Empirical Characteristics of Dynamic Trading Strategies: The Case of Hedge Funds

William Fung
Paradigm, LDC

David A. Hsieh
Duke University

This article presents some new results on an unexplored dataset on hedge fund performance. The results indicate that hedge funds follow strategies that are dramatically different from mutual funds, and support the claim that these strategies are highly dynamic. The article finds five dominant investment styles in hedge funds, which when added to Sharpe's (1992) asset class factor model can provide an integrated framework for style analysis of both buy-and-hold and dynamic trading strategies.

Sharpe (1992) proposed an asset class factor model for performance attribution and style analysis of mutual fund managers. The elegance of Sharpe's (1992) intuition was demonstrated empirically by showing 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. Based on this pioneering work, commercial software packages are now widely available for investors to analyze their asset allocation decisions and the "style mix" of their portfolios.

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The success of Sharpe's (1992) approach is due to the fact that most mutual fund managers have investment mandates similar to traditional asset managers with relative return targets. They are typically constrained to hold 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 their asset classes. Therefore they are likely to generate returns that tend to be highly correlated to the returns of standard asset classes.[1] Consequently, stylistic differences between managers are primarily due to the assets in their portfolios, which are readily captured in Sharpe's (1992) "style regressions."

In this article, we propose an extension to Sharpe's (1992) model for analyzing investment management styles. The objective is to have an integrated framework for analyzing traditional managers with relative return targets, as well as alternative managers with absolute return targets. These alternative managers tend to generate returns that are less correlated to those of standard asset classes. Consequently, the original Sharpe (1992) model must be modified to capture the stylistic differences of these alternative managers.

In particular we focus on 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.[2] 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. Accordingly, we extend Sharpe's (1992) asset class factor model to accommodate the differences between these alternative managers' approaches and those of traditional mutual fund managers.

Our work is based on the intuition that managers' returns can be characterized more generally by three key determinants: the returns from assets in the managers' portfolios, their trading strategies, and their use of leverage. In Sharpe's (1992) model, the focus was on the first key determinant, the "location" component of return, which tells us the asset categories the manager invests in. Our model extends Sharpe's approach by incorporating factors that reflect "how a manager trades" — the strategy component of return and the use of

[1] 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.

[2] Hedge fund managers and CTAs 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 requires them to make up all previous losses before an incentive fee is paid. Thus these alternative managers are called absolute return managers.

"leverage" — the quantity component of return. Adding new factors to Sharpe's (1992) model allows us to accommodate managers that employ dynamic, leveraged trading strategies. It is these additional factors that 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 relative return styles are considered, the extended model provides a framework for analyzing the asset mix decision with an absolute return target.

We apply our model to 3,327 U.S. mutual funds from Morningstar and 409 hedge funds/CTA pools from a unique database that has never been analyzed heretofore. As in Sharpe (1992), we find that mutual fund returns are highly correlated with standard asset classes. In contrast, we find that hedge fund managers and CTAs generate returns that 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 CTA pools. To capture this effect, we propose three additional "style" factors to Sharpe's (1992) model. This improves the model's performance significantly.

The article is organized as follows. In Section 1 we begin with an eight-asset class factor model similar to Sharpe's (1992). We call these asset or location factors. Updates to Sharpe's (1992) results for U.S. mutual funds are in Section 2. The results show that the eight-factor linear model provides satisfactory estimates of asset mix for a much wider sample of mutual fund managers, with only minor modifications.

In Section 3 we apply Sharpe's style regressions to hedge fund and CTA pool returns. Section 4 discusses the difference between location choice and trading strategy. Section 5 deals with the common styles in hedge funds and CTA pools. Section 6 comments on the issues of performance evaluation and survivorship bias. Section 7 addresses the implications of our findings and provides some concluding remarks.

1. An Asset Class Factor Model

We begin with the return on a portfolio of assets in period t:

$$R_t = \sum_j x_{jt} r_{jt}, \tag{1}$$

where x_{jt} is the weight on asset j during period t (from $t-1$ to t), and r_{jt} is the return on asset j in period t, $j = 0, \ldots, J$, and $\sum_j$ denotes the summation operator over all values of j. For convenience, the $j = 0$ asset is the risk-free asset. By assumption, the borrowing and lending rates are the same and equal the risk free-return. The number of assets (J) is assumed to be large. For example, there are more than 2,000 equities listed on the New York Stock Exchange alone. By the time we include foreign stocks, government bonds, corporate bonds, mortgages, commodities, foreign exchange, and so on, the number of assets is in the tens of thousands.

It is unwieldy to work with a large number of assets, particularly when many of them are highly correlated with each other. To reduce the task to a more manageable level, we assume that there is a factor structure for returns as in a standard arbitrage pricing theory (APT) model:

$$r_{jt} = \sum_k \lambda_{jk} F_{kt} + \epsilon_{jt}. \tag{2}$$

There are K systematic factors, F_{kt}, $k = 1, \ldots, K$; λ is the factor loading; and ϵ is the idiosyncratic returns. We assume that the systematic factors are exogenously specified and, following Sharpe (1992), we interpret the factors as "asset classes."

Using the factor model, we can rewrite the portfolio returns as

$$R_t = \sum_k w_{kt} F_{kt} + e_t, \tag{3}$$

where

$$w_{kt} = \sum_j x_{jt} \lambda_{jk},$$

$$e_t = \sum_j x_{jt} \epsilon_{jt}.$$

Instead of the portfolio's return being a weighted average of a large number of asset returns, it is now a weighted average of a small number of asset classes. Thus Sharpe's (1992) "style regression,"

$$R_t = \alpha + \sum_k b_k F_{kt} + u_t, \tag{4}$$

works well in capturing the styles of open-ended mutual funds, whose returns are highly correlated to those of standard asset classes. Sharpe (1992) calls this an asset class factor model.[3] In this article we use three equity classes: MSCI U.S. equities, MSCI non-U.S. equities, and IFC emerging market equities. There are two bond classes: JP Morgan U.S. government bonds and JP Morgan non-U.S. government bonds.

