Performance Attribution and Style Analysis:
From Mutual Funds to Hedge Funds

by

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Abstract

This paper explores the investment styles in mutual funds and hedge funds. The results indicate that there are 39 dominant mutual fund styles that are mixes or specialized subsets of nine broadly defined asset classes. There is little evidence of market timing or asset class rotation in these dominant mutual fund styles. There are five dominant hedge fund styles. Two are correlated with broadly defined asset classes, while the other three are dynamic trading strategies on a number of asset classes. Thus, a 12-factor model with nine asset classes and three dynamic trading strategies should provide a good first step in a unified approach for performance attribution and style analysis of mutual funds and hedge funds.

1. Introduction

Institutional portfolios typically contain a core holding of stocks to earn the long term equity premium. Consistent exposure to equity is achieved by hiring traditional managers using a buy-and-hold strategy. Asset allocation achieves diversification by adding asset classes having low correlation to equity. As the number of suitable asset classes is finite, institutional investors have increasingly turned their interests towards dynamic trading strategies of alternative managers. The number of dynamic trading strategies is potentially unlimited, so that there are many more opportunities for adding diversification without the need for finding new asset classes.

Alternative managers using dynamic trading strategies cannot be analyzed in the traditional approach to performance attribution and style analysis, which has focused on buy-and-hold strategies. The goal of performance attribution and style analysis is to divide a fund manager's returns into two parts: "style" and "skill". "Style" is the part of the returns that is attributable to market movements, while "skill" is the part unique to the manager.[1]

Up until now, the finance literature has dealt with performance attribution and style analysis for traditional buy-and-hold strategies, associating "style" with "asset class mixes" and "skill" with "security selection". Jensen (1968) implemented the style/skill decomposition by regressing a stock mutual fund's returns (R_t) on the market return (R_{mt}) and a risk-free return (R_{ft}):

$$R_t = \alpha + \beta\ R_{mt} + (1-\beta)\ R_{ft} + u_t. \qquad \text{I.}$$

The β coefficient provides the proportions of risky and risk-free assets to replicate the fund's returns. The constant term (α) measures the manager's ability to generate returns beyond this static mix of assets. In this decomposition, $[(1-\beta)R_{ft}+\beta R_{mt}]$ is "style" and $[\alpha+u_t]$ "skill."

Sharpe (1992) extended this single factor model to a multiple factor framework, and showed that only a limited number of major asset classes was required to successfully replicate the performance of an extensive universe of U.S. mutual funds. The success of Sharpe's (1992) approach is due to the fact that most mutual fund managers are typically constrained to buying and holding assets in a well defined number of asset classes and are frequently limited to little or no leverage. Their mandates are to meet or exceed the returns on a given mix of asset classes. They tend to generate returns which are highly correlated to the returns of standard asset classes.[2] Consequently, stylistic differences between managers are primarily due to the assets in their portfolios, which are readily captured in Sharpe's (1992) "style regressions."

This decomposition into style (i.e. asset class mix) and skill (i.e. security selection) serves two purposes. For each manager, an investor can verify the source of the manager's performance and distinguish between performance based on security selection versus asset class mix. For the portfolio, an investor can allocate investments across managers to achieve style (i.e. asset class) diversification.

Unfortunately, the success of Jensen's and Sharpe's approach does not extend to managers who use very dynamic trading strategies, such as hedge fund managers and commodity trading advisors (CTAs). This is an important class of managers within the category of "alternative managers." Hedge fund managers and CTAs typically have mandates to make an absolute return target, regardless of the market environment.[3] To achieve the absolute return target, they are given the flexibility to choose among many asset classes and to employ dynamic trading strategies that frequently involve short sales, leverage, and derivatives. These alternative managers generate returns that have low correlation with the returns of standard asset classes, even if they trade the same asset classes. Sharpe's (1992) asset class factor model does not apply to them. The goal of this paper is to propose an extension to Sharpe's (1992) asset class factor model to allow a uniform treatment of buy-and-hold strategies as well as dynamic trading strategies.

Our work is based on the intuition that a manager's returns can be characterized more generally by three key determinants: the assets in the manager's portfolio, directional exposure, and leverage. In Sharpe's (1992) model, the focus was on the first key determinant, the "location" component of return, which tells us "where" the manager invests in. The proposed extension incorporates factors that reflect "how a manager trades" --- the "directional exposure" or long/short component of return, and the "leverage" or quantity component of return. A group of managers with the same investment style (i.e. using similar leverage and directional exposure to the same assets) should generate returns correlated to each other, even if the returns are not correlated with any buy-and-hold strategy. This gives rise to an operational definition of "style" in Fung and Hsieh (1997), namely, that an investment style is the common factor in the highly correlated returns of a group of managers. By extracting these common factors, we obtain the most popular investment styles.[4]

These additional factors extend the concept of style beyond static buy-and-hold asset class mixes to include dynamic, leveraged trading strategies, and provide insight on the strategic difference between "relative return" versus "absolute return" investment styles. Just as Sharpe's model provides insight to the asset mix decision when only buy-and-hold styles are considered, the extended model provides a framework for analyzing the asset mix and trading strategy decisions.

We apply our model to 2,525 U.S. mutual funds from Morningstar and 409 hedge funds/CTA funds used in Fung and Hsieh (1997). As in Sharpe (1992), we find that mutual fund returns are highly correlated with those of standard asset classes. In particular, we do not find corroborating evidence to Christopherson's (1995) critique of Sharpe's (1992) model, that it is unable to accommodate changing asset class mixes. We conclude that the distortion arising from non-stationary parameters in Sharpe's "style regression" to be of minor empirical consequence, especially when compared to our results from hedge funds/CTAs.

In contrast, we find that hedge fund managers and CTAs generate returns which have low correlation to the returns of mutual funds and standard asset classes. Furthermore, there is a great deal of performance diversity within hedge funds and CTAs. With these managers, parameter stability does matter as a natural consequence to the use of dynamic trading strategies and leverage. To capture this effect, we propose three additional "style" factors to Sharpe's (1992) model. This improves the model's performance significantly.

These results confirm the intuition that hedge funds and CTAs can deliver a diversifying set of returns to major asset classes, by blending traditional relative return investment styles with absolute return investment styles. Our extension of Sharpe's (1992) model provides a framework for analyzing the desired mix between these two styles. However, this new benefit comes with some added complications. New tools are needed to assess the performance and to control new elements of risk that come with an absolute return investment style.

The paper is organized as follows. In section 2, we begin with a nine asset class factor model similar to Sharpe's (1992). We call these location factors. Updates to Sharpe's (1992) results for U.S. mutual funds are in sections 3 and 4. The results show that the nine-factor model provides satisfactory estimates of the asset mixes of the dominant investment styles of mutual fund managers.

In section 5, we apply Sharpe's style regressions to hedge funds' and CTAs' returns. Section 6 discusses the difference between location choice and trading strategy. Section 7 deals with the common styles in hedge funds and CTAs. Section 8 contains some comments on survivorship bias in hedge funds and CTA funds. Section 9 addresses the implications of our findings and provides some concluding remarks.

2. An Asset Class Factor Model

We begin with Sharpe's (1992) asset class factor model:

$$R_t = \Sigma_k \, w_{kt} \, F_{kt} + e_t, \tag{2}$$

where R_t is the return on a portfolio, w_{kt} the portfolio weight of asset class k in period t, F_{kt} the return of the k-th asset class in period t, and e_t is the error term in the regression. In Sharpe (1992), the choice of asset classes is more oriented towards U.S. based funds. In this paper, we group assets into nine classes with a global emphasis. There are three equity classes: MSCI U.S. equities, MSCI non-U.S. equities, and IFC emerging market equities. There are three bond classes: JP Morgan U.S. government bonds, JP Morgan non-U.S. government bonds, and the Merrill Lynch high yield corporate bond index. For cash, we use the one month eurodollar deposit. For commodities, we use the price of gold. For currencies, we use the Federal Reserve's Trade Weighted Dollar Index.[5]

To determine the asset class mix of a mutual fund, Sharpe (1992) regresses the monthly returns of the fund on the returns of the asset classes:

$$R_t = \alpha + \Sigma_k \, b_k \, F_{kt} + u_t, \tag{3}$$

where α and b's represent the intercept and slope coefficients, respectively, and u's are the residuals. Here, [$\Sigma_k \, b_k \, F_{kt}$] captures the "style" or asset class mix, while [$\alpha+u_t$] captures the "skill" or security selection of the manager. Sharpe (1992) showed that this asset class factor model is very effective for a wide variety of mutual funds.

3. Mutual Fund Performance Attribution

We replicate Sharpe's (1992) result on a larger sample of mutual funds. We run Sharpe's style regression for all open ended mutual funds in the Morningstar database which has at least 36 months of returns. Excluding municipal bond funds (which are not appropriate for institutional investors), there are 2,525 funds.[6] Figure 1 summarizes the distribution of the R^2s of the regressions. It shows that 73% of the mutual funds have R^2s above 0.80, and 56% have R^2s higher than 0.90. Mutual fund returns are strongly correlated to standard asset classes.

Table 1 provides the distribution of the (statistically) most significant asset class in these regressions. Nearly 80% of mutual funds are correlated to two asset classes: U.S. equities and U.S. government bonds. In more than 99% of the funds, the coefficients of the most significant asset class are positive.

