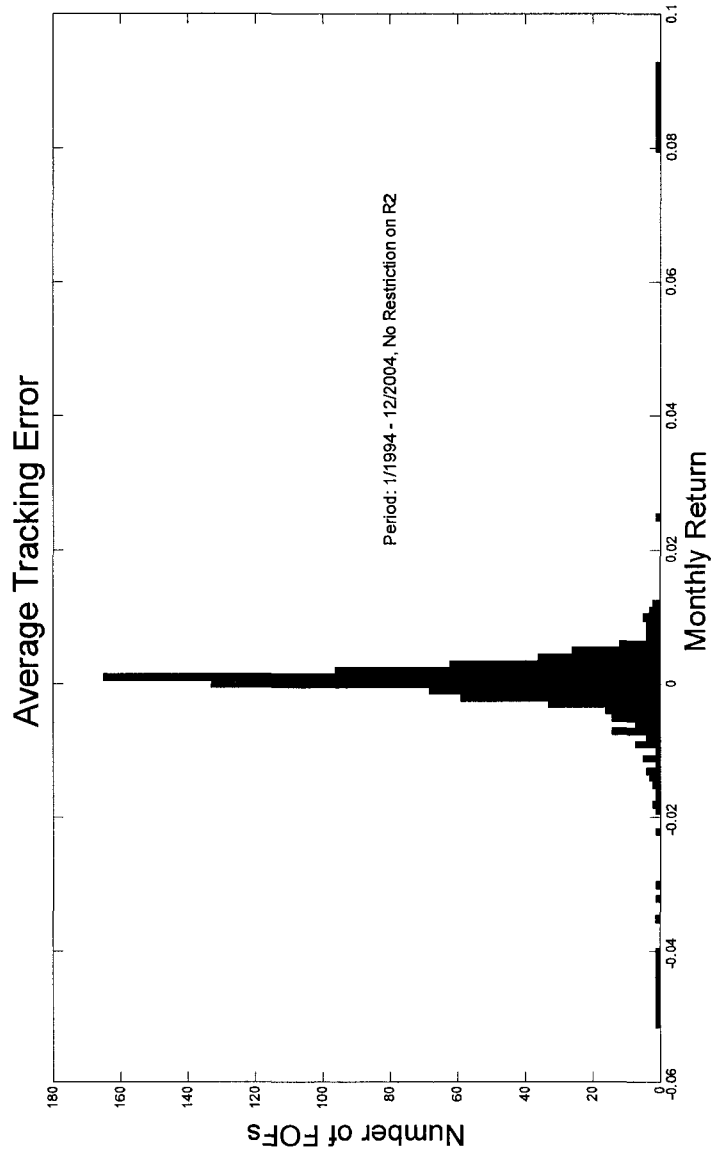
Description	Number of Months	Annualized Mean	Annualized Std	t-stat	PVal
FOFs Excess Return above the Style Benchmark Portfolio	132	-0.64%	2.26%	(0.94)	0.35
FOFs Excess Return above the Market Portfolio	132	-0.73%	3.12%	(0.77)	0.44
Style Benchmark Return minus the Market Portfolio Return	132	-0.09%	1.78%	(0.16)	0.87

Figure 10: Tracking errors, No Restriction on R-Square, Full period (1994-2004)

A fund's tracking error is the difference between its return and that on a style benchmark portfolio during a month. A fund's monthly tracking errors are determined from Sharpe's Style analysis, using rolling windows of 24 months:

$$R_{i,w} = \beta_{1i}F_{1,w} + \beta_{2i}F_{2,w} + \dots + \beta_{8i}F_{8,w} + e_w$$

where $R_{i,w}$ is fund i return during month t , $F_{k,w}$ is the return on strategy index k during w period, β_{ki} is the style exposure of fund i on the HFR sub strategy index k during the past two years, e_w is error term with expected value of zero, No constant term.



