Hedge Funds:
Do They Do What They Say They Do?

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ABSTRACT

The purpose of this research is two-fold, to determine if hedge funds follow their stated strategy styles and to examine how hedge funds' strategy allocations evolve over time in response to changed economic and market conditions. Our key advance is that we show that standard linear style models like that of Sharpe (1992) can be applied to hedge fund returns as long as the returns of the style indices in the model themselves display the nonlinear option-like characteristics of hedge fund returns. For our research, the returns of our sample of Funds of Hedge Funds are strongly correlated to the returns of portfolios of hedge fund investment style indices. In this way, we capture the spirit of Fung & Hsieh's (2002) Asset-Based Style Factors for Hedge Funds. Based on our results, it appears that the answer to the first question is "somewhat", while we find ample evidence of significant shifts in allocation among the Fund of Hedge Funds from the first sample period (1997-2001) to the second (2002-2006). The changes in allocation appear to rationally reflect the changed economic conditions and investment opportunities existing at the time.

Keywords: Hedge Funds, Fund of Funds, Classification, Style Analysis, Asset Allocation

INTRODUCTION

In this paper we investigate two basic questions: first, do hedge funds appear to follow the strategy styles they self-report to hedge fund database vendors, and second, do we find evidence that hedge funds change investment strategy allocations over time in response to changed economic and market conditions? These questions touch on many areas of research including asset allocation, strategy classification, fund replication, style consistency, style drift, and performance measures. However, what sets our research questions apart from previous research is that we are not starting from a universe of individual hedge funds of various investment styles and then systematically grouping them into similar styles, rather we are starting with a group of Funds of Hedge Funds (Fund of Funds, FoFs), the most common approach to hedge fund investing, and systematically checking their self-reported investment strategies against actual hedge fund indices, e.g. themselves portfolios of funds following a particular investment style. We do this for two time periods of very different US and global economic and market conditions; we use a sample of both onshore and offshore based FoFs in order to investigate our second research question. As you will see in the following sections our approach recognizes the latest developments in hedge fund return-based studies; we attempt to account for the difficulties inherent in using hedge fund returns in a unique way and employ a slightly modified version of a popular model first developed by Sharpe (1992).

It is widely recognized in the hedge fund literature that hedge fund returns are highly non-linear. Fung & Hsieh (2007) offer an excellent review of the developments of hedge fund returns-based models. Briefly, Fung & Hsieh (1997) showed that the low to negative correlations of hedge fund returns with standard asset classes was actually a result of non-linear hedge fund returns caused by dynamic long/short trading strategies. This in turn meant that linear models such as that of Sharpe (1992) would not work well for hedge funds and instead they used rule-based trading strategies in principal components analysis to determine five major hedge fund investment styles. With this method, they were able to capture approximately 45% of the variation in cross-sectional hedge fund returns. In addition, Fung & Hsieh (2007) notes that the non-linearity in hedge fund returns arises not only from the dynamic nature of the trading strategies themselves, but also from dynamic asset allocation across hedge fund styles as economic conditions change.

Brown & Goetzemann (2003) also recognize both sources of hedge fund non-linearity and employ a time-varying multifactor style model where the betas (or style weights) are allowed to vary with time; they use a Generalized Least Squares (GSC) algorithm (first described in Brown & Goetzmann (1995)) to find eight major hedge fund styles from the universe of hedge funds. In addition, they find that the fund's self-reported strategy description reported to the TASS database was nearly as accurate as the GSC algorithm and other model results they ran. However, they are careful to point out that because the asset allocation decision is so critical to an investor and because hedge funds, like mutual funds, can often "game" their strategy by choosing a classification popular at the time, careful due diligence and analysis should always be performed prior to investment.

Schneeweis, Kazemi, and Karavas (2004) is the closest paper that we could find that looks at similar questions that we are investigating here. They did use individual funds' self-described strategy database classifications, but they were for individual strategies, e.g. Convertible Arbitrage, rather than for FoFs. Another part of their methodology we thought was interesting was that they used a composite of actual hedge fund style indices from EACM, CFSB/Tremont, and HFR to correlate returns with the returns of individual hedge funds with the particular self-reported style. They were mainly looking at style consistency and performance over time, but they do produce some interesting results important for investors; they also note that diversified FoFs and hedge fund style indices are unlikely to have static market sensitivity characteristics over time, e.g. the funds or weightings of the funds comprising the FoFs or indices change with time.