These results are very similar to those in the original Sharpe (1992) article. The high correlation of mutual fund returns to standard asset class returns means that performance attribution can be accomplished by finding the appropriate mix of asset classes to replicate a mutual fund's performance, which implies that choosing the style mix among mutual funds is similar to determining the asset mix in one's portfolio. It also affords the inference that mutual fund performance is largely location driven in the sense that the underlying strategy, given the choice of markets, is similar to a "buy and hold" strategy. Consequently, *where* they invest, and much less *how* they invest, is the key determinant of performance in mutual funds.

4. Asset Allocation and Mutual Fund Styles

In this section, we address the key question: what are the important mutual fund styles and how many are there? In principle, there can a style for each fund. That, however, would not be useful information. Mutual funds tend to be highly correlated with each other. It is useful to group similar funds together and determine the dominant styles, so that an investor can allocate investments across the dominant styles.

We use the method of factor analysis to determine the dominant styles in mutual funds. The idea is quite simple. Funds with the same style (i.e. location choice and trading strategy) should have highly correlated returns. Factor analysis extracts principal components which correspond to the most important correlations across mutual funds, without the need to specify what the styles are.

This procedure not only complements, but has an advantage, over Sharpe's style regression. Factor analysis can detect and extract common styles, regardless of their correlation with asset class returns. This provides a way to test for significant style dynamics (e.g. asset class rotation) in mutual funds. If all of the important principal components are highly correlated to asset class returns, then we can claim with confidence that the dominant mutual fund styles are primarily location choices. If, however, some principal components are uncorrelated to any identifiable asset class, then we will have evidence that trading strategies (including asset class rotation) are also present. The analysis will provide insight to Trzcinka's (1995) observation on the empirical relevance of style dynamics among mutual funds.

Since there are no prior identification rules on what and how many styles there should be, we need some information beyond mutual fund returns. Here we appeal to the qualitative categories used by Morningstar, which is basically a crude catalogue of location choices. We perform factor analysis on the funds in each of the 33 Morningstar categories (excluding municipal bond funds). If each category has a distinctive style, we expect to see no more than one main principal component. If that style is a location choice, we can use the dominant principal component to identify its location.

The results of the factor analysis are in Table 2. It gives the percentage of cross sectional variation explained by the first five principal components in each category. In all 33 categories, there is at least one important style, as the first principal components explain upwards of 60% of the cross sectional variation of returns and are by and large correlated with the eight asset classes.

Twenty four Morningstar categories[7] (accounting for 85% of the mutual funds in our sample) have only one dominant style, since each category's second principal component explains less than 10% of that category's cross sectional variation. Each of these 24 dominant styles has high correlation with a well defined asset class, as shown in Table 3. This is strong evidence that most mutual funds perform as if they follow a buy-and-hold strategy in well defined mixes of standard asset classes.

The remaining nine Morningstar categories (accounting for 15% of the mutual funds in our sample) have two important styles each, since each category's second principal component explains more than 10% of the cross section variation but the third principal component does not. In these 18 principal components, 15 have high correlation with well defined asset classes, as shown in Table 3. There are only three principal components which cannot be easily identified with any asset class mix. Upon closer examination, it turns out that these three principal components cannot be considered dominant styles, since they correspond to six mutual funds whose returns are unusually different from their peers.

In total, we have identified 39 dominant investment styles in mutual funds. Most of these turn out to be specialized subsets or mixes of our nine broadly defined asset classes. The dominant trading strategies among mutual fund managers are similar to buy-and-hold strategies. There is no evidence to suggest that dynamic trading strategies (such as asset class rotations or market timing) are important in mutual funds.[8]

5. Hedge Fund/CTA Performance Attribution

We now turn to hedge funds and CTA funds. Hedge funds are private investment partnerships/vehicles in which the managing partner/entity is given a broad investment mandate. These vehicles are restricted to "sophisticated high net worth" investors. A commodity trading advisor (CTA) is an individual or trading organization, registered with the Commodity Futures Trading Commission (CFTC) through membership in the National Futures Association, granted the authority to make trading decisions on behalf of a customer in futures, options, and securities accounts established exclusively for the customer ("managed account"). Until the advent of the diversified futures pools in the 1980's, CTAs were limited as to what they could trade (commodities, commodity futures, and futures options). The globalization and expansion of all markets and reduction in regulatory constraints over the past years have given CTAs the ability to trade an increasing number of instruments, such as world interest rate, currency, equity, and physical commodity markets. Therefore, while historically CTAs have been viewed separate from hedge fund managers, over the past ten years the distinction between the two has become blurred as CTAs have established private investment partnerships with broad mandates in almost any financial market. In fact, a number of managers have both hedge funds and CTA pools. For the purposes of this paper, hedge fund managers and CTAs are treated as a single group of managers, referred to as "hedge funds" in the remainder of this paper.

It is appropriate to comment on the scope of our sample. Unlike mutual funds, hedge fund managers are not required to disclose their performance and assets under management publicly. *Futures* (February 1995, p. 62-64) estimates that there are somewhere between 1,000 to 2,000 hedge funds, with $100 to $160 billion of assets under management at the end of 1994. Although these numbers appear to be small in comparison to the mutual fund industry, which has upwards of 6,000 funds and $2 trillion of assets, on a leveraged basis the positions taken by a large hedge fund often exceed those of the largest mutual funds.

Our hedge fund universe consists of nearly 700 hedge fund programs and 240 CTA funds, with asset under management of $79 billion. Excluded from this universe are duplicated funds created for regulatory reasons, which would overweight the style participation in our factor analysis. Excluded are also funds of funds, which have considerable assets that represent double counting of asset under management. A major source of difficulty in constructing our sample is the lack of performance history. This is a natural consequence of the fact that the majority of funds were started in the 1990s, and many funds have limited assets for prolonged periods. As a consequence, the usable sample falls to 409 funds, as we require three years of monthly returns with at least $5m of assets under management. This is the same data set used in Fung and Hsieh (1997).

Figure 1 summarizes the style regression results. They are striking when compared with those of mutual funds. While more than half the mutual funds have R^2s above 0.90, nearly half (45%) of the hedge funds have R^2s below 0.30. Table 1 shows that no single asset class is dominant in the regressions. Unlike mutual funds, a substantial fraction (22%) of hedge funds are negatively correlated with the standard asset classes.

The evidence indicates that hedge funds are dramatically different from mutual funds. Mutual fund returns have high and positive correlation with asset classes returns, which suggests that they behave as if deploying a buy-and-hold strategy. Hedge fund returns have low, and sometimes negative, correlation with asset class returns. In the next section, we provide an explanation on the differences between the results of hedge funds versus those of mutual funds.

6. Two Dimensions of Style: Location Choice and Trading Strategy

It is well publicized that most hedge funds use many of the same liquid asset classes as mutual funds. For example, Quantum was long U.S. stocks and short Japanese stocks in the October 1987 stock market crash, short the British pound in September 1992, long precious metals in April 1993 (including a 13% stake in Newmont Mining), and long the U.S.Dollar/short the Japanese Yen in February 1994.[9] The fact the Quantum's returns have low correlation to the returns of asset classes must be due to it's dynamic use of leverage and choice of asset exposure.

To see this, compare the style regression in equation (3) and the definition of returns in equation (2). The style regression can attribute a manager's returns to asset classes only if his returns are correlated to the asset class returns. Sharpe is clearly aware of this problem. He refers to the style regressions as finding "an average of potentially changing styles over the period covered" (Sharpe, 1992, p. 3) by the regression.

From our earlier discussions, the concept of "style" should be thought of in two dimensions: namely location choice and trading strategy. Location choice refers to the asset classes, i.e., the F's in equation (2), used by the managers to generate returns. Trading strategy refers to the direction (long/short) and quantity (leverage), i.e., the w's in equation (2), applied to the assets to generate returns. The actual returns are, therefore, the products of location choice and trading strategy.

To illustrate this point, consider a manager trading S&P futures contracts. Without leverage, a fully invested position of being consistently long 1 futures contract (i.e. buy-and-hold) will result in the style regression showing a coefficient of 1 on the S&P 500 index. If the manager leverages up to 2 futures contract, the regression coefficient will be 2. Conversely, if he is short 1 futures contract, the regression coefficient will be -1. However, if he alternates between long and short each month, the regression coefficient will be close to 0. In this example, the location is the US stock market in all cases. The returns, on the other hand, are very different depending on the trading strategy. In the first two cases, the returns are positively correlated with US stocks. In the third case, the returns are negatively correlated with US stocks. And in the fourth case, the returns are uncorrelated with US stocks.

This example illustrates how return is a function of the location choice as well as trading strategy. While dynamic trading strategies have been discussed in the mutual fund literature, the strategies employed by hedge funds can be very different. In the first place, the range of trading strategies is far greater in hedge funds than in mutual funds. Market timing in the mutual fund literature has focused on the ability of managers to time the market on the long side. Hedge fund managers can make money on the short side as well. In addition, hedge fund managers can use derivatives and complex options, so that the number of proxies needed to pick up these trading strategies explodes dramatically.