[3] Sharpe's choice of asset classes is more oriented toward U.S.-based funds, whereas we group assets into eight clases with a global emphasis.

For cash we use the 1-month eurodollar deposit. For commodities we use the price of gold. For currencies we use the Federal Reserve's Trade Weighted Dollar Index.[4]

We begin by updating Sharpe's (1992) results on U.S. open-ended mutual funds on a wider sample. The empirical result on mutual funds serves as a background against which the analysis of hedge fund and CTA pool returns can be compared.

2. Mutual Fund Performance Attribution and Style Analysis

We run Sharpe's style regression for 3,327 open-ended mutual funds in the Morningstar database (updated through December 1995), which have at least 36 months of returns. Figure 1 summarizes the distribution of the R^2s of the regressions. It shows that 47% of the mutual funds have R^2s above 75%, and 92% have R^2s higher than 50%. Figure 2 provides the distribution of the (statistically) most significant asset class in these regressions. Eighty-seven percent of mutual funds are correlated to two asset classes: U.S. equities and U.S. government bonds. In 99% of the funds, the coefficients of the most significant asset class are positive, and 52% of them are statistically greater than zero and not statistically different from one.

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 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." Consequently, *where* they invest, much less *how* they invest, is the key determinant of performance in mutual funds. It is this static nature of mutual fund styles that makes Sharpe's style regression well suited to analyze mutual fund performance, and perhaps more generally performance attribution of traditional managers with a relative return investment style.

The high level of correlation between mutual fund returns and asset classes indicates that mutual fund styles are basically buy-and-hold strategies utilizing various asset classes. There are two exceptions.

[4] The eight asset classes are different from those in Sharpe (1992). Sharpe's asset classes are predominantly weighted toward 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.

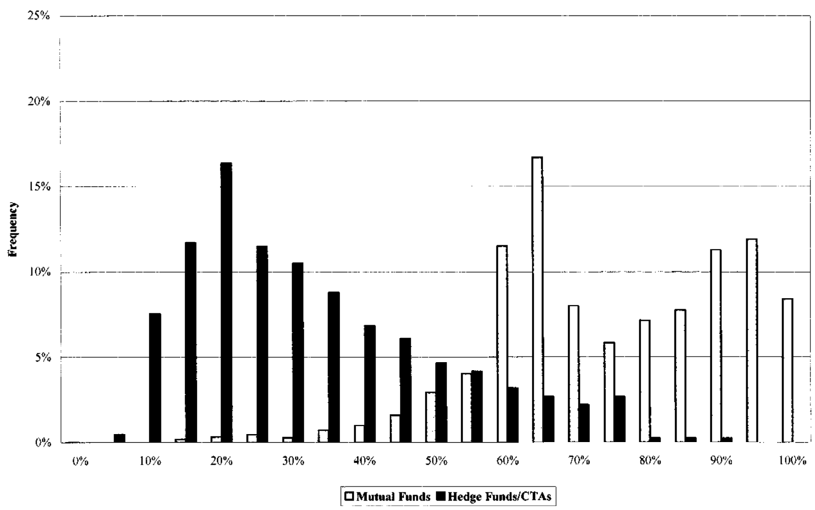

Figure 1
Distribution of R^2 versus asset classes

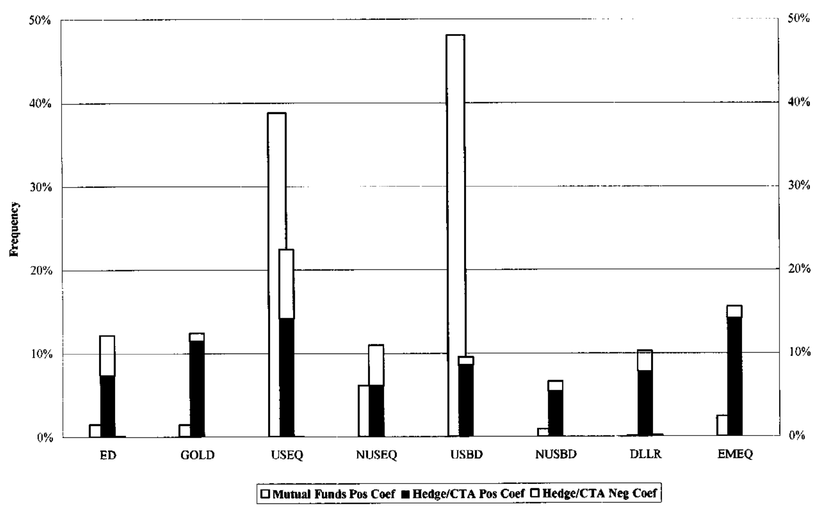

Figure 2
Distribution of most significant asset class

High yield corporate bond funds and municipal bond funds have low correlation with the eight asset classes. Given the number of high yield corporate bond funds, and the interest in distressed securities by institutional investors, the inclusion of a high yield corporate bond index is warranted. Given that municipal bond returns have a low correlation with governments, one may consider adding a municipal bond index for taxable investors to account for the distinction between taxable and tax-exempt returns.

3. Hedge Fund Performance Attribution

We now turn to hedge funds and CTA pools. 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 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 diversified futures pools in the 1980s, CTAs were limited as to what they could trade (commodities, commodity futures, and futures options). The globalization and expansion of all markets and the reduction in regulatory constraints 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 10 years the distinction between the two has become blurred as CTAs operate private investment partnerships with broad mandates in almost every financial market. In fact, a number of managers have both hedge funds and CTA pools. For the purposes of this article, hedge funds and CTA pools are treated as a single group of funds, referred to simply as "hedge funds."