Although Brown & Goetzmann (2003) do point out that Sharpe's (1992) linear style model was not specifically designed for determining a portfolio's composition of investment styles, it still remains the most widely-utilized style model for standard asset classes. The underlying assumption is that if the returns of the portfolio in question are modeled well by the Sharpe style model, then it is likely that the betas represent a close approximation of the weights of the asset class in the actual portfolio; we follow this assumption also.

For the reasons we have just discussed it would seem that Sharpe's (1992) model is not applicable for hedge fund return-based studies. Indeed we do modify Sharpe's model, but we simply remove the constraints imposed by Sharpe, e.g. that the beta's all sum to 1 and that there are no negative betas, to accommodate the leverage and short positions that hedge funds utilize. We are effectively running an "unconstrained" version of Sharpe's model. The way that we deal with the problem of nonlinear hedge fund returns arising from dynamic trading strategies and dynamic asset allocation is essentially this: *we regress the returns of the FoFs against portfolios of hedge fund style indices which are themselves comprised of hedge funds with nonlinear returns; the two are highly correlated*. This is in essence what Fung & Hsieh (2002) do with their asset-based style factors for hedge funds where, for example, they utilize portfolios of lookback straddles (nonlinear returns) on stocks, bonds, interest rates, currencies, and commodities. The key is that the portfolios of lookback straddles returns are highly correlated with those of trend-following hedge funds. Thus, we have essentially captured the spirit of the idea by utilizing portfolios of hedge fund style indices which will also have nonlinear returns similar to those of the FoFs.

With this in mind, we next conduct a three-stage OLS regression process that is somewhat iterative in nature utilizing a sample of FoFs and close to 250 actual hedge fund indices. Our three-step process works first from broad styles down to finer styles in an iterative feedback loop which we hope will allow us to more finely capture the individual FoFs' investment styles. As previously mentioned, we run our regressions for two time periods of very different economic conditions and find that the same individual FoFs have very different investment strategy allocations and the iterative process is guided by our prior knowledge of what economic and market conditions were likely to be most favorable for a particular style. In other words the results were not simply the result of data mining, but rather we determined that certain styles became less prevalent due to limited opportunities, e.g. Global Macro and Market Timing, while others were much more prevalent such as CTAs due to rising global demand for commodities.

Thus far we have introduced our research questions, reviewed some of the problems and developments in conducting hedge fund returns-based studies, briefly reviewed some of the surrounding literature, and introduced our approach to producing empirical results that will help us answer the research questions we posed. The rest of the paper is organized in sections as follows: Data, Methodology, Results, Conclusions and Future Research.

DATA

We used the CISDM hedge fund database for our sample of FoFs; we wanted two sample time periods of very different economic and market conditions so we chose the following two periods which represent ten years of continuous data: one from January 1997 through December 2001 and the other from January 2002 through December 2006. Of the hundreds of FoFs contained in the CISDM database, only 162 funds met the criteria of ten years of continuous data. Survivorship bias (as well as other widely-known database biases) is certainly an issue here and it may be that funds that went defunct during this time period displayed very different characteristics than the surviving funds, but we suspect that the surviving funds actually adhered to their self-reported investment styles better than the non-surviving funds. However, we do not believe that survivorship bias or any of the other database biases such as instant history or backfill bias have too much of an impact on our study primarily because we are not concerned with performance metrics.

As previously mentioned, we wanted two time periods of very different economic and market conditions and the first time period represents the extraordinary growth in the US and the US stock markets during the mid-to-late 1990's while the second time period represents the recession and slow economic growth of the early part of the 21st century. We were careful to end our second time period at December of 2006 because we did not want to incorporate too much of the early warning signs of the impending credit crisis of fall 2008; research shows that credit spreads (and other indicators) were clearly changing as early as 2006 and some research indicates signs go back as early as 2005.