In the second place, dynamic trading strategies in hedge funds can involve time horizons shorter than a month. A case in point is George Soros's Quantum Fund. It is well known that Quantum gained 25.5% in September 1992 by betting on the devaluation of the British Pound. Using monthly returns, the regression of Quantum against the Pound has only an R^2 of 23%. Using daily returns for the month of September 1992, the R^2 is only 10%! The bet appeared to have been put on around September 11 and taken off around September 22. This example is typical of the trading styles of many hedge funds, and shows that the number of proxies needed to pick up very short term dynamic trading strategies is virtually infinite.

Simply put, hedge fund returns are much harder to "explain" or replicate using simple asset class mixes. They look more like "selectivity" than "market timing" in the terminology of the mutual fund literature. Presumably, this is why investors are willing to pay hedge fund managers sizable incentive compensation based on absolute performance which is not easily replicable.

7. Hedge Funds Style Analysis

In principle, Sharpe's style regression can be extended by adding regressors to proxy the returns of dynamic trading strategies. The success of this procedure depends on finding the dynamic trading strategies which replicate hedge fund returns. This is a very difficult task, for the number of dynamic trading strategies may be infinite. In this paper, we take a different approach. Rather than trying to replicate hedge fund returns with specific trading strategies, we determine the dominant styles in hedge funds by factor analysis.

We factor analyze the 409 hedge funds as a single group, and we are able to extract five mutually orthogonal principal components, explaining approximately 43% of the cross sectional return variance.[10] Using the hedge funds most highly correlated with these principal components, we construct five "style factors" whose returns are highly correlated to the principal components.[11]

This quantitative method of defining investment styles should be contrasted with the qualitative method used by hedge fund consultants, who categorize hedge funds based on the trading strategies described in their disclosure documents. To the best of our knowledge, there has been no formal statistical definition of these qualitative styles. Indeed, different consultants publish differing "style categories." Often, reported returns for the same style category will differ across the source, and the same manager can appear in different style categories depending on the source. In fact, data vendors frequently regard information on hedge fund styles to be proprietary. This paper shows that there exist style categories which are discernable in the return data. We are of the view that it is what fund managers *do*, not what they *say* they do, that determines stylistic differences. Thus, we focus on the return characteristics rather than the self-described strategies provided by hedge fund managers.

For labeling purposes, however, we have associated names to the five quantitatively identified hedge fund styles that are broadly consistent with the industry nomenclature. By researching the disclosure documents of the funds in each style factor, we identify the five hedge fund styles as: "Systems/Diversified", "Global/Macro", "Value", "Systems/FX", and "Distressed".

The term "Systems Traders" is used to describe managers who use technical trading rules. "Systems/FX" refers to traders who use technical trading rules on foreign currencies, while "Systems/Diversified" refers to technical traders who trade diversified markets (typically bonds, currencies, and commodities). "Global/Macro" refers to managers who primarily trade in the most liquid markets in the world such as currencies and government bonds, typically betting on macroeconomic events such as changes in interest rate policies and currency devaluations relying mostly on their assessments of economic fundamentals. "Value" refers to traders who buy securities of companies they perceive to be undervalued based on their micro analysis of the fundamentals. "Distressed" refers to managers who invest in companies near, in, or recently emerged from or in bankruptcy/corporate restructuring.[12]

To determine whether the five style factors are location choices or dynamic trading strategies, we apply Sharpe's style regression using the nine asset classes. Two style factors are each correlated with a single asset class. The "Value" style has an R^2 of 70% against the nine asset classes plus high yield corporate bonds, and is strongly correlated to U.S. equities (with a coefficient of 0.95 and a t-statistic of 7.73). This is due to the fact that most "Value" managers have a long bias in U.S. equities. The

"Distressed" style has an R^2 of 56%, and is strongly correlated to high yield corporate bonds (with a coefficient of 0.89 and a t-statistic of 6.06). This is not surprising, since "Distressed" managers and high yield corporate bond funds both invest in companies with low or no credit ratings. Furthermore, it is common practice to price unrated, unlisted securities at a spread to the traded, high yield bonds, which explains the correlation between the "Distressed" style and high yield corporate bonds. The two "Systems" style factors ("Systems/Diversified" and "Systems/FX") have low R^2s (29% and 17%, respectively) and are not correlated to any of the asset classes.

The "Global/Macro" style is the hardest to interpret. It has an R^2 of 55%, and is correlated with US Bonds (coefficient: 0.84, t-statistic: 3.47), US Dollar (coefficient: 0.46, t-statistic: 2.43), and the IFC emerging market index (coefficient: 0.15, t-statistic: 2.90). The correlation to US bonds and the Dollar are not surprising, given highly publicized reports regarding the bond and currency trades of the 'Global/Macro' managers in 1993 and 1994. However, the correlation with the IFC emerging market index could conceivably be a consequence of spurious cross correlations with other major asset classes.

A problem with the regression approach is that the results are very sensitive to outliers. The fact that the "Global/Macro" style is statistically correlated with three asset markets does not necessarily mean that it is using a buy-and-hold strategy in these markets. A buy-and-hold strategy generates returns which have a linear relationship with those of an asset class, while a dynamic trading strategy does not. We resort to a different technique, similar to nonparametric regressions, to distinguish between these two trading strategies. In Table 4, we divide the monthly returns of each asset class (excluding cash) into five "states" or "environment" of the world, ranging from severe declines to sharp rallies, by sorting the monthly returns into five quintiles. The average returns (and associated standard errors) of that asset class, as well as those of the five style factors, are computed in each state of the world.

If a style uses a buy-and-hold strategy in a given asset class, then it's return in the five states of the world should align with those in the asset class in a straight line. Using this method, we identify that the "Value" style uses a buy-and-hold strategy in U.S. equities. The other four styles do not use buy-and-hold strategies in any of the asset classes. In particular, the "Distressed" style is not quite a buy-and-hold strategy in high yield corporate bonds, because its returns in states "4" and "5" for high yield corporates are out of line with those of the other states. For the same reason, the "Global/Macro" style does not use buy-and-hold strategies in U.S. bonds, currencies, or emerging market equities.

If a style uses a dynamic trading strategy in a given asset class, then it's return should be large (positive or negative) when the underlying asset returns are at extremes (i.e. states "1" and "5"). In the case of the "Systems/Diversified" style, it is most profitable during rallies in US bonds, non-US bonds and gold, and during declines in the US dollar. The "Systems/FX" style is most profitable during rallies in non-US equities and bonds, and during declines in the US Dollar. The "Global/Macro" style is most profitable during rallies in Gold, the US Dollar, and emerging markets. The locations we have identified are consistent with the disclosure information provided by the traders. It is important to point out that this type of nonlinear, state dependent return tabulation is helpful only to infer the "location" of a trading style, but it is not very informative on the nature of the trading strategies employed.

Based on the evidence, it is reasonable to conclude that the "Value" style is highly sensitive to the movements of the overall U.S. equity market. The "Distressed" style is also quite sensitive to the performance of high yield corporate bond market. The other three styles are dynamic trading strategies in a variety of markets. They are not sensitive to the asset markets in the normal states (i.e. "2", "3", and "4"), but can be sensitive to selective markets during extreme states.

Given that we are measuring extreme or tail events, there is little hope of attaching statistical significance. Indeed, we are making a much weaker statement. Table 4 shows that there exist nonlinear correlations between three style factors and some of the standard asset classes, which can give rise to option-like payouts. Figures 2, 3, and 4 illustrate three of the most dramatic examples of option-like payouts. Figure 2 shows that the Systems/FX style has a return profile similar to a straddle (i.e. long a put and a call) on US equities. Figure 3 shows that the Systems/Diversified style is like a call option on gold. Figure 4 shows that the Global/Macro style behaves like a straddle on the US Dollar.

Lastly, we examined the correlation between the five hedge fund style factors and the 39 mutual fund styles in Table 5, to see if the hedge fund style factors correspond to any of the narrower asset classes used by mutual funds. The "Distressed" hedge fund style has a 54% correlation with high yield corporate bond mutual funds. The "Value" hedge fund style is highly correlated with growth, aggressive growth, and small company funds. The "Global/Macro" hedge fund style is correlated with a variety of mutual funds, including US and foreign equities, emerging markets, US and foreign bonds. The two "Systems" style have very low correlations to the 39 mutual fund styles.

A few remarks are appropriate here. We are not advocating that it takes only five style factors to completely characterize the myriad of strategies deployed by hedge fund managers. Contrary to the case of mutual funds where the statistically identified styles account for the lion share of performance variation, here, the five style factors can only account for 43% of the return variance of hedge funds. In the world of private investments, it is quite common to have a few "niche" arbitrageurs operating in illiquid markets where large hedge funds would find it unsuitable given their size. Therefore, the style factors represent the most "popular" trading strategies that can operate in asset markets with adequate depth and liquidity. Indeed, the lack of dominant style factors attests to the wealth of performance diversity available among these managers.[13]

A different way to illustrate this point is to see how many hedge funds have "exposure" to the five hedge fund styles. Here, we regress the returns of each of the 409 hedge funds on six variables: the five style factors plus the IFC emerging market index.[14] 271 of them have at least 1 statistically significant coefficient. 78 have exposure to the "Systems/Diversified" style, 67 to "Global/Macro", 56 to "Value", 74 to "Systems/FX", 43 to "Distressed", and 41 to the IFC emerging market index.