We run Sharpe's style regression on the returns of 409 hedge funds. 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, pp. 62–64) estimates that there are somewhere between 1,000 and 2,000 hedge funds, with \$100–\$160 billion in assets under management at the end of 1994.[5] Although these numbers appear to be small in comparison to the mutual fund industry, which has upwards of 6,000 funds and \$2 trillion in assets, on a leveraged basis the positions taken by a large hedge fund often exceed those of the largest mutual funds.

[5] *Barron's* (February 20, 1995, pp. 23–26) listed 277 hedge funds with \$29.4 billion in assets under management as of the end of 1993. *Barron's* (February 19, 1996, MW74–MW75) listed 146 hedge funds that have a minimum of \$20 million in assets under management and a 2-year track record as of the end of 1995. These funds have a total of \$25.1 billion in assets under management.

Our universe consists of approximately 700 hedge fund programs and 240 CTA pools, with assets under management totaling some $80 billion. A major source of difficulty in constructing this universe 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 only limited assets for much of their existence. Also many managers have practically identical offerings listed under different names targeted at offshore investors. Additionally, there are "funds of funds," which are portfolios of hedge funds. In arriving at the universe of 940 funds, we have excluded duplicate funds and funds of funds. However, the assets of the duplicate funds (but not funds of funds) are included in the $80 billion in assets under management. The usable sample of funds falls to 409 because we require 3 years of monthly returns with at least $5 million in assets under management. Further details are provided in the Appendix.

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 75%, nearly half (48%) of the hedge funds have R^2s below 25%. Figure 2 shows that no single asset class is dominant in the regressions. For each asset class, we separately report the fraction of funds with positive coefficients (solid black bars) and negative coefficients (empty white bars). Unlike mutual funds, a substantial fraction (25%) of hedge funds are negatively correlated with the standard asset classes. In addition, in only 17% of hedge funds are the coefficients of the most significant asset class statistically greater than zero and not statistically different from one.

The evidence indicates that hedge funds are dramatically different from mutual funds. Mutual fund returns have high and positive correlation with asset class 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 for the differences between the results of hedge funds versus those of mutual funds.

4. 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, George Soros's Quantum Fund 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.[6] The fact that the Quantum Fund's returns have low correlation to the returns of asset classes ($R^2 = 40\%$) must be due to it's dynamic use of leverage and choice of asset exposure.

To see this, compare the style regression in Equation (4) and the definition of returns in Equation (3). 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: location choice and trading strategy. Location choice refers to the asset classes, that is, the F's in Equation (3), used by the managers to generate returns. Trading strategy refers to the direction (long/short) and quantity (leverage), that is, the w's in Equation (3), 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 one futures contract (i.e., buy and hold) will result in the style regression showing a coefficient of one on the S&P 500 index. If the manager leverages up to two futures contract, the regression coefficient will be two. Conversely, if he is short one 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 zero. In this example, the location is the U.S. 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 U.S. stocks. In the third case, the returns are negatively correlated with U.S. stocks. In the fourth case, the returns are uncorrelated with U.S. stocks.

This example illustrates how return is a function of the location choice as well as trading strategy. With the traditional managers (i.e., mutual fund managers), their emphasis centers on "where" to invest. Consequently, the observed returns on average resemble a buy-and-hold strategy with limited leverage. In other words, the w's generally lie between zero and one, with perhaps a modest adjustment due to stock betas. Our empirical results also indicate that time variation of the w's have limited impact on the return characteristics of the dominant styles, which are highly correlated to the asset class returns.

[6] See *Barron's* (November 2, 1987, pp. 35–36), *Forbes* (November 9, 1992, pp. 40–42), *Barron's* (May 17, 1993, p. 53), and *Futures* (April 1994, pp. 24–28).

This is not so with hedge funds. Their managers' trading strategies have weights (w) that are not constrained to be between zero and one. In principal, the w's can be between negative infinity and positive infinity. In practice, the w's are usually between -10 and $+10$. In addition, the managers can be opportunistic, so that the w's can and do change quickly. Their returns are not likely to be correlated to the asset class returns. These are dynamic trading strategies. This helps to explain why Sharpe's style regression, which is better suited to buy-and-hold returns on asset classes, is not appropriate for performance attribution when applied to hedge fund managers who use dynamic trading strategies.

5. Hedge Funds Style Analysis

In principle, Sharpe's style regression can be extended by adding regressors to proxy the returns of dynamic trading strategies. In practice, this is impossible to implement on monthly returns because there is a finite number of monthly returns but an infinite number of dynamic trading strategies. Instead we use factor analysis to determine the dominant styles in hedge funds. The idea is quite simple. If two managers use similar location choices and trading strategies, their returns should be correlated. Factor analysis can extract the dominant common styles, whether or not they are correlated to the asset classes.

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.[7] 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.[8]

[7] 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 that had returns over a common 36-month period. We standardized the returns for each fund so that they all had mean zero and variance one. This removes differences in variances caused by leverage differences. (For example, two funds empolying the exact same trading strategy but different leverage will have different return variances.) Principal components are 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.

[8] We actually rotated the first five prinicipal components slightly to allow us to better interpret the data. The five "style factors" represent investable 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 that 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

This quantitative method of defining investment styles should be contrasted with the qualitative method used by the hedge fund industry, which is based on the trading strategies described in the disclosure documents of hedge funds. By researching the disclosure documents of the funds in each style factor, we can associate our five style factors with some of these commonly used qualitative style categories used by the hedge fund industry to describe trading strategies: "Systems/Opportunistic," "Global/Macro," "Value," "Systems/Trend Following," and "Distressed." In the absence of generally accepted and well-defined "style names," we have attempted to adhere to commonly used terms to describe hedge fund styles in the investment community. We acknowledge that the terminology is imprecise. To the best of our knowledge, there has not been formal statistical analysis of these loosely defined qualitative styles, nor do we have well-established sources such as Morningstar for reference as in the case of mutual fund styles. Indeed, various industry sources frequently publish a much wider range of "style classifications." Often, reported returns for the same style category will differ across sources and the same manager can appear in different style categories depending on the source. Data vendors frequently regard information on hedge fund styles to be proprietary. One of the objectives of this article is to see if there are indeed style categories that are consistent with return data. We are of the view that it is what fund managers do, not what they say they do, that determines stylistic differences. However, for labeling purposes, it is helpful to generally adhere to industry conventions where possible.