Each of the 162 FoFs in the sample were provided with a strategy description in the CISDM hedge fund database. The strategy descriptions are self-reported and ranged from a very brief description of "FoF: Diversified" (or no specific strategy definitions) to detailed strategy allocations. Unfortunately, of the 162 funds 94 (58%) of the funds fall in the "FoF: Diversified"-only category while the remaining 68 funds (42%) fall in the detailed strategy description category. In addition to the strategy descriptions it was often the case that the name of the fund provided additional strategy information, e.g. Asian Fund or European Equities Fund.

CISDM also provided data on the returns of over 250 hedge fund style indices (both on-shore and off-shore) but some of them did not have a complete ten-year return history so we were left with 243 total hedge fund style indices to choose from. Complete indices and return information from the following hedge fund index providers are included in our index sample: Altvest, Barclays, CISDM, CSFB/Tremont, Hennessee, HFRI, MSCI, and Tuna for a total of eight index providers. Where possible the funds were matched with appropriate on-shore or off-shore style indices. The HFRI indices provided the most comprehensive list of both on-shore and off-shore strategy indices so these indices were used for the bulk of the main strategy indices. However, they were supplemented with other indices from providers that did not distinguish between on-shore or off-shore status. The goal was to provide the best possible reflection of each individual fund's strategy allocations using the information and indices available.

We realize that there are serious differences in hedge fund index construction, constituents, whether they are "follow forward" (retain "Dead" fund's return histories), whether they are asset or equal weighted, as well as issues as to provider maintenance, oversight, etc. For example, in any given month an Equity Long/Short index may provide significantly different return values for the style. Another example is whether the index constituent funds change their style or bias their style so that they are no longer representative of the very style they were selected to represent. After some rather painstaking methodology checks, correlations analyses, etc. we realized that these issues were largely out of our control. We can report a high degree of within-style correlation between style indices from different providers, but that shall have to suffice.

Both the hedge fund style indices and the investment strategies described in the "Strategy" information field for the individual FoFs represent a heterogeneous mix of classifications and we grouped them into similar styles based on previous research, experience and knowledge of the hedge fund industry; we ended up with a total of 15 different hedge fund styles. For the hedge fund style indices we also included two other classifications: the first, simply labeled as "OI" for Other Index which represents an unusual or specialized index, e.g. Other Arbitrage Index;

the second is simply labeled "NONE" which refers to FoFs for which we could determine no significant style factors that matched the FoFs returns[1]. Fortunately, there were relatively few of these funds: about 2% to 3% of the total number of funds for both sample time periods. Table 1 below presents a key to the hedge fund style abbreviations we utilized for both the 162 individual FoFs and the 243 hedge fund style indices.

Table 1: Key to Abbreviations for Hedge Fund Style Indices

Strategy	Full Name
ED	Event Driven
EH	Equity Hedge
EMN	Equity Market Neutral
EMNSA	EMN: Statistical Arbitrage
EH-MT	Equity Hedge: Market Timing
EH-NH	Equity Hedge: Non-Hedge
EH-RF	Equity Hedge: Regional Focus
EH-S	Equity Hedge: Sector
EH-SS	Equity Hedge: Short Selling
EM	Emerging Markets
M	Macro (Global Macro)
RV-A	Relative Value: Arbitrage Strategies
RV-FI	Relative Value: Fixed Income Strategies
CTA	Commodity Trading Advisor
FoF	Fund of Fund Strategy
OI	Other Index
NONE	No Significant Factors

Note that for funds classified only as "FoF: Diversified", we used the FoF: Diversified investment strategy mix description provided by HFRI to compare to the significant strategies we found using our methodology. This description is presented below and is taken from the HFRI website; we have permission to use their data for research purposes.

"FOFs classified as "Diversified" exhibit one or more of the following characteristics: invests in a variety of strategies among multiple managers; historical annual return and/or a standard deviation generally similar to the HFRI Fund of Fund Composite index; demonstrates generally close performance and returns distribution correlation to the HFRI Fund of Fund Composite Index. A fund in the HFRI FOF Diversified Index tends to show minimal loss in down markets while achieving superior returns in up markets."