Notice that there are 138 hedge funds which have no significant exposure to the five hedge fund styles or emerging markets. They are candidates for what has come to be known as "Market Neutral" strategies. There is a growing literature on what constitutes a market neutral strategy, its attractive characteristics and its potential pitfalls (e.g. Lederman and Klein (1996)). A detailed analysis of this category of trading styles, which often includes the "Distressed" style, is beyond the scope of the present paper. However, we note that return orthogonality to the traditional asset classes is a poor screening device for market neutral funds. As our example in section 6 shows, a market timing strategy can appear to be uncorrelated to the very asset class it has directional exposure to, yet market timing strategies are generally not regarded as "market neutral". A better screening device is to require a market neutral fund to be orthogonal to the popular hedge fund styles as well as the traditional asset classes. Our analysis shows that three hedge fund style factors (i.e., "Systems/Diversified", "Systems/FX", and "Global/Macro") appear to use market timing strategies in various asset classes, so that they have directional exposure even if they are uncorrelated to the asset classes on average. Hedge funds correlated to these styles are not market neutral. In addition, two other hedge fund styles ("Value" and "Distressed") are correlated to, respectively, US Equity and High Yield Corporate Bonds. Hedge funds correlated to these styles are also not market neutral. Beyond using correlation as a screening device, truly market neutral funds should not have excessive exposures to traditional asset classes in extreme moves. For example, a typical "duration neutral" fixed income strategy may have no correlation to normal movements in interest rates, yet have directional exposure to extreme movements (see Fung and Hsieh (1996) for details). Limiting the amount of tail exposure, as done in Table 4, is also a good device to screen for market neutral funds.

In terms of portfolio diversification, three hedge fund styles seem particularly interesting to institutional investments with large core holdings in US equities. Table 4 shows that Systems/Diversified and Systems/FX tend to have large positive returns during the largest down months in stocks. Fung and Hsieh (1997b) show that this happens fairly regularly. These two styles should add diversification. In addition, the "market neutral" hedge funds (which are uncorrelated with standard asset classes as well as the five hedge fund styles) tend to generate steady positive returns regardless of the performance in stocks. They should also add to diversification.

8. Survivorship Bias

Our hedge fund sample contains mainly funds which are in operation as of December 1995, as we are unable to obtain returns of most hedge funds which ceased operation. This creates potential survivorship bias in our analysis. There are at least two problems: fund survivorship and style survivorship.

Fund survivorship refers to the problem that the true performance of hedge funds may be overstated by the historical returns of the funds in our sample. The presumption in the finance literature is that poor performance leads to a fund's dissolution. This means the returns of the surviving funds are upwardly biased estimates of the returns of all funds. For this reason, we have avoided discussing the actual returns of the funds in our sample, until we obtain a proper estimate of this upward bias in hedge fund performance.

Survivorship bias has been studied extensively in the mutual fund literature. For example, Grinblatt and Titman (1989), Brown, Goetzman, Ibbotson, and Ross (1992), Brown and Goetzman (1995), and Malkiel (1995) found this bias to be 50-150 basis points per year in mutual funds.

It is exceedingly difficult to estimate the upward bias in average performance of hedge fund due to survivorship bias, because the population of hedge funds is unknown. Unlike mutual funds, hedge funds need not register with the Securities Exchange Commission, nor does a hedge fund industry association exist that can document the entry and exit of funds. Fung and Hsieh (1997) argued theoretically that the survivorship bias in hedge funds may be either higher or lower than that in mutual funds, given that hedge funds typically have a capacity constraint which leads to diminishing returns to scale. Thus, the performance of surviving funds (which tend to be large) may not be much higher than the performance of dissolved funds (which tend to be small).

Fung and Hsieh (1997b) obtained dissolved CTA funds from Tass Asset Management. They found that the survivorship bias of CTA funds is 342 basis points per year, quite a bit higher than mutual funds.[15] Limited evidence suggest that hedge fund survivorship bias is smaller, even though hedge funds are similar to CTA funds in terms of compensation structure and return characteristics.

Style survivorship refers to the problem that the styles of surviving funds are different from the styles of deceased funds. The presumption is that if an investment style suffers poor performance over a prolonged period, that style may disappear because funds using that style will either cease operation or shift to a different style. A classic example is the "short selling" style, which has virtually vanished during the bull market in stocks over the last fifteen years. Style survivorship must be studied on a style by style basis. For CTA funds, Fung and Hsieh (1997b) found that there is a single CTA style, which persists through the entry and exit of individual CTA funds. Similar analyses have to be carried out for the other styles.

9. Implications

In this paper, we analyze investment styles in mutual funds and hedge funds. We have shown that there are 12 important investment styles --- buy-and-hold in nine asset classes and three dynamic trading strategies. There are a number of implications. In terms of performance attribution and style analysis, we have extended Sharpe's style factor model. A style regression using these 12 variables should produce reasonably high R^2's in at least 85% of mutual funds and perhaps 40% of hedge funds. We believe that this provides a good starting point in performance attribution and style analysis that can cope with both relative as well as absolute return managers.[16] In terms of portfolio construction, the investor can now allocate across both location choices and trading strategies.

There are, however, complications in portfolio construction and risk management arising from the use of dynamic trading strategies which do not exist under a static buy-and-hold type of trading strategy. For the traditional portfolio which focuses only on the "location" aspect of style management, portfolio risk management is straight forward. The asset allocation decision selects the portfolio's exposure to each asset class and sets the relative return targets. To ensure that the manager selection process preserves the target asset mix, we can apply Sharpe's "style regression" to each manager. From this, the investor can "predict" whether a particular mix of managers' styles is likely to deliver the target asset mix's performance. In terms of continuing assessment and performance attribution, when a manager's returns deviate substantially from the original prediction (both on the upside and the downside), the investor has a framework to determine whether a manager's style has changed or excess performance ("alpha") has been achieved.

For the portfolio which includes dynamic trading strategies, portfolio construction and risk management are potentially more complex, depending on the investor's risk preferences. Suppose an investor has quadratic preferences. Here, standard mean-variance tools are appropriate for asset allocation and risk management. We can show that the dynamic trading strategies can improve the performance of a traditional stock-bond portfolio without substantially increasing its risk. For example, a portfolio of 60% US equities and 40% US bonds has an annualized mean return of 11.55% and annualized standard deviation of 7.97% between 1990 and 1995. By shifting 50% of the portfolio into the three dynamic trading strategies with equal weights, the annualized mean return increases to 15.92% and the annualized standard deviation decreases to 7.10%. This is an economically significant benefit.

For investors with non-quadratic preferences, mean-variance tools are inappropriate for portfolio construction and risk management, because some of the style factors involving dynamic trading strategies exhibit highly non-normal distributions.[17] Furthermore they may have nonlinear correlation with those of the nine buy-and-hold styles. Portfolio construction and risk management must take into account investor preferences and the joint distribution of the 12 investment styles.

The proper technique for portfolio construction when investors have non-quadratic preferences is a subject beyond the scope of this paper.[18] We can, however, illustrate how it may differ from the mean-variance approach. Suppose an investor is willing to give up some of the gains in a strongly rising stock market in order to reduce the downside risk in a rapidly falling one. This type of option-like payout profile (similar to that of a "portfolio insurance" strategy) is generally not available from traditional managers. For example, consider Table 5 under the column "Systems/Diversified." This particular style underperformed seven of the eight non-cash asset classes during major rallies or extreme positive states. However, it delivered positive performance in the states when extreme negative outcomes were recorded in equities and bonds, which constitute the core of most institutional portfolios. An equally weighted portfolio of the three dynamic trading strategies can deliver superior performance in the states when extreme negative outcomes were recorded in the 4 equity and bond asset classes. Thus, blending the three dynamic trading strategies to traditional managers can provide some down side protection.

For example, take an investor who is highly averse to negative returns. The traditional 60/40 stock/bond portfolio suffered a maximum monthly loss of

5.93% during the 1990-95 period. If 40% of that portfolio is replaced by an equally weighted portfolio of the three dynamic trading strategies, the maximum monthly loss would be reduced to 2.79%. For this investor, the latter portfolio would strongly dominate the traditional 60/40 stock/bond portfolio. In other words, it is possible to achieve option like return profile (relative to standard bench marks) with direct investment into existing hedge funds.

Risk management in the presence of dynamic trading strategies is also more complex, regardless of investor preference. Hedge fund managers have a great deal of freedom to generate returns which are uncorrelated with those of asset classes and traditional fund managers. This diversification comes at a cost. Care must be taken to ensure that proper infrastructure is in place to operate broad investment mandates involving a wide range of financial instruments. Another important element of risk is that, periodically, the portfolio can become overly concentrated in a small number of markets.