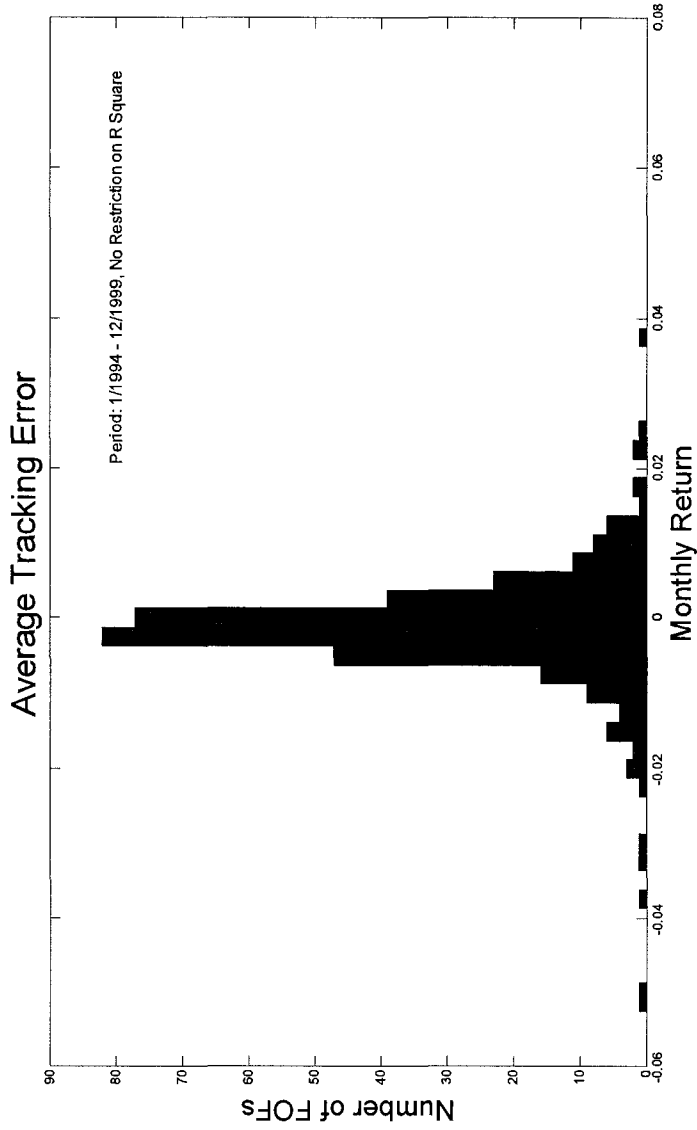
Average Monthly Tracking Error	<-1%	-1% -0.5%	-0.5% -0	0 -0.5%	0.5% -1%	> 1%	Total
Number of FOFs	25	42	241	447	40	7	802
Percentage	3%	5%	30%	56%	5%	1%	100%

Figure 11: Tracking errors, No Restriction on R-Square, Subperiod 1 (1994-1999)

A fund's tracking error is the differences between its return and that on the style benchmark portfolio during a month. A fund's monthly tracking errors are determined from Sharpe's Style analysis, using rolling windows of 24 months:

$$R_{i,w} = \beta_{1i}F_{1,w} + \beta_{2i}F_{2,w} + \dots + \beta_{8i}F_{8,w} + e_w$$

where $R_{i,w}$ is fund i return during month t, $F_{k,w}$ is the return on strategy index k during w period, β_{ki} is the style exposure of fund i on the HFR sub strategy index k during the past two years, e_w is error term with expected value of zero, No constant term.