The term "systems traders" is used to describe managers who use technical trading rules. Thus "Systems/Trend Following" refers to traders who use technical trading rules and are mostly trend followers, while "Systems/Opportunistic" refers to technically driven traders who also take occasional bets on market events relying on rule-based models. "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 and 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 microanalysis of the fundamentals. "Distressed" refers to managers who invest in companies near, in, or recently emerged from bankruptcy/corporate restructuring.[9]

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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.

[9] We have investigated the stationarity of these style factors by dividing the data into two subperiods.

In order to determine whether the five style factors are location choices or dynamic trading strategies, we apply Sharpe's style regression on the original eight asset classes plus high yield bonds to the five style factors. Two style factors are each correlated with a single asset class. The Value style has an R^2 of 70% against the eight 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/Opportunistic and Systems/Trend Following) have low R^2s (29% and 17%, respectively) and are not correlated to any of the asset classes.

The Global/Macro style is difficult to interpret. It has an R^2 of 55% and is correlated with U.S. bonds (coefficient: 0.84, t-statistic: 3.47), the U.S. dollar (coefficient: 0.46, t-statistic: 2.43), and the IFC emerging market index (coefficient: 0.15, t-statistic: 2.90). The correlation to U.S. 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 that 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 1 we divide the monthly returns of each asset class (excluding cash) into five "states" or "environments" of the world, ranging from severe declines to sharp rallies, by sorting the monthly returns into five quintiles. The average returns (and the associated standard errors) of that asset class, as well as those of the five style factors, are computed in each state of the world.

Basically the principal components are unaffected. However, the style factors are somewhat affected, perhaps because traders have changed styles, or perhaps because of statistical variations.

Table 1
Returns of hedge fund style factors across different market environments: January 1991–December 1995 (in percent per month)

Environment	Mean|S.D.	Sys/Opp Mean|S.D.	Global/Mac Mean|S.D.	Value Mean|S.D.	Sys/Trend 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
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

If a style uses a buy-and-hold strategy in a given asset class, then its return in the five states of the world should align with those in the asset class in a straight line. Using this method we identified that the Value style is akin to 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 its 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/Opportunistic style, it is most profitable during rallies in U.S. bonds, non-U.S. bonds, and gold, and during declines in the U.S. dollar. The Systems/Trend Following style is most profitable during rallies in non-U.S. equities and bonds, and during declines in the U.S. dollar. The Global/Macro style is most profitable during rallies in gold, the U.S. 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 the 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 1 shows that there exist nonlinear correlations between three style factors and some of the standard asset classes, which can give rise to optionlike payouts. Figures 3, 4, and 5 illustrate three of the most dramatic examples of optionlike payouts. Figure 3 shows that the Systems/Trend Following style has a return profile similar to a straddle (i.e., long a put and a call) on U.S. equities. Figure 4 shows that the Systems/Opportunistic style is like a call option on gold. Figure 5 shows that the Global/Macro style behaves like a straddle on the U.S. dollar.