As an example, take a portfolio with exposure in three markets: US equities, US bonds, and non-US bonds. A part of the portfolio is managed traditionally, using buy-and-hold strategies. The remainder is in hedge funds allocated in the three styles with dynamic trading strategies. Suppose a steady trend develops in the international bond markets, as was the case in 1993. The "Global/Macro" traders would have been long and leveraged. The "Systems/FX" and "Systems/Diversified" traders would have been long as well, to take advantage of the trend. By December 1993, the portfolio could have been highly concentrated in non-US bonds. It would have made a lot of money in 1993. But when the world bond market declined sharply in 1994, the portfolio would have lost a lot of money. We refer to this phenomenon as "diversification implosion." The intuition here is that, although style exposures are still diverse, market exposures can converge.

In conclusion, the empirical results point to diversification benefits from including a particular class of absolute return managers, e.g., hedge funds, into the asset mix. However, there is also an implicit cost. The flexibility in hedge fund managers' investment mandate allows them to deliver a diversifying set of return characteristics. But "freedom" has its price. An investor using managers with dynamic trading strategies should take steps to reduce the chance of diversification implosion and exposure to extreme or tail events. This calls for greater efforts in due diligence, portfolio construction, and risk monitoring. In this paper, we outline some tools to extend traditional "style" analysis to alternative managers employing dynamic trading strategies. Hopefully this would provide an analytical framework for managing portfolios with a wider diversity of styles than traditional managers employing buy-and-hold strategies.

Reference:

Brown, Stephen J., and William N. Goetzman. 1995. "Performance Persistence." *Journal of Finance*, 50, 679-698.

Brown, Stephen J., William N. Goetzmann, and Roger G. Ibbotson. 1996. "Offshore Hedge Funds: Survival & Performance 1989 - 1995." Working Paper, NYU Stern School of Business and Yale School of Management.

Brown, Stephen J., William N. Goetzmann, Roger G. Ibbotson, and Stephen A. Ross. 1992. "Survivorship Bias in Performance Studies." *Review of Financial Studies*, 5, 553-580.

Christopherson, J. 1995. "Equity Style Classifications," *Journal of Portfolio Management*, 21, 32-43.

Fung, William, and David A. Hsieh. 1996. "Global Yield Curve Risk." *Journal of Fixed Income*, 6, 37-48.

Fung, William, and David A. Hsieh. 1997. "Empirical Characterizations of Dynamic Trading Strategies: the Case of Hedge Funds," *Review of Financial Studies*, 10, 275-302.

Fung, William, and David A. Hsieh. 1997b. "The Information Content of Performance Track Records: Investment Style and Survivorship Bias in the Historical Returns of Commodity Trading AdvisorsCTA Survivorship Bias," *Journal of Portfolio Management*, 24, 30-41.

Fung, William, and David A. Hsieh. 1997c. "Is Mean-Variance Analysis Applicable to Hedge Funds?" Working Paper, Fuqua School of Business, Duke University.

Glosten, L., and R. Jagannathan. 1994. "A Contingent Claim Approach to Performance Evaluation," *Journal of Empirical Finance*, 1, 133-160.

Grinblatt, Mark, and Sheridan Titman. 1989. "Mutual Fund Performance: An Analysis of Quarterly Portfolio Holdings." *Journal of Business*, 62, 393-416.

Hlawitschka, W., 1994, "The Empirical Nature of Taylor-Series Approximations to Expected Utility," *American Economic Review*, 84, 713-179.

Jagannathan, Ravi, and Robert A. Korajczyk. 1986. "Assessing the Market Timing Performance of Managed Portfolios." *Journal of Business*, 59, 217-236.

Jensen, Michael C. 1968. "The Performance of Mutual Funds in the Period 1945-1964." *Journal of Finance*, 23, 389-416.

LeBaron, Dean. 1994. "A Universal Mode of Equity Style," *Journal of Portfolio Management*, 21, 85-88.

Lederman, J., and R. A. Klein. 1996. *Market Neutral: State of the Art Strategies for Every Market Environment*. Irwin Professional Publishing, Chicago.

Levy, H. and H. M. Markowitz, 1979, "Approximating Expected Utility by a Function of Mean and Variance," *American Economic Review*, 69, 308-317.

Malkiel, Burton. 1995. "Returns from Investing in Equity Mutual Funds 1971 to 1991," *Journal of Finance*, 50, 549-572.

Merton, Robert C., and Roy D. Henriksson. 1981. "On Market Timing and

Investment Performance II: Statistical Procedures for Evaluating Forecasting Skills." *Journal of Business*, 41, 867-887.

Sharpe, William F. 1992. "Asset Allocation: Management Style and Performance Measurement," *Journal of Portfolio Management*, 18, 7-19.

Trzcinka, C. 1995. "Equity Style Classifications: Comment", *Journal of Portfolio Management*, 21, 44-46.

Treynor, J., and K. Mazuy. 1966. "Can Mutual Funds Outguess the Market?" *Harvard Business Review*, 44, 131-136.

Footnotes:

1. This decomposition is analogous to the capital asset pricing model, in which the returns of a security is decomposed into a market return and an idiosyncratic return.

2. Mutual fund managers are compensated based on the amount of assets under management. Since mutual fund inflows have been going to the top rated funds, rated according to their respective benchmarks, managers have incentive to outperform their benchmarks.

3. Hedge fund managers and commodity trading advisors derive a great deal of their compensation from incentive fees, which are paid only when these managers make a positive return. In addition, a "high watermark" feature in their incentive contracts require them to make up all previous losses before an incentive is paid. Thus these alternative managers are called absolute return managers.

4. These factors are analogous to the factors in a multi-factor model of individual equities.

5. The eight asset classes are different from those in Sharpe (1992). Sharpe's asset classes are predominated weighted towards U.S. securities. He uses several U.S. stock returns --- large cap growth, large cap value, and small cap. Their differences are rather small, when compared to broader and more global asset classes, such as gold, emerging market equity, etc. Since these asset classes are important in the hedge fund universe, and since we need to restrict the number of asset classes in our regressions, we have selected the broader, more global, indices. In addition, we have omitted real estate and venture capital, because these assets are not important in mutual funds, hedge funds, and CTAs.

6. The results would not change if we add in municipal bond mutual funds after adding municipal bonds as a tenth asset class.

7. Categories #2 through 11, 13 through 17, 19, 25, 27, 28, 29, 32, 33, 34, and 36.

8. This is not to say that there exist no mutual funds which rotate frequently between asset classes, thus generating parameter instability in Sharpe's style regression. One would expect to fund market timing styles in "asset allocation" funds. Even in this category, the dominant style is a buy-and-hold mix of stocks and bonds.

9. See *Barron's* (Nov. 2, 1987 p. 35-36), *Forbes* (Nov. 9, 1992, p. 40-42), *Barron's* (May 17, 1993, p. 53), and *Futures* (Apr 1994, p. 24-28).

10. We omitted funds specializing in emerging markets, since there is limited opportunity to employ dynamic trading strategies in emerging markets. Emerging markets do not have sufficient liquidity to allow managers to get in and out quickly, and many have prohibitions against short sales. Above all, available performance history is sketchy. Since our sample of hedge funds have returns over different time periods, the factor analysis was conducted on 297 funds which had returns over a common 36 month period. We standardized the returns for each fund so that they all have mean zero and variance one. This removes differences in variances caused by leverage differences. (For example, two funds employing the exact same trading strategy but different leverage will have different return variances.) Principal components is performed on the standardized returns. The first five principal components

explain, respectively, 11.87%, 10.00%, 9.42%, 6.35%, and 4.93% of the cross sectional return variance.

11. We actually rotated the first five principal components slightly, to allow us to better interpret the data. The five "style factors" represent investible returns on five portfolios of hedge fund managers which closely replicate the five rotated factors. This is done as follows. For each factor, we form a portfolio using hedge funds/CTA pools which are correlated only to that principal component. The portfolio weights are chosen so that the portfolio returns have maximal correlation with the corresponding principal component. Short sales constraints are imposed since it is not possible to sell short hedge funds and CTA pools. The correlations of the five style factors to the corresponding principal components are all above 93%. We use the maximal correlation portfolio, rather than the optimal mean-variance tracking portfolio, because the principal components and the rotated factors are based on standardized returns, while the style factor portfolios are based on the actual returns.

12. We have investigated the stationarity of these style factors by dividing the data into two subperiods. Basically, the principal components are unaffected. However, the styles factors are somewhat affected, perhaps because traders have changed styles, or perhaps because of statistical variations.

13. We are aware of a number of trading strategies which are not captured by the 5 dominant style factors. There are short sellers who only short equities. There are also traders who specializes in spread trading, such as (i) warrants versus stocks, (ii) convertible securities versus stocks, (iii) the short end versus the long end of the yield curve, (iv) mortgage securities versus government securities, (v) interbank swaps versus government securities. These strategies do not show up as dominant styles, because there are only a small number of players in each strategy.

14. We add the IFC emerging market index because we omitted the hedge funds which invest in emerging market securities in the factor analysis.

15. Using annual returns, Brown, Goetzman, and Ibbotson (1997) found similar results in offshore hedge funds.

16. Since the three dynamic trading strategies exhibit nonlinear correlation with the 8 non-cash asset classes, it is picking up some of the Jensen's alphas when only the buy-and-hold strategies are used. See, for example, Glosten and Jagannathan (1994). The main difference between our approach and that of Glosten and Jagannathan (1994) is that the factor analysis does not pre-specify the underlying assets to which the dynamic trading strategies are related. The factor analysis could have picked up an important hedge fund/CTA investment style using an asset class which is statistically independent of the 8 non-cash asset classes. The fact that the important hedge fund styles are either linearly or nonlinearly correlated to the 8 non-cash assets indicates that this is not so. We could not have known this before the factor analysis was performed.