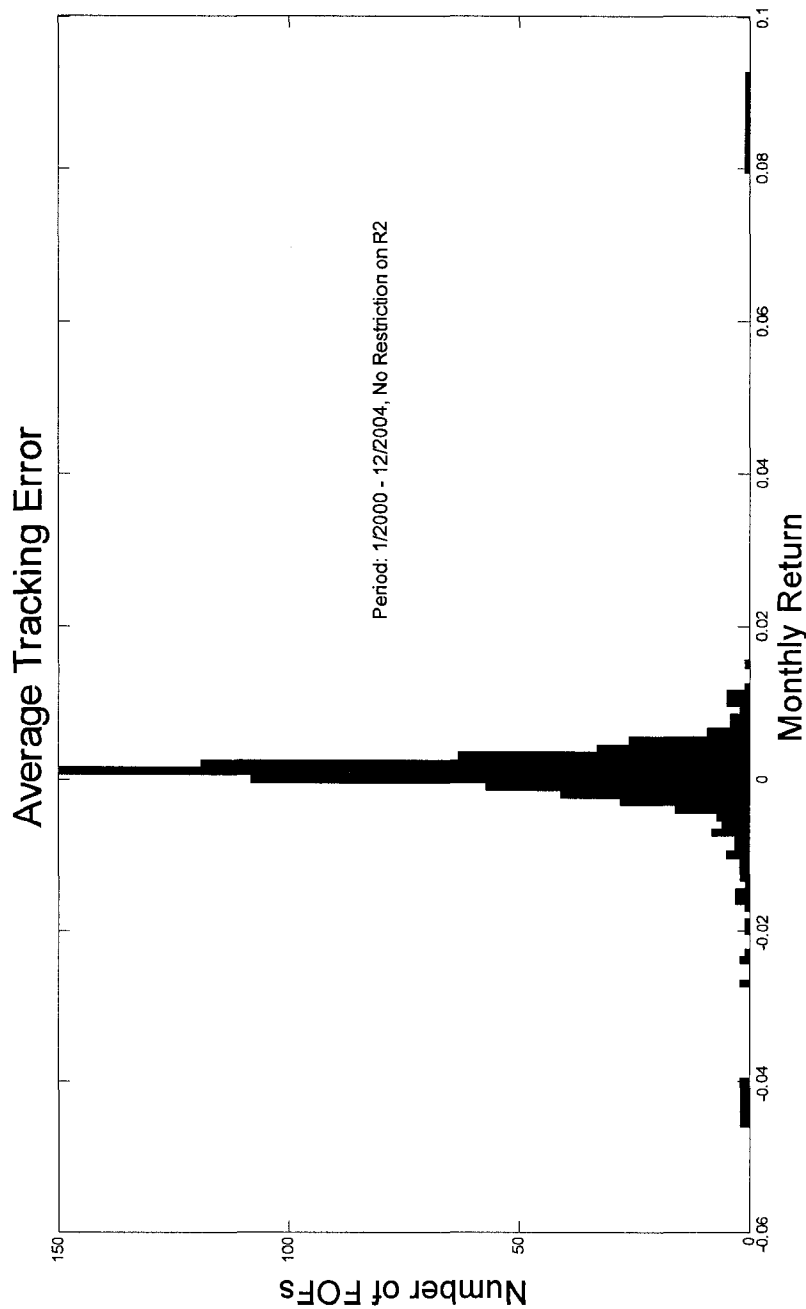
Average Monthly Tracking Error	< -1%	-1% -0.5%	-0.5% - 0	0 -0.5%	0.5% -1%	> 1%	Total
Number of FOFs	22	28	140	107	28	20	345
Percentage	6%	8%	41%	31%	8%	6%	100%

Figure 12: Tracking errors, No Restriction on R-Square, Subperiod 2 (2000-2004)

A fund's tracking error is the differences between its return and that on the style benchmark portfolio during a month. A fund's monthly tracking errors are determined from Sharpe's Style analysis, using rolling windows of 24 months:

$$R_{i,w} = \beta_{1i,t}F_{1,w} + \beta_{2i,t}F_{2,w} + \dots + \beta_{8i,t}F_{8,w} + e_w$$

where $R_{i,w}$ is fund i return during month t, $F_{k,w}$ is the return on strategy index k during w period, $\beta_{ki,t}$ is the style exposure of fund i on the HFR sub strategy index k during the past two years, e_w is error term with expected value of zero, No constant term.