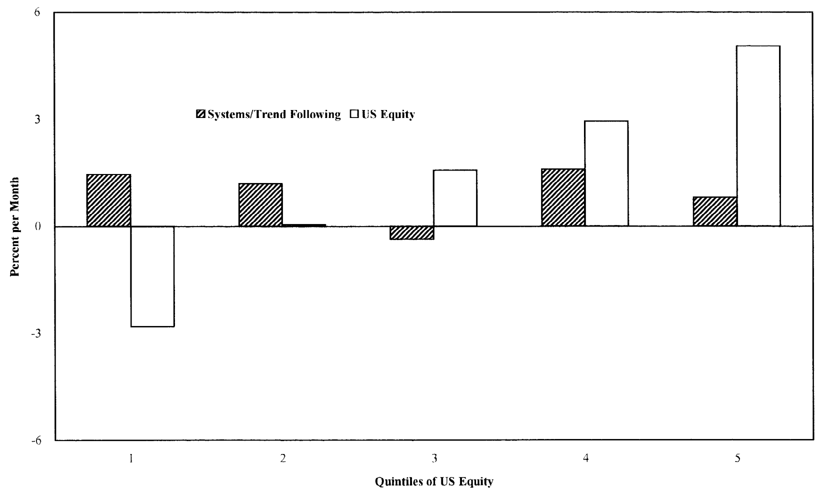

Figure 3
Systems/trend following style versus U.S. equity

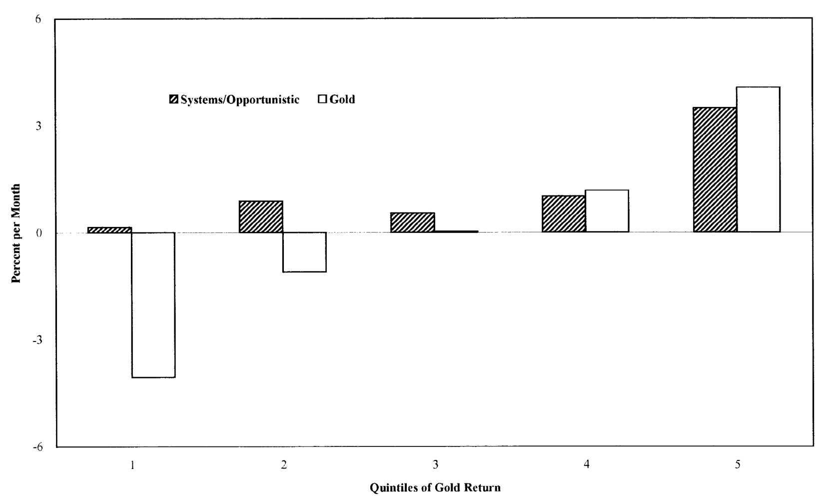

Figure 4
Systems/opportunistic style versus gold

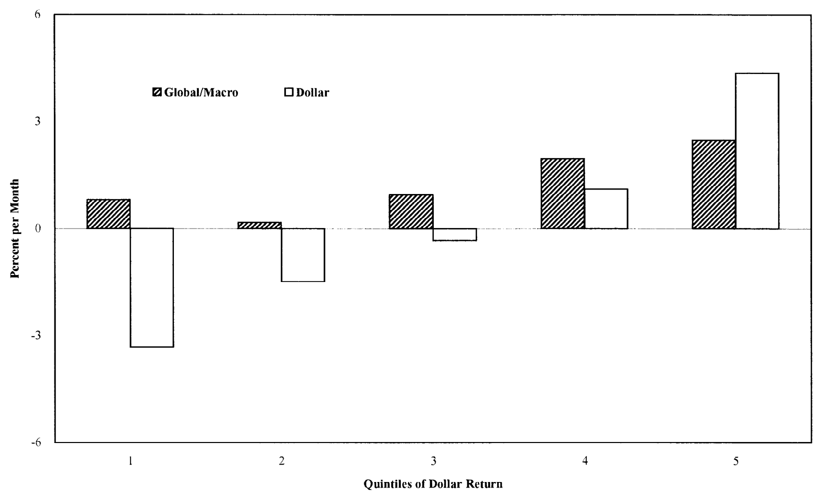

Figure 5
Global/macro style versus dollar

A few remarks are appropriate here. The terms "Systems," "Value," "Global/Macro," and "Distressed" are *qualitative* descriptors used by the hedge fund industry to describe the investment styles of hedge fund managers based on their disclosure documents. Here we are able to *quantify* the actual returns of these investment styles using factor analysis.

It is important to remark that 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.[10]

[10] We are aware of a number of trading strategies that are not captured by the five dominant style factors. There are short sellers who only short equities. There are also traders who specialize in spread trading, such as (1) warrants versus stocks, (2) convertible securities versus stocks, (3) the short end versus the long end of the yield curve, (4) mortgage securities versus government securities, and (5) interbank swaps versus government securities. These are typically arbitrage

Lastly, a brief remark on what has come to be known as "market neutral" strategies is in order. 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 this article. 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 4 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 criterion is to require a market neutral fund to be orthogonal to the five hedge fund styles as well as the traditional asset classes. Our analysis shows that three hedge fund style factors (i.e., Systems/Opportunistic, Systems/Trend Following, 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 U.S. equity and high yield corporate bonds, respectively. 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 may have directional exposure to extreme movements [see Fung and Hsieh (1996) for details]. Limiting the amount of tail exposure, as is done in Table 1, is also a good device to screen for market neutral funds.

6. Insights on Performance Evaluation and Survivorship Bias for Hedge Funds

Of the many differences between traditionally managed funds and hedge funds, two issues stand out: performance evaluation and survivorship bias, respectively. In this section, we contrast our findings with the literature on these two important issues reported on mutual fund managers.

In a simplistic setting, performance attribution and evaluation involve decomposing a manager's returns into the part that can be repli-

strategies that have gained popularity over the last few years. The limited history, together with the diversity in the strategies employed, makes it less likely for their return characteristics to converge into identifiable factors.

cated by standard asset baskets, or market indices, and the residual that is attributed to the manager's "skill." The purpose of this decomposition rests on the assumption that investors are only willing to reward a manager for superior performance that cannot be easily replicated. Applying this concept to mutual funds, Jensen (1968) used a single-factor model, regressing a stock mutual fund's returns (R_t) on market returns (R_{mt}) with α being the constant term:

$$R_t = \alpha + bR_{mt} + u_t. \tag{5}$$

Sharpe (1992) extended this to a multiple-factor model for the general mutual fund:

$$R_t = \alpha + \sum_k b_k F_{kt} + u_t. \tag{6}$$

The slope coefficients of the regression tell us the replicating static mix of asset classes that would capture the fund's performance. The constant term is used to measure the manager's average ability to generate returns beyond this static mix of assets. In this decomposition, $\sum_k b_k F_{kt}$ was referred to as "style," and $\alpha + u_t$ as "skill." The evidence in Figure 1, consistent with the mutual fund literature, shows that this regression works well for mutual funds, as indicated by the high R^2 values. However, this regression works very poorly for hedge funds because the R^2 values are very low. In the present context this would imply that mutual fund returns are generated primarily from static asset mix decisions, while hedge fund returns are generated primarily from "skill."

It is common practice to go beyond static asset class mixes in order to analyze the performance of mutual fund managers using simple trading strategies. This is achieved by further decomposing $[\alpha + u_t]$ in Equation (5) into "selectivity" (which has its genesis from the equity world for describing the ability to pick stocks) and "market timing" (the ability to predict market direction). The identifying assumption is that "selectivity" consists of idiosyncratic, diversifiable risks of individual stocks, while "market timing" consists of nondiversifiable, nonlinear payouts of asset class returns based on trading strategies. Empirically the decomposition is implemented by adding proxies for market timing strategies to Equation (5). For example, Treynor and Mazuy (1966) used the square of the market return to proxy for market timing ability, while Merton and Henriksson (1981) used an option payout on the market return. Glosten and Jagannathan (1994) also provided some justification for using selected option-index portfolios as additional factors to proxy for dynamic trading strategies.

The jury on the success of using a small number of proxies to pick up market timing abilities for mutual funds is still out. Jagannathan and Korajczyk (1986) pointed out that a separation between selectivity and market timing is not in general possible when managers can follow dynamic trading strategies or use options. While this problem of identification may not be too severe in mutual funds, because managers do not use dynamic trading strategies or options extensively, it is likely to be very severe in hedge funds. Furthermore, with the flexibility available to hedge fund managers, it is unclear whether the choice to bet on the currency market instead of stocks is to be interpreted as a "selection" decision or as a "market timing" decision. The only conclusive evidence we have is that the static asset mix component plays only a minor role in hedge fund performance in general. Consequently the important component of hedge fund performance is "skill." In a sense, our model proposes a more detailed decomposition of the "skill" set to further characterize performance differences among hedge funds.