The next section describes the methodology and is followed by detailed results and tables.

METHODOLOGY

As introduced previously, we use the "unconstrained" version of Sharpe's (1992) style model. We present the details here. The basic model can be written as follows:

$$\tilde{R}_i = \left[\beta_{i1}\tilde{F}_1 + \beta_{i2}\tilde{F}_2 + ... + \beta_{in}\tilde{F}_n\right] + \tilde{e}_i \qquad (1)$$

In the above equation, R_i represents the return on fund i, the factor terms, $F_{1..n}$ represent the returns on each style factor or hedge fund index in our case, the terms $\beta_{i1...n}$ represent the sensitivities of the returns of the fund to the style factors and can also be thought of as the style weight or allocation[2]; the term e_i represents the return not attributable to the style factors. In Sharpe's (1992) paper, he referred to the terms in brackets of equation (1) as the return attributable to *style* while the non-factor component, e_i, represents the return attributable to *selection*. The tildes (~) simply represent the fact that the values may not be known ex-ante.

Fung & Hsieh (2002) present essentially the same model as equation (1), but in the more familiar regression form with the addition of the component α, to get:

$$R_t = \alpha + \sum_k \beta_k SF_{k,t} + \varepsilon_t \qquad (2)$$

Again, R_t represents the return of the fund at time t, the $SF_{k,t}$ variables represent the style factors, the β_k terms represent the factor loadings, and ε_t is the residual term. This is perhaps the more familiar style model to which most researchers have become accustomed to. Fung & Hsieh point out that the factor loadings, the β_k's, represent both the hedge fund manager's capital allocation and the degree of leverage utilized. Fung & Hsieh argue that linear models such as that of Sharpe (1992) cannot be currently utilized due to non-linearity in hedge fund returns, selection bias, and other problems. We disagree with the first proposition but cannot refute the others; however, we believe that we are indeed providing explicit and unambiguous descriptions of hedge fund strategies that will reveal the nature of the fund's strategy relative to its database described strategy. We cannot quantify risk, or risk-adjusted performance, nor can we control for selection bias and other problems inherent in the hedge fund style index construction, maintenance, and oversight. Our key contribution rests in our use of actual investible FoFs and actual hedge fund style indices so that we are comparing portfolios of hedge fund returns to portfolios of hedge fund returns; i.e. we are comparing non-linear returns of one portfolio to non-linear returns of another[3].

Further minor modifications to Sharpe's (1992) model need to be made before we are ready to introduce our three-step process. The modifications are focused on the constraints used for quadratic programming: 1) to constrain all betas to sum to 1, and 2) to constrain all betas to have values between 0% and 100%. As previously discussed, the first restraint is unpractical given that the β_k's also represent a funds' use of leverage and values in excess of 1 are expected. The second constraint is primarily focused on preventing "short" or negative index weightings and this is also not appropriate for hedge funds. For example, a negative index weight for a Fixed Income: High Yield index may be a reflection of cash or low-yielding cash equivalent positions. Another example of a reasonable negative index weighting could be a particular equity sector which could reflect short positions in that sector. We ran an unconstrained version of equation (1) or equivalently equation (2) where we were not concerned with α, the return to manger performance or the average return of the fund in excess of it's style average. Our goal then was to minimize the squared deviations between the returns on the actual FoFs and the returns of the final modeled portfolio of hedge fund indices proxy.

For each time period, the analysis proceeded in three steps (all three steps involve the use of the unconstrained "multi-index model"): 1) run the multi-index model on all funds using a common set of "core" indices in order to identify general areas of allocation, e.g. Emerging Markets and Equity Hedge, 2) run regressions of each fund against specific indices selected based on the results of the "core" regressions and on strategy information, and 3) choose the indices with the strongest evidence of significance from the second regressions and in some cases supplement these indices with additional style-specific indices. The "core" indices consist of eight broad strategies, while the second regressions tended to have as many as nine strategy-specific indices; the third stage regressions were the most parsimonious with generally five or fewer style indices (generally, these last indices produced adequate results to positively identify at least some of the main strategies).