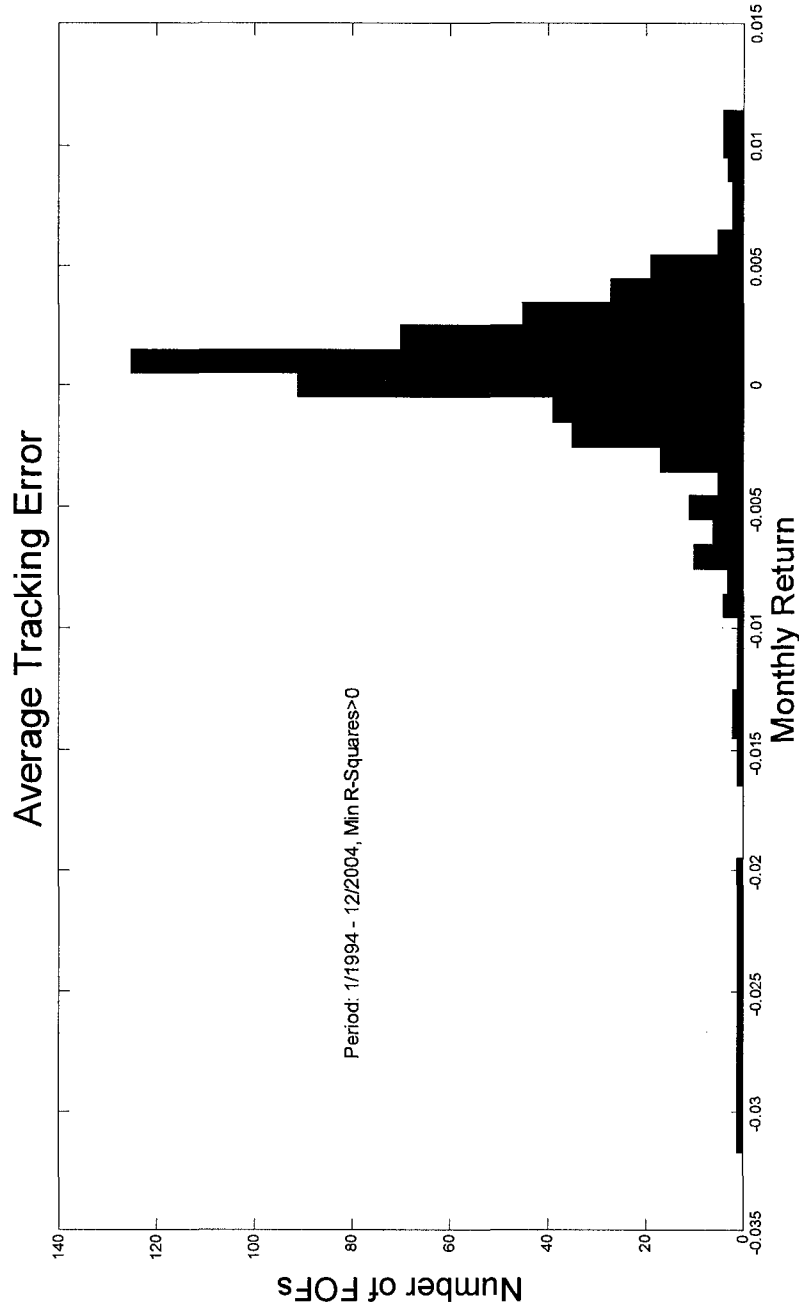
Average Monthly Tracking Error	<-1%	-1% -0.5%	-0.5% -0	0 -0.5%	0.5% -1%	> 1%	Total
Number of FOFs	24	27	188	443	37	9	728
Percentage	3%	4%	26%	61%	5%	1%	100%

Figure 13: Tracking errors, Full period, Min R-Square >0

A fund's tracking error is the differences between its return and that on the style benchmark portfolio during a month. A fund's monthly tracking errors are determined from Sharpe's Style analysis, using rolling windows of 24 months:

$$R_{i,w} = \beta_{1,i}F_{1,w} + \beta_{2,i}F_{2,w} + \dots + \beta_{8,i}F_{8,w} + e_w$$

where $R_{i,w}$ is fund i return during month t , $F_{k,w}$ is the return on strategy index k during w period, $\beta_{k,i}$ is the style exposure of fund i on the HFR sub strategy index k during the past two years, e_w is error term with expected value of zero, No constant term.