A simplistic way of summarizing the difference between a manager that draws most of his return from the asset mix decision (the location decision) versus one that relies heavily on dynamic trading strategies is to think in terms of the intertemporal "deltas" to any given market. A manager that depends critically on the right location decision will have a slow-moving delta within a limited range (most mutual funds are limited in their use of short sales and leverage.) In contrast, a hedge fund manager can and will have deltas in orders of magnitude greater that can shift dramatically over very short intervals of time. 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 an R^2 of only 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 can be seen from Figure 6, which plots Quantum's daily net asset value per share versus the British pound/U.S. dollar exchange rate (measured in pounds per U.S. dollar). The inability of simple statistical procedures in picking up the correlation between Quantum and the pound means that the number of proxies needed to pick up very short-term dynamic trading strategies is virtually infinite. In the spirit of the present discussion, it is unclear whether this type of "event" return should be classified as "selectivity" or "market timing." On the face of it, it appears to be market timing, but then why not bet on the other currencies? Simply put, hedge fund returns are much harder to "explain" or replicate using simple trading rules.

It is the recognition of these difficulties that led us to add hedge fund styles to Sharpe's asset class factor model. These new styles are

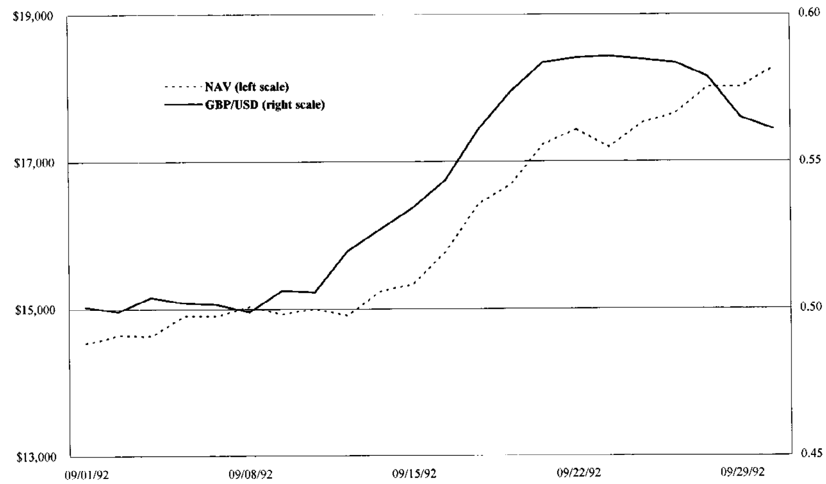

Figure 6
Quantum net asset value versus GBP/USD exchange rate, September 1992

analogous to the "market timing" proxies in the mutual fund performance evaluation literature. The good news is that these new styles are uncorrelated to asset class returns. The bad news is that they are correlated with market returns during extreme moves or tail events.[11] The exposure to tail events in asset markets is not diversifiable, which substantially complicates risk management. Furthermore, we emphasize the limitations in using these new styles in performance attribution. The factor analysis indicates that there are many niche styles in the hedge fund universe still unaccounted for. It is conceivable that, with such a heterogeneous population, performance attribution may ultimately require in-depth due diligence on a case-by-case basis.

Next we turn to the effect of survivorship bias on our empirical results. Here we need an estimate of the attrition rate in hedge funds. This turns out to be an exceedingly difficult task. Unlike mutual funds, hedge funds need not register with the Securities and Exchange Commission, nor does a hedge fund industry association exist that can document the entry and exit of funds. In short, it is almost impossible to know exactly how many funds existed as of a given point in time.

Given that the population of hedge funds is unknown, there are two ways to estimate an attrition rate. The first method takes a sample

[11] Some of the more dramatic losses in the so-called market neutral funds occurred during large "event" moves in the asset markets. This can be attributed partially to a failure of their risk management system to cope with the abrupt increase in the correlation between their positions in the market.

of currently existing hedge funds and tracks them going forward in time. This *prospective* method of estimating attrition rate can only be done as a future research project.

The second method to estimate the attrition rate is to go back in time to find all funds that existed at a given point in time, say December 1994, and determine how many did not survive until a later point in time, say December 1995. This *retrospective* method of determining the attrition rate is appropriate in mutual funds, since the population of mutual funds on both dates is known. As the population of hedge funds at any given date is unknown, one is tempted to estimate a retrospective attrition rate by taking the funds in a database with returns in December 1994 and see how many of them dropped out by December 1995. This procedure would yield a downward bias in the attrition rate.

To understand the bias of the retrospective attrition rate in a hedge fund database, one must understand the process and objectives in creating and maintaining a hedge fund database. Suppose there are N funds in the hedge fund population on December 1994 and A funds are in our database.

Assume that there are no new funds coming into the population. The attrition rate is d per year. At the end of 1995, Nd funds have exited the population and Ad funds have exited our database. If no funds were added into the database during 1995, the retrospective attrition rate would have been $d = (Ad)/A$. However, database vendors have an incentive to add "quality" funds into the database. In 1995 there are still $(N - A)(1 - d)$ funds which were not in the database. Suppose B of them are added to the database, along with their past returns. At the end of 1995, there are $A + B$ funds in the database with returns in December 1994, but Ad of them had dropped out by December 1995. The retrospective attrition rate would be given by $(Ad)/(A+B)$, which is a downward biased estimate of d by the factor $A/(A + B)$.

