Asset-Based Style Factors for Hedge Funds

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Asset-based style factors link returns of hedge fund strategies to observed market prices. They provide explicit and unambiguous descriptions of hedge fund strategies that reveal the nature and quantity of risk. Asset-based style factors are key inputs for portfolio construction and for benchmarking hedge fund performance on a risk-adjusted basis. We used previously developed models to construct asset-based style factors and demonstrate that one model correctly predicted the return behavior of trend-following strategies during out-of-sample periods—in particular, during stressful market conditions like those of September 2001.

An extensive literature has documented that hedge fund returns differ from the returns of traditional asset classes. But investors looking for alternative return characteristics in hedge funds must be concerned about the consistency between historical and future hedge fund returns. To go beyond relying on historical hedge fund performance repeating itself, one needs to answer the key question about hedge fund performance: What is the wind behind this sail? After all, hedge fund managers typically transact in asset markets similar to those used by traditional managers. How then do hedge fund managers deliver return characteristics that are different from the returns of the very asset classes they are trading? We believe the answer to this question will emerge from understanding the value of hedge fund strategies and how they can be directly related to traditional asset-class benchmarks. In this study, we propose to use the term "asset-based style factor" to denote the returns of trading strategies in traditional asset classes that can explain the returns of a group of hedge funds.

To understand this idea, consider trend-following hedge funds. We previously reported that trend-following hedge funds have performance characteristics that resemble straddles on the equity market (Fung and Hsieh 1997a). They deliver positive returns when the equity markets are at extremes—both up and down. This return profile is attractive for diversification purposes.

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To verify that this phenomenon is not merely an empirical coincidence, we recently used traded options to explicitly model the unusual return characteristics of trend-following hedge funds (Fung and Hsieh 2001). We showed that the returns from trend-following strategies can be replicated by a dynamically managed option-based strategy known as a "lookback option." A perfect trend follower is one that buys an asset at the low and sells it at the high over a given investment horizon. This pattern is the payout of a lookback option on that asset. The return of the strategy is, therefore, the payout of the lookback option less the option premium. Individual trend-following strategies, depending on the details of their models, will capture some fraction of the perfect trend-follower's payout from the option strategy.[1]

The return of this option-based replication strategy has been shown to have a high degree of explanatory power for hedge funds that adopt a trend-following style (Fung and Hsieh 2001). These results demonstrate that the unusual return characteristic of trend-following funds is a systematic consequence of a broad class of trend-following strategies. Thus, we can consider lookback options to be an asset-based style factor for trend-following hedge funds. In addition, the model can be applied to compute the manager's alpha over and above the expected return of a class of complex hedge fund strategies that cannot be directly observed.

Another example of an asset-based style factor for hedge funds can be found in the work of Mitchell and Pulvino (2001). They modeled the return to merger arbitrage funds by using announced transactions from 1963 until 1998 to construct the return of a specific merger arbitrage strategy.

The purpose of the study reported here is to persuade readers that there are systematic reasons why hedge fund strategies offer unusual and diversifying return characteristics for a portfolio of traditional assets by casting the analysis in a broader framework.[2] Beyond the recent research on trend-following strategies and merger arbitrage strategies, future research should uncover explicit links between other hedge fund strategies and observable asset returns. Through these links, the myriad of hedge fund styles may eventually be expressed in the form of a simple, unifying model of familiar asset classes in the spirit of Sharpe's (1992) style model for mutual funds.[3]

Style Model

Ideally, a fully specified style model for hedge funds would look like

$$R_t = \alpha + \sum_k \beta_k SF_{k,t} + \varepsilon_t, \tag{1}$$

where R_t is a fund's return at time t, the $SF_{k,t}$ variables are the style factors, the β_k variables are the factor loadings, and ε_t is the residual.

The Role of Hedge Fund Style Factors. A model such as Equation 1 cannot be applied to hedge funds without identification of the style factors. In Equation 1, the manager's alpha is expressed relative to a set of hedge fund style factors (the $SF_{k,t}$ factors). The betas of the factors reveal the manager's capital allocation to each style factor, which in the case of hedge funds, also reflects the degree of leverage the fund uses. For example, consider the application of such a model to Long-Term Capital Management. Was the bet at LTCM on an unusual set of hedge fund trades, or was it a highly levered bet on familiar trades? From the numerous reported accounts of the LTCM episode, what led to the firm's demise was the betas (or leverage). Nothing about the strategies LTCM used—bond basis, long–short equity, risk arbitrage, and volatility mean reversion—was inherently unsound.[4] But LTCM may have had double-digit betas with respect to the underlying style factors. The key point is that the failure of LTCM does not imply the failure of the strategies it used, and it certainly does not imply a systemic failure of all hedge fund styles. It was an overly leveraged investment style that failed. A model like Equation 1 makes this point explicit.