17. The 39 mutual fund dominant styles are typically normally distributed. The median kurtosis is 2.84, and the largest kurtosis is 5.81. In contrast, the 5 hedge fund style factors are substantially more non-normally distributed, having kurtosis of 3.22, 4.29, 2.64, 6.66, and 7.32.

18. Fung and Hsieh (1997c) showed that mean-variance analysis may be useful

in portfolio construction involving hedge funds but not risk management. This extends the results in Hlawitschka (1997) and Levy and Markowitz (1979) for mutual funds.

Table 1
Distribution of the Most Significant Asset Classes
Having Positive or Negative Signs

Asset Class	Mutual Funds >0	Mutual Funds <0	Hedge Funds >0	Hedge Funds <0
ED	0.83%	0.20%	1.96%	4.89%
GC	2.02%	0.00%	11.00%	0.73%
USEQ	51.09%	0.04%	10.76%	5.38%
NUSEQ	8.12%	0.00%	5.13%	3.42%
USBD	28.28%	0.16%	8.56%	1.22%
NUSBD	1.39%	0.00%	7.33%	1.22%
DOLLR	0.24%	0.32%	8.31%	1.71%
IFC	2.73%	0.00%	11.49%	1.47%
HIYLD	4.59%	0.00%	13.20%	2.20%

Notes:
ED: 1 month Eurodollar deposit.
GOLD: London p.m. gold.
USEQ: MSCI US equity index.
NUSEQ: MSCI Non-US equity index.
USBD: JP Morgan US government bond index.
NUSBD: JP Morgan non-US government bond index.
DLLR: FRB dollar index.
IFC: IFC emerging market index.
HIYLD: Merrill Lynch high yield corporate bonds.

Table 2
Percentage of Cross Section Variation Explained
By the First Five Principal Components
in the 37 Morningstar Categories

	Category	# of Funds	Principal Components #1	#2	#3	#4	#5	Style Regression of Prin Component #1 R^2	Significant Asset Class
1	Adj. Rate Mtg.	37	78%	13%	2%	1%	1%	53%	ED
2	Aggr Growth	52	77	4	2	2	1	57	USEQ
3	Asset Alloc	56	72	7	4	3	1	95	USEQ
4	Balanced	134	81	4	2	1	1	94	USEQ
5	Convert Bond	23	78	6	3	2	1	74	USEQ
6	Corp General	191	92	2	1	0	0	98	USBD
7	Corp Hi Qlty	123	92	1	1	0	0	99	USBD
8	Corp Hi Yld	72	83	4	2	1	1	58	USBD
9	Div Emerg Mkts	8	92	2	1	1	0	94	IFC
10	Equity-Inc	67	82	4	2	1	1	94	USEQ
11	Europe	19	85	4	2	1	1	82	NUSEQ
12	Foreign	124	76	12	2	1	1	95	NUSEQ
13	Growth	447	80	3	2	1	0	82	USEQ
14	Growth-Inc	262	82	3	2	1	1	96	USEQ
15	Gvt General	189	90	2	1	1	0	99	USBD
16	Gvt Mortgage	79	86	7	1	0	0	91	USBD
17	Gvt Treasury	48	90	4	1	0	0	95	USBD
18	Mult-Asst Glbl	27	58	24	5	3	1	88	GOLD
19	Mult-Sect Bond	23	83	5	3	1	1	89	USBD
24	Pacific	32	65	28	1	0	0	85	IFC
25	Small Company	176	75	5	2	1	1	56	USEQ
26	Sp. Comm	9	78	10	4	3	1	64	USEQ
27	Sp. Financ	13	81	8	3	2	1	62	USEQ
28	Sp. Health	13	84	5	2	1	1	47	USEQ
29	Sp. Metals	29	89	5	1	0	0	80	GOLD
30	Sp. Nat. Res.	21	68	15	3	2	1	75	NUSEQ
31	Sp. Real Est	7	76	17	3	1	0	28	NUSEQ
32	Sp. Tech	14	79	9	3	2	1	42	USEQ
33	Sp. Unaligned	16	58	9	6	5	4	75	USEQ
34	Sp. Util	35	85	6	1	1	0	73	USBD
35	ST World Inc.	29	47	23	9	7	2	51	DOLLR
36	World	66	80	4	3	2	1	90	NUSEQ
37	Worldwide Bond	71	52	21	8	4	2	80	IFC

Table 3
Identification of the Mutual Fund Principal Components: 1991-1995

	Category	# of Funds	Principal Component	Asset Class	Correlation Coefficient
1	Adj. Rate Mtg.	37	#1	None [a]	-
			#2	Two Year Notes	78%
2	Aggr Growth	52	#1	Russell 2000	93
3	Asset Alloc	56	#1	S&P 500	94
4	Balanced	134	#1	S&P 500	94
5	Convert Bond	23	#1	Merrill Convert Bd	97
6	Corp General	191	#1	SB Corp	99
7	Corp Hi Qlty	123	#1	JPM US Govt	99
8	Corp Hi Yld	72	#1	Merrill High Yield	94
9	Div Emerg Mkts	8	#1	IFC	95
10	Equity-Inc	67	#1	S&P 500	98
11	Europe	19	#1	MSCI Europe	97
12	Foreign	124	#1	MSCI World	88
			#2	MSCI Latin Amer	76
13	Growth	447	#1	Russell 2000	91
14	Growth-Inc	262	#1	S&P 500	98
15	Gvt General	189	#1	JPM US Govt	99
16	Gvt Mortgage	79	#1	SB Mortgage	95
17	Gvt Treasury	48	#1	JPM US Govt	96
18	Mult-Asst Glbl	27	#1	MSCI World	74
			#2	Gold	71
19	Mult-Sect Bond	23	#1	Merrill High Yield	92
24	Pacific	32	#1	MSCI Asia Ex Japan	90
			#2	Nikkei 225 in $	86
25	Small Company	176	#1	Russell 2000	95
26	Sp. Comm	9	#1	DJ Communications	81
			#2	None [b]	
27	Sp. Financ	13	#1	DJ Finance	96
28	Sp. Health	13	#1	DJ Medical/Biotech	82
29	Sp. Metals	29	#1	DJ Precious Metal	91
30	Sp. Nat. Res.	21	#1	DJ Energy	87
			#2	DJ Basic Material	71
31	Sp. Real Est	7	#1	NAREIT Index	94
			#2	None [c]	
32	Sp. Tech	14	#1	DJ Technology	84
33	Sp. Unaligned	16	#1	DJ Cyclical	92
34	Sp. Util	35	#1	DJ Utility	98
35	ST World Inc.	29	#1	JPM Emerg Mkt Bd	72
			#2	JPM Non US Bonds	74
36	World	66	#1	MSCI Europe	87
37	Worldwide Bond	71	#1	JPM Emerg Mkt Brady	76
			#2	JPM Non US Bonds	86

Table 3 (cont.)

Note:

a) This principal component corresponds to the three ASTRA funds (ASTRA Adj Rate Secs I, I-A, and II), which experienced large losses in Dec 94, Jan 95, and Oct 95.

b) This principal component corresponds to only one fund.

c) This principal component corresponds to two funds, Evergreen Global Real Estate Equity Y, and Templeton Real Estate Security I, in this category. This is perhaps because of their global nature, as opposed to the U.S. nature of the other REIT funds.

Table 4
Returns of Hedge Fund Style Factors
Across Different Market Environments: Jan 1991-Dec 1995
(in percent per month)