If we multiply the retrospective attrition rate by the adjustment factor $(A+B)/A$, we will have an unbiased estimate of the true attrition rate. Unfortunately we cannot calculate the adjustment factor $(A + B)/A$ because we do not know when a given fund was added to the database. But we can obtain an upper bound for the adjustment factor. It is reasonable to assume that the sampling rate of the surviving funds in 1995 is the same as that of the original sample in 1994, that is, $B/[(N - A)(1 - d)] = A/N$. This means $B = (N - A)(1 - d)(A/N)$. The adjustment factor, (A+B)/A, now becomes 1+(1-A/N)(1-d). As the adjustment factor is decreasing in A/N and d, its maximum is two, when $A/N = 0$ and $d = 0$. Thus doubling the retrospective attrition rate gives an upper bound of the true attrition rate.

A further complication arises when new hedge funds enter the population. Unlike the mutual fund industry, in which new "entrants" arrive without return histories, it is common practice in the hedge fund industry to expect new funds to come with a "track record" accumulated either over an incubation period prior to launching the fund or from their previous trading history with a financial institution. Typically, new funds are added to a database with a performance history. This will further bias downward the retrospective attrition rate.

In estimating the retrospective attrition rate, we define the population of hedge funds to be those that have operated for at least 3 years to avoid picking up new funds whose incubation period is typically less than 3 years. We examined 139 funds in the Paradigm database with returns in December 1994. To the best of our knowledge, at most, six funds had ceased operation by the end of 1995.[12] That represents a retrospective attrition rate of 4.3% in 1 year and a maximum upper bound of 8.6% for the true attrition rate.[13]

This estimate of the attrition rate in hedge funds is comparable to that in mutual funds. Grinblatt and Titman (1989) found an average attrition rate of 4.3% per year between 1974 and 1984 for mutual funds. Brown et al. (1992) found the average attrition rate to be 4.8% between 1977 and 1985, ranging from 2.6% in 1985 to 8.5% in 1977. The low attrition rate in hedge funds means that survivorship bias is unlikely to affect the result that hedge fund returns are uncorrelated with those of asset classes. Even if we added back the 8.6% of hedge funds that had exited the sample, and even if their style regression R^2's were 1.00, it would not dramatically change the distribution graphed in Figure 1.

Survivorship bias is unlikely to impact the number of hedge fund styles in the factor analysis. It is conceivable that survivorship bias in funds can result in survivorship bias in our style estimates, if the funds that exited the sample had the same style and no surviving funds had that style. We were able to determine that this did not occur by examining the funds that ceased operation in 1995. Based on their returns and their disclosure documents, we determined that the exiting funds did not come from the same style. Some were "systems" traders, while others were "niche" funds that fell outside the five dominant styles.

The broader and more interesting question is to what extent survivorship biases the returns of the styles extracted from factor analysis based on a sample of surviving funds. Grinblatt and Titman (1989)

[12] Four have ceased operations and the status of two more are unknown.

[13] The authors are pursuing a project with Tass Management to study entry and exit in the Tass databases in conjunction with the behavior of assets under management going back a few years. Preliminary results on CTA funds indicate that the survivorship bias is similar to that in mutual funds.

found that survivorship biased upward mutual fund returns by 0.50% per year. For hedge funds, it is unclear if survivorship biases their returns upward or downward. The reason has to do with the "life cycle" of hedge funds when assets under management interact with performance. A small fund that has good performance attracts assets. Unlike mutual funds, hedge fund strategies have limited capacity. This means that, over any given time period, performance may well decline when a fund's size gets too large. If it subsequently experiences poor performance, assets begin to flow out. In some cases the fund can return to some equilibrium level of assets under management and the fund "survives." However, there will be other cases where assets shrink so much that it is no longer economical to cover the fund's fixed overhead and the manager closes it down and the fund "exits." This can occur even if the returns during the latter stage are above the surviving funds' average, but compares poorly to its peers in the same trading style. In other words, funds exiting the sample can easily have returns higher than the population average of the survivors.

There are less common, but nonetheless anecdotal, examples where an exiting fund has better performance than the population average. It is frequently the case that with private investment pools like hedge funds, acceptable performing funds can go unnoticed for prolonged periods of time. After all, one would hardly expect marketing to be high on these traders' list of skills. In these cases the managers can get impatient and simply close down the business and return to trade for a financial institution. Another example is with successful funds. There are successful funds that have reached their perceived capacity and have stopped accepting new investments.[14] At this stage, there is no incentive to report their performance to third parties outside of their own investor base. In other words, funds can drop out of a data vendor's universe simply because they have chosen not to report their otherwise stellar performance.

Other reasons unrelated to poor performance may cause a data vendor to cease reporting a fund's performance. Tass Management, for example, delists a fund to avoid any liability in potential reporting errors. This can happen to funds with above average returns as well as below average returns. Ultimately one must recognize that hedge fund managers are a heterogeneous lot, thus survivorship bias needs careful interpretation. It is unclear to us that survivorship necessarily puts an upward bias on observed mean returns. More carefully conducted empirical work is needed.

[14] The fact that George Soros's Quantum Fund is closed to new investors and has been distributing assets to investors since 1992 illustrates our point that even large macro funds must limit their size in order to continue to turn in a good performance.

7. Implications

In this article we analyze investment styles using mutual fund returns from Morningstar and hedge fund returns from a dataset that has never been subjected to formal analysis. We have shown that there are 12 important investment styles — buy-and-hold in nine asset classes (our eight original asset classes plus high yield corporate bonds) and three dynamic trading strategies. There are a number of implications.

In terms of performance attribution and style analysis, we provide an extension to Sharpe's style factor model. A style regression using these 12 variables should produce reasonably high R^2 values 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.[15]

The results of our article also have implications for portfolio construction. An investor can now allocate across both location choices and trading strategies. There are, however, complications arising from the use of dynamic trading strategies that do not exist under a static buy-and-hold type of trading strategy.