In summary, the idea is to start with broad style indices and then in an iterative fashion, utilizing information from the database, fund name, websites if they could be located, and any other source we could find, including calling a few limited managers, narrow down the focus of the strategies in our style mix to the final third stage regression. We would like to reiterate that we performed this analysis for both time periods, but for each time period we did have prior expectations as to which styles were likely to be most dominant based on our following of the hedge fund industry and economic and market conditions. However, there was limited iterative work when we simply failed to find any indices that performed adequately with a specific fund's return history. Otherwise, we did not perform additional iterations of the three-step process. The next section discusses the results of the analyses and it is presented in two sections along with accompanying Tables.

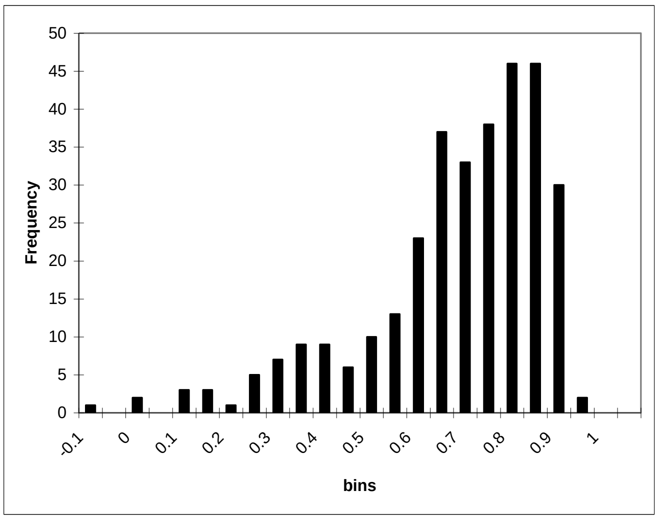
RESULTS

We present the results in two parts with the first section dealing with research question 1: how well do the return patterns of the sample of FoFs appear to match those of portfolios of hedge fund style strategy indices designed to replicate the fund's self-described strategy mix in the CISDM database. The second section covers the second research question: is there evidence that the FoFs' strategy allocations appear to shift in major patterns over the two sample periods in response to very different economic and market conditions.

Results for Research Question 1

The style regression results for all three steps resulted in an average adjusted R^2 value of approximately 0.65 while the average regression F-Statistic increased to a value of approximately 50 for the final regressions (third stage). For the final regressions about 50% of the funds had adjusted R^2 values less than or equal to 0.7 while the remaining 50% produced adjusted R^2 values greater than 0.7. Figure 1 on the following page shows a histogram of the adjusted R^2 values for both sample periods combined (for a total of 324 observations).

Figure 1: Histogram of Adjusted R^2 Values:



Note: Both sample periods combined

In order to answer the first question of this research of whether the funds do appear to follow their self-described strategy descriptions, qualitative judgments were made for each fund using the overall quality of the final regression results and the significant strategies (at the 0.05 level) each fund was exposed to during each of the two time periods. These results for both time periods combined are summarized in Table 2. As can be seen from this table, for both the FoFs described only as "FoF: Diversified" and for the FoFs with specific strategy information (labeled "FoF: Strategy"), approximately 50% of the funds are characterized as "Somewhat" following their strategies; for the "Diversified" FoFs in this category it was often the case that the funds did not have a particularly diversified strategy mix and for the "Strategy" FoFs it was most common that only some of the strategies indicated in their descriptions were followed and that this changed from the two time periods. The remaining funds are approximately evenly split between the categories of "Good" and "Poor" as to the quality of the results and their descriptions.

Table 2: Descriptive Quality of Strategy Descriptions

		Description Quality			
FoF: Type	**Fund Count**	**Good**	**Somewhat**	**Poor**	**Totals**
FoF: Diversified	94	31	48	15	94
	58%	33%	51%	16%	100%
FoF: Strategy	68	17	36	15	68
	42%	25%	53%	22%	100%

Note: Both sample periods combined

Overall, these results suggest that database strategy descriptions are only somewhat useful as a starting point for fully describing a particular fund's strategy allocations. At first glance, the results are at least encouraging in that the database strategies do not appear to be completely useless and do appear to serve as a "general" strategy allocation. Indeed, it appears that for approximately 75% of the funds we were able to reasonably capture at least some of the funds' database described strategy mix.