Given the hedge fund style factors, Equation 1 can help quantify the effect of placing investments with more than one manager with a similar style (a popular strategy). Two managers using an identical set of strategies can differ in important ways. First, their use of leverage can be different. The result will be differences in their betas. Second, the efficiency of their trade executions can differ.[5] This divergence will show up in their alphas. Third, each manager's choice of securities to implement the strategy can be different. For example, some funds specialize in mergers and acquisitions in a specific industry group. This difference will affect the managers' alphas and betas. Overall, Equation 1 provides a framework for quantifying the degree of diversification in a hedge fund portfolio in terms of its exposure to various hedge fund style factors.

Finally, the style factors required by Equation 1 can be applied to manage the risk of hedge fund portfolios. Take the example of calculating the value at risk of a hedge fund investment. Conventional measures of VAR applied to hedge fund positions can be misleading because hedge fund positions are typically not static. In addition, applying conventional VAR tools to hedge fund returns is fraught with difficulties because hedge fund returns tend to be reported at monthly intervals and generally do not have long histories. Using asset-based style factors allows an analyst to make use of data sets with much longer histories. In addition, asset-based style factors can be used to analyze "what if" scenarios. The asset-based style factors provide a *qualitative* assessment of the risks a hedge fund investment is exposed to beyond the *quantitative* risk measures that conventional statistical tools provide.

Constructed from market prices, asset-based style factors are directly observable and can be used to benchmark hedge fund performance on a risk-adjusted basis. As performance benchmarks, asset-based style factors have the desirable properties of being transparent and investable.

Applying Equation 1 to hedge funds, however, is not straightforward. One problem is that hedge fund style factors are likely to be substantially different from those Sharpe used. Hedge fund returns are *intended* to be alternatives to the returns of traditional asset classes and have been found to have low to insignificant betas (see, for example, Fung and Hsieh 1997a, Schneeweis and Spurgin 1998, and Liang 2000).[6] To extend Sharpe's model requires style factors that explain hedge fund performance and have return characteristics that can be directly related to the returns of traditional asset classes. We need a small set of factors whose returns can be measured by using observed prices of traditional assets (and their derivatives); these factors are the asset-based style factors.

Classifications of Hedge Fund Style Groups. Existing methods for defining hedge fund styles focus on peer-group-based style factors or return-based style factors.

- *Peer-group style*. To help investors understand hedge funds, consultants and database vendors group the funds into categories based on managers' self-disclosed strategies (i.e., how they trade and leverage securities and derivatives positions) and locations (i.e., which securities and derivatives positions are used). Averages of the returns of the funds in each group are reported as style factors. We refer to these group averages as "peer-group-based style factors."

The objective of the peer-group approach is to capture the performance characteristics of funds following similar strategies. Although this first step to understanding the myriad of styles (i.e., strategy and location pairs) in the hedge fund universe is useful, in the absence of a well-formulated model of hedge fund styles, the allocation of funds to peer (or style) groups is largely judgmental and can be *ad hoc*. Periodically, curious performance differences emerge between similar-sounding style groups.[7]

Without a model to discern meaningful differences in performance, when suppliers of peer-group-based style factors are confronted with inconsistent performance results, they tend to increase the number of style groups. The result is a proliferation of hedge fund styles.

Moreover, over the years, the value of a stable stream of returns through different market cycles has attracted hedge fund managers to multistrategy approaches (despite the economy of scale in research and development to support similar strategies). This tendency increases the difficulty in identifying peer-group-based style factors.

In addition, with peer-group-based style factors, only two types of information on the hedge funds in each group are available—a qualitative description of the strategies and the historical return average of the group. In other words, providers of the peer-group-based style factors (or indexes) state briefly "here's what they do" and "this is what investors got" over some historical period.

The lack of an analytical framework to support the construction of peer groups leaves a number of questions unanswered (see Brittain). In addition, without a model to relate the criteria used to form groups of hedge funds to the reported return characteristics, a number of biases in measuring returns can occur (see, for example, Fung and Hsieh 2000, 2002 and Liang).