For the portfolio that 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% U.S. equities and 40% U.S. bonds has an annualized mean return of 11.55% and an 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 nonquadratic preferences, it is unclear whether mean-variance tools are appropriate for portfolio construction and

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[15] Since the three dynamic trading strategies exhibit nonlinear correlation with the eight noncash 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 prespecify 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 that is statistically independent of the eight noncash asset classes. The fact that the important hedge fund styles are either linearly or nonlinearly correlated to the eight noncash assets indicates that this is not so. We could not have known this before the factor analysis was performed.

risk management because some of the style factors involving dynamic trading strategies exhibit nonnormal distributions.[16] 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 nonquadratic preferences is a subject beyond the scope of this article.[17] 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 optionlike payout profile (similar to that of a "portfolio insurance" strategy) is generally not available from traditional managers. For example, consider Table 1 under the column "Systems/Opportunistic." This particular style underperformed seven of the eight noncash 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 four equity and bond asset classes. Thus blending the three dynamic trading strategies to traditional managers can provide some downside protection.

For example, take an investor who is highly averse to negative returns. The traditional 60% stock/40% bond portfolio suffered a maximum monthly loss of 5.93% during the 1990–1995 period. If 50% of that portfolio is replaced by an equally weighted portfolio of the three dynamic trading strategies, the maximum monthly loss would be reduced to 2.87%. For this investor, the latter portfolio would strongly dominate the traditional 60% stock/40% bond portfolio. In other words, it is possible to achieve an optionlike 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. Hedge fund managers have a great deal of

[16] The five hedge fund style factors have kurtosis of 3.22, 4.29, 2.64, 6.66, and 7.32, with a standard error of 0.63. This indicates that at least three of the five style factors are not normally distributed.

[17] In a recent article Hlawitschka (1996) extended the Levy and Markowitz (1979) article to examine the use of mean-variance models when options are present in the opportunity set. Although the results generally favor the mean variance approximation, the dataset used is limited. Given that historical returns from a wide cross section of dynamically managed portfolios were generally unavailable to these previous studies, the present dataset could provide useful input to address the question of portfolio selection with nonquadratic preferences.

freedom to generate returns that are uncorrelated with those of asset classes and traditional fund managers. This style 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: U.S. equities, U.S. bonds, and non-U.S. 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/Trend Following and Systems/Opportunistic 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-U.S. 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.

Overall the empirical results show that style diversification can be achieved by blending the traditional “relative return” investment approach to the “absolute return” investment styles. However, there is also an implicit cost. Conceptually it is the flexibility in the absolute return managers’ investment mandate that allows them to deliver an uncorrelated set of returns. But “freedom” has its price. It is important for an investor using managers with dynamic trading strategies to take extra 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 article we outlined some tools to extend traditional “style” analysis to alternative managers employing dynamic trading strategies. Hopefully this will provide an analytical framework for managing portfolios with a better diversity of styles.[18]

[18] A diskette containing the monthly returns of the 409 hedge funds used in this study will be made available for academic research purposes for a nominal fee of $15.00 U.S. from Duke University. Please send all requests to David A. Hsieh. Each academic researcher should write, on the letterhead of his/her academic institution, a statement stating that the data will be used only for academic purposes, that the data will not be redistributed to other parties, and that the work will acknowledge *The Review of Financial Studies*, AIG, Tass, and Paradigm LDC for making the data available. Updates of the data, which came from Tass Management, can be purchased

Data Appendix

Generally hedge funds are private investment pools structured in such a way as to minimize regulatory and tax impediments in operating the strategy. Consistent with this objective, most funds have adopted a low profile and often secretive posture. This is especially so with some of the offshore funds catering to non-U.S. domiciled investors. Not only are performance statistics not readily given out, periodic returns are only legally released via the offshore administrators, even for investors in the funds. Similarly, marketing materials are only available on a very restricted basis. This is particularly so because some of the largest fund managers have no interest in increasing the assets under management. In contrast, data on CTAs who are regulated by the CFTC are much more readily available. Unfortunately pools of capital managed by CTAs are much smaller in comparison to hedge funds. For example, one of the largest CTA's is John W. Henry & Co., managing a little under $2 billion. In comparison, George Soros's Quantum Fund controls well over $8 billion in assets. The hedge fund universe is where a much wider range of dynamic trading strategies are used, as opposed to the CTA universe which mostly consists of technical traders operating in the commodity and financial futures markets. Consequently the more interesting set of the data is also the harder set to assemble.

Our universe of hedge funds and CTA pools consists of 250 hedge funds from Paradigm LDC (with assets under management of $44.6 billion), 451 hedge funds from Tass Management (with assets under management of $27.7 billion), and 239 CTA pools from Tass Management (with assets under management of $6.7 billion).

Paradigm LDC is the general partner to Paradigm LP, a Cayman Island–based consulting firm specializing in hedge fund portfolios. Paradigm's database has been assembled through information on investments made by its clients, as well as direct contacts with hedge fund managers it follows as potential investments. Tass Management is one of the few database vendors specializing in supplying data on hedge funds and CTAs. Tass obtains its data directly from fund managers.

To construct the universe of funds used in this article we carefully excluded similar funds offered by the same management company. Some of these are created for regulatory reasons, while others are created because of investor demand. Most of these funds within the same family are based on similar strategies with highly correlated returns. Without filtering out such duplications, they would overweigh

directly from Tass. However, Paradigm LDC will not be able to supply updates.

certain style participation and bias our analysis. Excluded also are funds of funds, which invest in other hedge funds and are not central to our style analysis.

From this universe we extracted funds that have at least 3 years of monthly returns and at least $5 million in assets under management. Excluding the small funds is important. Frequently CTA databases include funds that manage as little as a few hundred thousand dollars employing very high leverage with wildly volatile returns. These funds are, for all practical purposes, not viable investment targets for professional investors. As a result, the usable database has 409 funds consisting of 168 hedge funds and 89 CTA pools from Tass and 152 hedge funds from Paradigm LDC. Each fund is identified by a fund number, followed by its latest 36 monthly returns. Another point to note is that nearly all of these returns are adjusted for ex post audit changes. Frequently a fund's monthly returns are revised after year-end audit. We have made all of the adjustments known to us to date.

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