We investigated these initial results further by focusing on the distributions of the regression statistics. Table 3 summarizes these results for each category of classification description for both time periods ('97-'01 and '02-'06). It can be seen that the overall trend in both the adjusted R^2 and overall regression F-statistic average and median values is decreasing from larger values for the "Good" category to lower values for the "Poor" category. In addition, the standard deviation of the distribution of the adjusted R^2 value increases proceeding from the "Good" to the "Poor" category while little pattern in variation is noted for the regression F-statistic.

These results suggest that the three-step style regression methodology of identifying fund strategy exposure simply may be inadequate to capture the full range of hedge fund investment styles. We say this despite the fact that we had access to over 243 hedge fund style indices and that our results suggest that our methodology was at least partially successful at capturing at least some of the FoF styles for approximately 70% to 75% of the funds in our sample. We believe that there are several areas of concern: there appears to be major overlap and strong correlation *across* style indices; in addition to the obvious problem of multicollinearity, there is likely too much subjectivity involved in choosing the correct style indices for each fund. The latter difficulty is exacerbated by the lack of information of any kind on the strategy allocation of over 50% of the FoFs in the sample. Finally, we note that even given the relative maturity of hedge fund investments, there remains a major lack of unique, robust, and relevant hedge fund style indices. At least one major hedge fund index vendor, Hedge Fund Research (HFRI), has recently (2008) attempted to address this problem by introducing a brand new set of what they claim are unique "style robust" hedge fund indices. However, the historical track record of these indices is only a little more than one-and-a-half years. The next section presents results for research question 2: the time-variation in strategy allocations.

Table 3: Distribution of Regression Summary Statistics

97-01			
Adj. R^2	**Good**	**Somewhat**	**Poor**
Average:	0.77	0.65	0.41
Stdev:	0.09	0.19	0.23
Median:	0.78	0.70	0.48
Regression F-Stat			
Average:	64.7	52.9	20.8
Stdev:	30.6	43.3	21.8
Median:	63.4	44.2	14.8
02-06			
Adj. R^2	**Good**	**Somewhat**	**Poor**
Average:	0.76	0.68	0.48
Stdev:	0.09	0.13	0.20
Median:	0.77	0.68	0.48
Regression F-Stat			
Average:	59.8	52.4	24.1
Stdev:	30.1	45.0	17.5
Median:	52.1	38.0	21.4

Results for Research Question 2

US as well as global economic and market conditions were very different for the two five-year time periods in this study; as a consequence, the investment opportunities were also different so we should expect that hedge funds did change strategy allocations. For example, during the first time period, the US equity market experienced remarkable growth while during the second it was on a sharp downward trend followed by relatively volatile conditions. During the second time period some developed non-US economies performed well and the worldwide demand for commodities increased sharply. This is and should be reflected in the different strategy allocations of the FoFs.

Overall, the results show that the allocations of the funds appear to have shifted from perhaps a strong US-based equity market focus with a strong Macro and Relative Value focus in the first time period (1997-2001) to a more global, neutral, and selective equity allocation with a strong Event Driven and CTA presence during the second time period (2002-2006). These general trends can be seen in Tables 4 and 5. Table 4 compares the total number of times each particular strategy appeared in the strategy allocations of all 162 FoFs for both the first and second time period. Table 5 shows the difference and percentage difference between time periods in the total number of times a particular strategy appeared in combination with other strategies. An example will help to clarify the information in each Table: as shown in Table 4, Equity Hedge: Market Timing (abbreviated EH-MT) was present as a significant strategy only 1 time during the first time period and 12 times during the second time period but this table does not indicate how many times this strategy appeared in combination with other strategies; Table 5 shows that this strategy appeared in combination with other strategies 23 times more (an 1150% increase) in the second time period than in the first. To summarize, Table 4 only shows the total number of times a particular strategy was significant based on the regression results, while Table 5 summarizes the difference between the two time periods in the number of times a particular strategy appeared in combination with other strategies. While the general trends of both Tables do support each other, it is the strategy combinations differences (Table 5) that are most important to focus on. Note that some of the strategy style classifications were condensed in Tables 5 and 6 for ease of exhibition. Please refer to Table 1 for a key to the abbreviations used in Tables 4 through 6.