Environment Mean|S.D.	Sys/Div Mean|S.D.	Global/Mac Mean|S.D.	Value Mean|S.D.	Sys/FX Mean|S.D.	Distressed Mean|S.D.
Environment: US Eqty					
1 -2.82|0.29	1.62|0.99	-0.82|0.62	-1.98|0.61	1.45|1.26	1.56|0.38
2 -0.05|0.19	0.21|1.08	2.14|0.42	0.17|0.54	1.71|0.82	2.08|0.72
3 1.59|0.11	1.56|1.09	1.87|0.69	1.58|0.51	-0.77|0.51	1.72|0.47
4 3.04|0.12	0.31|1.36	1.42|0.29	3.74|0.88	1.91|1.70	1.56|0.36
5 5.13|0.59	1.51|1.91	1.67|0.44	5.19|0.80	0.50|1.55	1.86|0.53
Environment: Non-US Equity					
1 -5.16|0.42	1.60|1.29	0.50|0.55	-0.92|1.02	2.45|1.59	1.52|0.45
2 -1.77|0.22	1.05|1.29	1.25|0.75	1.84|0.70	-1.19|0.93	1.51|0.31
3 0.81|0.15	-0.82|0.89	0.90|0.42	1.88|0.70	0.00|0.70	2.33|0.62
4 3.35|0.19	1.49|1.25	1.85|0.54	2.42|0.81	-0.40|0.56	0.96|0.34
5 6.99|0.50	2.28|1.73	1.93|0.66	3.43|1.17	3.82|1.58	2.36|0.58
Environment: US Bond					
1 -0.95|0.18	0.07|0.96	-0.49|0.66	1.11|1.13	-1.18|0.70	1.00|0.42
2 0.21|0.07	0.03|1.04	1.42|0.67	1.95|1.10	-0.14|0.61	2.09|0.64
3 0.79|0.05	2.07|1.19	1.62|0.49	2.31|1.01	2.75|1.75	2.26|0.73
4 1.36|0.05	0.21|1.37	2.02|0.36	1.11|0.73	1.08|0.85	1.57|0.25
5 2.25|0.16	3.72|1.61	1.80|0.57	2.31|0.96	2.14|1.59	1.90|0.36
Environment: Non-US Bond					
1 -2.89|0.52	0.99|1.26	1.61|0.43	1.31|1.12	0.77|1.73	1.77|0.50
2 -0.11|0.11	-1.09|0.81	0.92|0.78	2.54|0.94	-1.24|0.29	1.72|0.55
3 1.05|0.07	0.84|1.34	1.14|0.60	0.90|0.91	0.27|0.40	2.38|0.76
4 2.12|0.11	1.96|1.13	1.07|0.67	1.37|0.73	0.46|0.88	1.62|0.42
5 4.52|0.49	3.39|1.61	1.63|0.54	2.67|1.17	4.40|1.60	1.33|0.20
Environment: US Dollar					
1 -3.33|0.27	3.55|1.61	0.81|0.50	1.53|1.14	5.58|1.28	1.35|0.20
2 -1.53|0.10	-0.69|1.26	0.14|0.81	1.85|1.00	-0.46|0.79	1.56|0.42
3 -0.34|0.08	0.57|1.04	0.95|0.40	1.94|0.73	-0.75|0.44	1.19|0.43
4 1.26|0.16	0.68|1.25	2.24|0.59	0.98|0.72	-1.04|0.49	2.63|0.60
5 4.48|0.58	1.26|1.18	2.29|0.43	2.34|1.22	1.47|1.73	2.14|0.66
Environment: Gold					
1 -4.06|0.45	0.16|1.49	1.27|0.63	2.44|1.10	0.74|1.60	0.86|0.35
2 -1.20|0.11	0.38|1.56	1.40|0.22	3.52|1.04	1.03|1.57	2.61|0.64
3 0.03|0.08	0.09|1.08	1.20|0.41	0.29|0.62	0.44|0.93	1.32|0.33
4 1.33|0.20	1.23|1.16	0.37|0.88	1.35|1.05	0.39|0.95	2.17|0.66
5 4.27|0.38	3.58|1.04	2.15|0.62	1.31|0.82	2.00|1.04	1.89|0.36

Table 4 (cont.)
Returns of Hedge Fund Factors
Across Different Market Environments

Environment Mean|S.D.	Sys/Div Mean|S.D.	Global/Mac Mean|S.D.	Value Mean|S.D.	Sys/FX Mean|S.D.	Distressed Mean|S.D.
Environment: IFC Emerging Markets					
1 -4.80|0.71	1.29|1.32	0.38|0.82	0.34|0.94	1.25|0.95	0.55|0.18
2 -1.59|0.19	1.77|0.77	0.81|0.55	1.01|1.07	2.42|1.22	1.44|0.33
3 0.56|0.14	1.14|1.02	1.17|0.42	2.23|0.77	1.46|1.40	2.08|0.41
4 2.76|0.22	0.70|1.48	1.47|0.41	1.57|0.74	-0.27|0.46	2.26|0.72
5 8.52|1.33	0.37|1.84	2.56|0.59	3.45|1.12	-0.42|1.61	2.38|0.55
Environment: High Yield Corporate Bonds					
1 -0.49|0.30	1.19|0.96	-0.98|0.58	-0.09|0.83	-0.22|0.63	0.36|0.22
2 0.80|0.05	0.47|1.05	2.17|0.58	1.63|0.81	-0.11|0.72	1.38|0.18
3 1.24|0.03	1.81|1.71	1.71|0.49	2.16|1.25	3.67|1.57	1.61|0.24
4 1.80|0.08	1.84|1.34	1.83|0.51	1.47|1.01	1.27|0.84	1.57|0.44
5 3.55|0.49	0.80|1.38	1.64|0.46	3.63|0.74	0.05|1.74	3.90|0.70

Table 5
Correlation Between Mutual Funds Principal Components and
Hedge Funds Principal Components: 1993-1995

	Mutual Fund Category	P.C.	Sys/Div	Global	Value	Sys/FX	Distressed
			Hedge Funds P.C.				
1	Adj. Rate Mtg.	2	0.16	0.19	0.11	0.04	0.38
2	Aggr Growth	1	-0.33	0.39	0.95*	-0.14	0.17
3	Asset Alloc	1	-0.08	0.54*	0.75*	-0.11	0.31
4	Balanced	1	-0.12	0.53*	0.78*	-0.12	0.30
5	Convert Bond	1	-0.16	0.52*	0.85*	-0.06	0.46*
6	Corp General	1	0.12	0.56*	0.28	-0.03	0.38
7	Corp Hi Qlty	1	0.12	0.53*	0.26	-0.03	0.36
8	Corp Hi Yld	1	0.02	0.53*	0.41*	0.05	0.54*
9	Div Emerg Mkts	1	0.09	0.66*	0.40	-0.25	0.36
10	Equity-Inc	1	-0.08	0.50*	0.71*	-0.07	0.30
11	Europe	1	-0.14	0.46*	0.59*	-0.14	0.28
12	Foreign	1	0.02	0.60*	0.56*	-0.07	0.36
		2	-0.09	0.24	-0.02	-0.35	0.09
13	Growth	1	-0.25	0.42*	0.94*	-0.14	0.22
14	Growth-Inc	1	-0.15	0.45*	0.81*	-0.11	0.24
15	Gvt General	1	0.11	0.54*	0.27	-0.03	0.34
16	Gvt Mortgage	1	0.09	0.50*	0.34	-0.02	0.39
17	Gvt Treasury	1	0.14	0.50*	0.17	-0.07	0.26
18	Mult-Asst Glbl	1	0.18	0.68*	0.62*	0.08	0.53*
		2	0.34	-0.16	-0.44*	0.36	0.13
19	Mult-Sect Bond	1	0.13	0.68*	0.44*	-0.03	0.47*
24	Pacific	1	0.19	0.58*	0.45*	-0.03	0.32
		2	-0.07	-0.20	0.03	0.31	0.13
25	Small Company	1	-0.30	0.37	0.95*	-0.13	0.17
26	Sp. Comm	1	-0.20	0.53*	0.81*	-0.13	0.27
27	Sp. Financ	1	-0.08	0.35	0.58*	-0.06	0.34
28	Sp. Health	1	-0.33	0.34	0.64*	-0.18	-0.17
29	Sp. Metals	1	0.29	0.39	0.30	0.21	0.44*
30	Sp. Nat. Res.	1	0.18	0.42*	0.56*	0.15	0.42*
		2	0.23	-0.26	-0.32	0.24	-0.15
31	Sp. Real Est	1	0.04	0.23	0.48*	-0.20	0.38
32	Sp. Tech	1	-0.35	0.19	0.89*	-0.07	0.15
33	Sp. Unaligned	1	-0.23	0.46*	0.89*	-0.09	0.38
34	Sp. Util	1	0.00	0.53*	0.37	-0.12	0.22
35	ST World Inc.	1	0.05	0.58*	0.12	-0.19	0.11
		2	0.23	-0.11	0.16	0.34	0.33
36	World	1	-0.05	0.60*	0.74*	-0.11	0.34
37	Worldwide Bond	1	0.29	0.75*	0.39	-0.04	0.35
		2	0.08	-0.15	0.20	0.41*	0.10

* Statistically significant at the 1% two-tailed test.