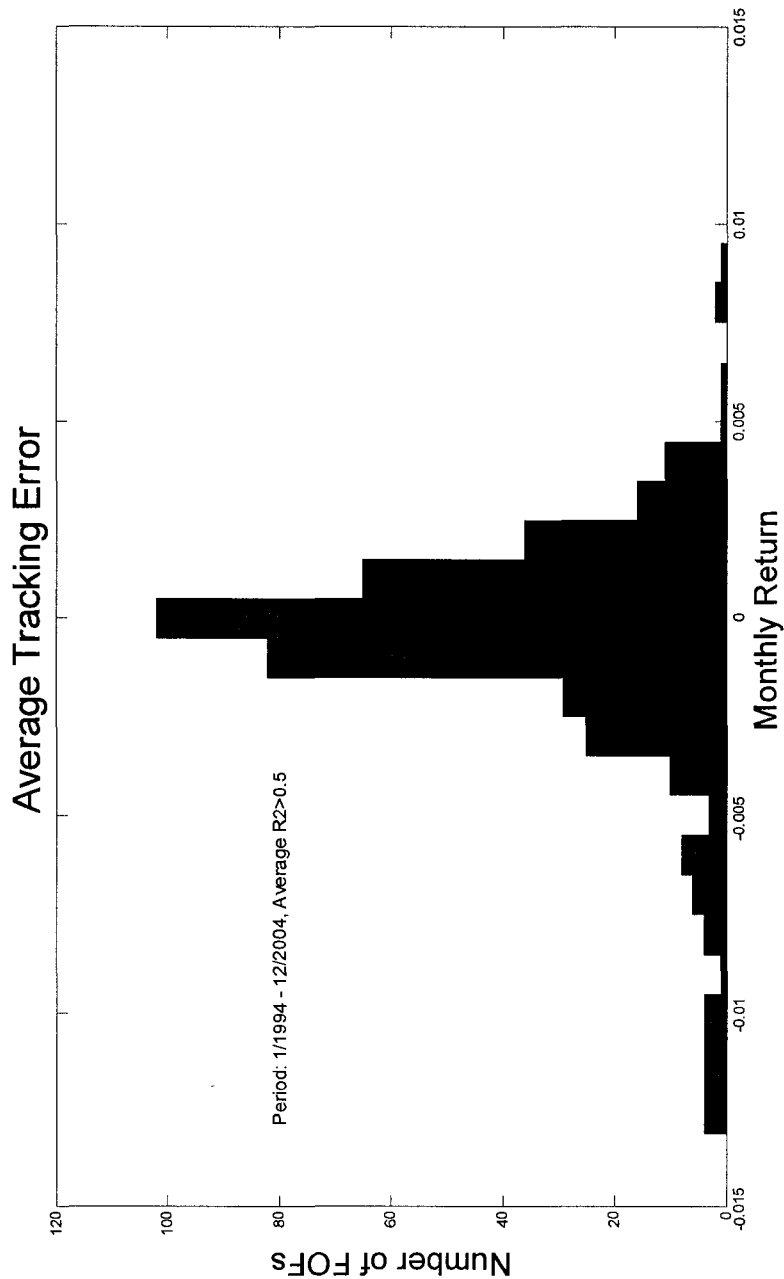
Average Monthly Tracking Error	< -1%	-1% -0.5%	-0.5% - 0	0 -0.5%	0.5% -1%	> 1%	Total
Number of FOFs	9	30	138	331	23	2	533
Percentage	2%	6%	26%	62%	4%	0%	100%

Figure 14: Tracking errors, Full period, Average R-Square >0.5

A fund's tracking error is the differences between its return and that on the style benchmark portfolio during a month. A fund's monthly tracking errors are determined from Sharpe's Style analysis, using rolling windows of 24 months:

$$R_{i,w} = \beta_{1,i}F_{1,w} + \beta_{2,i}F_{2,w} + \dots + \beta_{8,i}F_{8,w} + e_w$$

where $R_{i,w}$ is fund i return during month t, $F_{k,w}$ is the return on strategy index k during w period, $\beta_{k,i}$ is the style exposure of fund i on the HFR sub strategy index k during the past two years, e_w is error term with expected value of zero, No constant term.



Full Period		Average R2>.5						
Average Monthly Tracking Error		<-1%	-1% -0.5%	-0.5% -0	0 -0.5%	0.5% -1%	> 1%	Total
Number of FOFS	4	19	201	178	5	0	407	
Percentage	1%	5%	49%	44%	1%	0%	100%	