Table 4: Total Strategy Counts:

Strategy	97-01	02-06	Difference	% Difference
ED	43	67	24	56%
EH	47	37	-10	-21%
EMN/EMN-SA	22	31	9	41%
EH-MT	1	12	11	1100%
EH-NH	8	5	-3	-38%
EH-RF	10	15	5	50%
EH-S	19	11	-8	-42%
EH-SS	8	18	10	125%
EM-T/EM-G	21	18	-3	-14%
EM-Regional	19	17	-2	-11%
M	45	11	-34	-76%
RV-Arbitrage Strategies	46	37	-9	-20%
RV-Fix. Inc. Strategies	34	20	-14	-41%
CTA-Diversified	16	27	11	69%
CTA-Sector	8	25	17	213%
FoF-Strategy	6	5	-1	-17%
OI	18	24	6	33%
NONE	5	3	-2	-40%

Note: 1) "OI" refers to "Other Index" or a specialized index, and 2) "NONE" refers to FoFs for which no significant indices could be identified.

We investigated the strategy combinations changes further in order to better understand the prevalence of the different strategy combinations and the changes in allocations from the first sample time period to the next. Table 6 presents the results of detailed changes in the combinations of style strategies of the FoFs. The table shows the major (greater than about 8%) changes in percentage differences between the styles present in combination with other styles. In order to explain the information in Table 6 one should proceed by reading by row first. For example, read across the CTA row of Table 6 and it can be seen that of all the FoFs with CTA exposure there was a

10% increase in FoFs with both CTA and Equity Market Neutral (EMN) styles. Continuing across, it can be seen that there was also a 17% drop in combinations of CTA and Macro (M), a 9% increase in CTA and Relative Value Arbitrage (RV-A) combinations, and finally a 9% increase in FoFs with combinations of CTA with other CTA index exposures. Continuing with this example, one can also read Table 6 column-wise with a slightly different interpretation. If one reads the CTA column, it can be seen that of the 13 major styles presented 6 of them (46%) had significant increases in combinations involving CTA exposure.

Table 5: Differences in Total Strategy Combinations

Strategy	Difference	%Difference
ED	63	71%
EH	-16	-19%
EH-EMN/EMNSA	21	43%
EH-MT	23	1150%
EH-NH	-8	-42%
EH-RF	6	35%
EH-S	-10	-29%
EH-SS	21	105%
EM	-9	-12%
M	-62	-75%
RV-A	-15	-16%
RV-FI	-27	-36%
CTA	79	188%

Table 6: Detailed Changes in Strategy Combinations

Strategy	Comparison of Changes in Significant Strategy Combinations: 02-06 Less 97-01												
	ED	**EH**	**EH-EMN**	**EH-MT**	**EH-NH**	**EH-RF**	**EH-S**	**EH-SS**	**EM**	**M**	**RV-A**	**RV-FI**	**CTA**
ED													8%
EH								9%		-18%			
EH-EMN		-11%					-10%						22%
EH-MT	20%	12%	12%					16%	-42%	8%	-42%		12%
EH-NH							22%			-16%	-11%		
EH-RF									-9%		9%	-18%	
EH-S	11%		-14%		9%			9%	-9%	-11%		8%	
EH-SS		10%	-10%	10%							-15%		
EM			8%							-12%			
M	17%	-15%		10%					-11%			-12%	26%
RV-A	17%									-10%	-13%		17%
RV-FI										-13%			
CTA			10%							-17%	9%		9%