Figure 1: Distribution of R-squares Vs Asset Classes

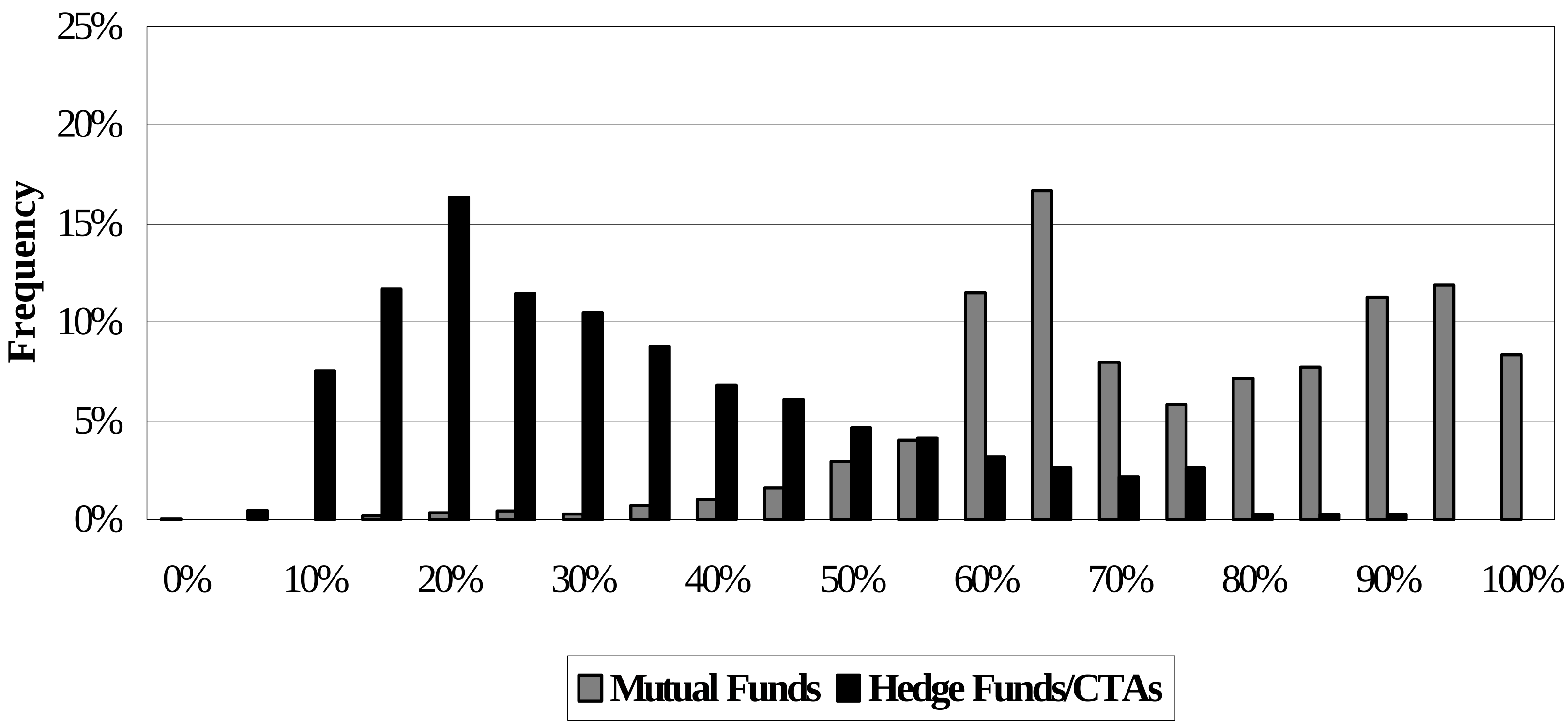

Figure 2: Systems/FX Following Style vs US Equity

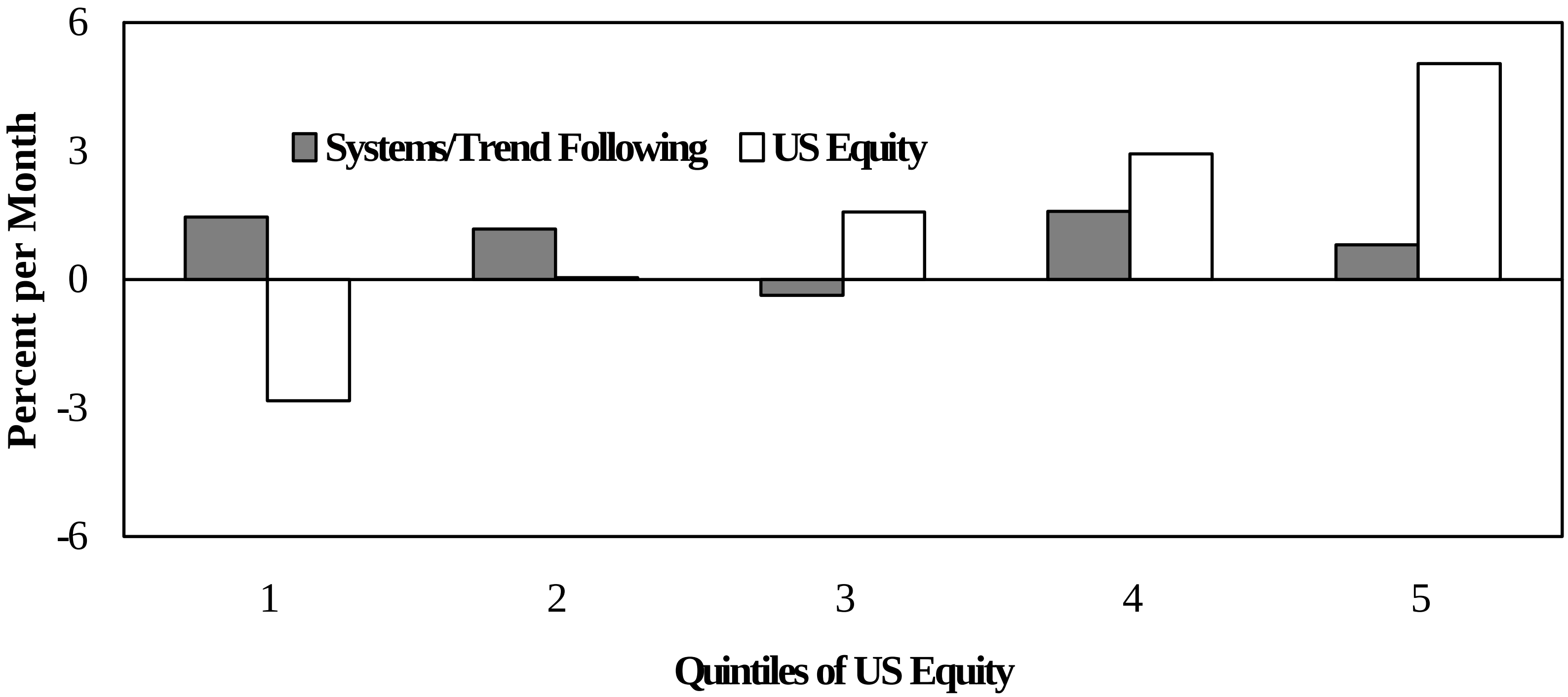

Figure 3: Systems/Diversified Style vs Gold

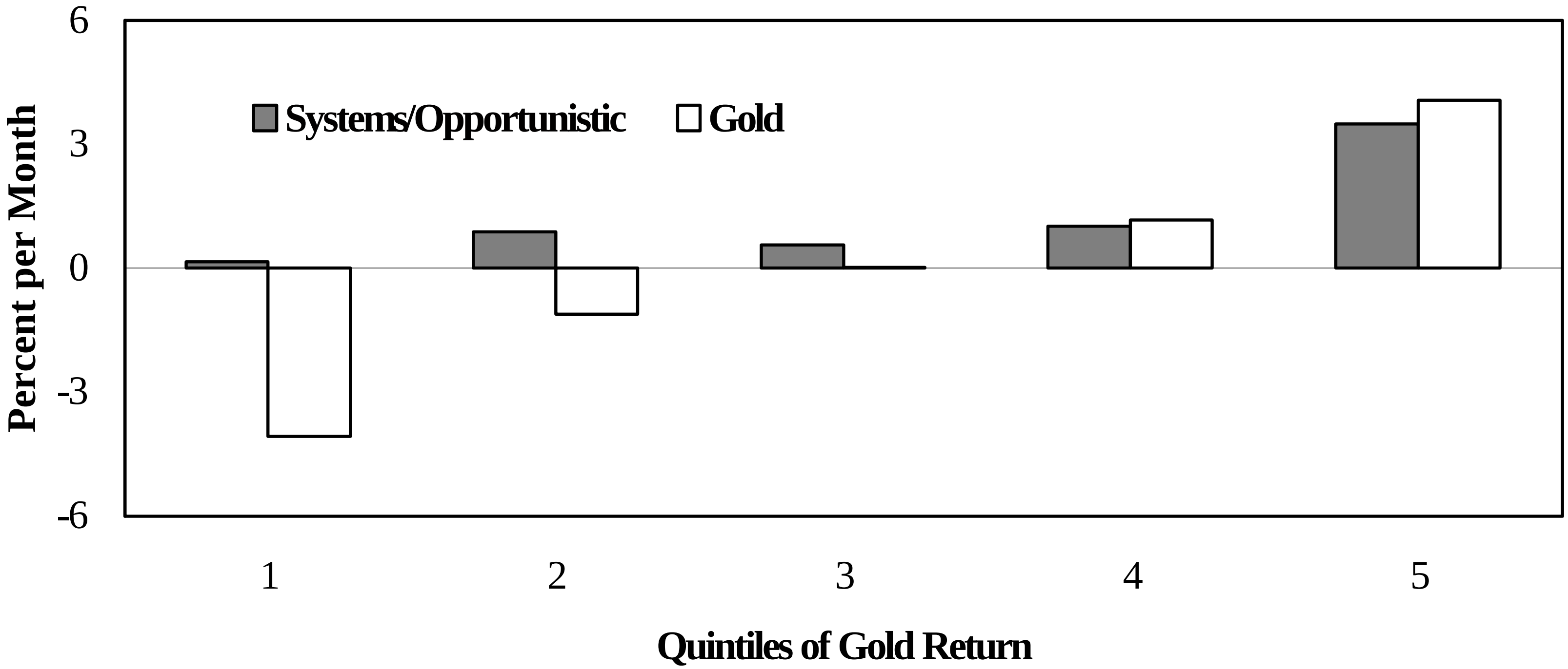

Figure 4: Global/Macro Style vs Dollar