The overall trends in changes in strategy allocations by FoFs can be summarized as follows: there were relatively large increases in exposure to CTA and Event Driven styles while on the equity market side there were significant increases in exposure to Equity Market Neutral and Equity Short Selling styles. In addition, there were large decreases in exposure of the FoFs to Emerging Markets, Macro, and Relative Value Arbitrage styles. Finally, note the changes in patterns of combinations of the Market Timing (EH-MT) strategy: large decreases with Emerging Markets and Relative Value Arbitrage and large increases with Event Driven, Equity Hedge, Equity Market Neutral, Short Selling, Macro, and CTAs; Market Timers are typically added to portfolios as a risk diversifier to take advantage of volatile markets and are often found with a more non-directional low-market exposure portfolio (see Fung & Hsieh (2002)); our results appear to support this. Generally, it appears that the FoFs within this sample did change their style allocations to reflect prevailing market conditions and curtail risk, e.g. increase in Equity Market Neutral and Equity Short Selling and decrease in Emerging Markets and Macro styles. As another example, the increase in CTA exposure likely reflects the increase in worldwide demand for commodities. The next section presents our conclusions and ideas for future research.

CONCLUSIONS AND FUTURE RESEARCH

We have shown that standard linear style models like that of Sharpe (1992) can be applied to hedge fund returns *as long as the returns of the style indices in the model themselves display the nonlinear option-like characteristics of hedge fund returns.* In our case, the returns of the FoFs are strongly correlated to the returns of portfolios of the hedge fund investment style indices. We have also shown that although the methodology is certainly subject to model misspecification, i.e. choosing the wrong style indices, we were still able to qualitatively surmise that approximately 70% to 75% of the FoFs displayed style characteristics at least somewhat similar to their stated style strategy in the CISDM database.

Moreover, we were able to find ample evidence of rational reallocation among styles based on changed economic and market conditions from the first time period as compared to the second time period. In summary, we have provided some initial results to answer our two basic research questions as well as offered an alternative approach to style analysis when risk-adjusted performance and other key statistics are not the main issue.

We wholly support the work of Fung & Hsieh (2002, 2007) on the use and development of Asset-Based Style Factors for hedge funds; their approach was simply not necessary for our current research questions. However, we have performed some preliminary work along the lines of Fung & Hsieh (2002, 2007) for developing asset-based style factors for several hedge fund styles and plan on presenting preliminary findings at upcoming conferences this fall.

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ENDNOTES

[1] Two-tailed t-tests were run to test the significance of the indices using a critical t-value of +/- 2.
[2] For hedge funds it also represents the degree of leverage since each beta may have a value greater in magnitude than 1.
[3] Note that the hedge fund style indices themselves may also be easily replicated for investment purpose through the use of specific FoFs or more conveniently, through the use of investible hedge fund style indices such as those of Dow Jones.

REFERENCES

1. Brown, S. J., Goetzmann, W.N. "Mutual Fund Styles." Working Paper, November, 1995, Final Version, *Journal of Financial Economics*, 43, 1997, pp. 373-399.
2. Brown, S. J., Goetzmann, W.N. "Hedge Funds With Style." NBER Working Paper 8173, March, 2001, Final Version, *Journal of Portfolio Management*, 29, Winter 2003, pp. 101-112.
3. Fung, W., and D. Hsieh. "Empirical Characteristics of Dynamic Trading Strategies: The Case of Hedge Funds." *Review of Financial Studies*, 10, 1997, pp. 275-302.
4. Fung, W., and D. Hsieh. "Asset-Based Style Factors for Hedge Funds." *Financial Analyst Journal*, 58, 2002, pp. 16-27
5. Fung, W., and D. Hsieh. "Hedge Fund Replication Strategies: Implications for Investors and Regulators." Banque de France, *Financial Stability Review – Special Issue on Hedge Funds*, No. 10, April 2007, pp. 55-66.
6. Schneeweis, T., Kazemi, H., and Karavas, V. "Hedge Fund Style Consistency and Performance." Center for International Securities and Derivatives Markets (CISDM), Working Paper, April, 2004, pp. 1-22.
7. Sharpe, W. F. "Asset Allocation: Management Style and Performance Measurement." *Journal of Portfolio Management*, Winter, 1992, pp. 7-19.

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