Assessing peer groups of hedge funds is much more difficult than assessing mutual fund peer groups. First, mutual fund strategies are predominantly long only. Location—where a mutual fund invests within the asset class—dictates style.[8] Second, mutual fund positions are a matter of public record.[9] Third, although the returns of mutual fund peer groups are affected by survivorship bias, a large body of research literature (Malkiel 1995, for example) can help investors deal with this problem. Finally, mutual funds rarely transact in OTC or private markets.

- *Return-based style*. Fung and Hsieh (1997a) used the idea that managers having the same style will generate correlated returns. They applied principal components and factor analysis of hedge fund returns to extract style factors. We call these principal components "return-based style factors."

The methodology adopted by Fung and Hsieh (1997a) is motivated by four factors. First, statistical clustering of funds' returns should approximate the common risk–return characteristics of the strategies they use. Second, to arrive at a linear style model like that of Sharpe (1992), the inherent return nonlinearity from hedge fund strategies is subsumed in the returns of the estimated factors.[10] This process, in turn, allows for a linear combination of these factors to be used to explain hedge fund styles. Third, the estimated return factor statistically proxies the return commonality among hedge funds, which can then be compared with the out-of-sample qualitative self-description of the funds' strategies to interpret the factors. This method provides a consistency check on not only what hedge funds say they do but also what they did do compared with other funds within the same cluster. Fourth, a principal components analysis is most likely to reduce the number of factors down to a manageable and orthogonal set. This result will lessen the problem of style proliferation and double counting.

A few caveats on the results in Fung and Hsieh (1997a) need to be noted. First, their methodology was targeted at explaining cross-sectional variation of hedge fund returns; therefore, they offered little insight into the dynamic behavior of hedge fund returns over time. Second, in the hedge fund sample used in Fung and Hsieh (1997a), a substantial amount of cross-sectional return variation remained that the main factors could not explain.[11] Third, a formal model for identifying the empirically generated style factors needs to be developed.[12]

The Problem. For a style factor to attain the level of information content of traditional asset indexes (as used in Sharpe's model), two properties are essential. First, complete transparency must characterize the way the factor returns are derived. Second, the performance history must be long enough to generate reliable statistics. Neither property is present in peer-group-based or return-based hedge fund style factors.[13] However, asset-based style factors can satisfy both properties.

Asset-Based Style Factors

To clarify what we mean by asset-based style factors, we first define and make distinctions among four terms—strategy, location, style, and style factor. *Strategy* is a description of how the long and short security positions (and their derivatives) are traded and levered to reflect the investment objective. *Location* is a statement of which assets the strategy is applied to. *Style* refers to a strategy and location pair. And *style factor* refers to a main style whose characteristics are common to many similar styles.

A comparison with familiar mutual fund styles helps explain the differences between these terms. In the mutual fund literature, a standard style would be something like small-capitalization/value stocks or large-capitalization/growth stocks. When styles are described in this way, the concept of strategy is not relevant because a buy-and-hold long-only strategy is implicit in the categorization. Typically, passive mutual funds hold assets as long positions, with minimal or no leverage, for a substantial length of time (months or years). For these mutual funds, stylistic differences involve only the location variable. In other words, *where* a passive mutual fund invests encapsulates its investment strategy. Often, for simplicity, the location is referred to as the fund's "style" (with the implicit assumption of a long-only strategy). With an active mutual fund, performance can be related to its passive counterpart via the usual manager's alpha and a beta coefficient to reflect systematic risk differences from timing and security selection.

For equity mutual funds, the essence of stylistic differences can generally be captured with a small number of standard benchmarks, as shown in Sharpe (1992). The situation is different for hedge fund strategies and hedge fund styles. A good example is the well-known long–short strategy that uses both long and short positions.[14] For long–short funds with the U.S. equity market as their location, the dramatic change in market sentiment for value stocks toward the end of the recent growth-stock-led rally gave rise to some striking illustrations of our point. For long–short equity hedge funds that applied the strategy only to value stocks, the pain they had to endure during the growth stock rally was limited. Presumably, even if all their value stocks lost value, the losses from long positions were offset by gains on short positions. For long–short equity hedge funds that were long value stocks and short growth stocks, however, the pain may have been substantial, even if a fund was dollar neutral or beta neutral. The *spread risk* inherent in a long value–short growth portfolio often overwhelms the market-directional component of the portfolio's risk exposure. Consequently, a beta-neutral position with respect to a broad-based index may not be effective in controlling spread risk.[15]

This example illustrates two important points. First, unlike the case of mutual funds, the details of a hedge fund strategy matter. Strategy and location can combine in different ways to yield significant performance differences. Second, unlike mutual funds, a *passive* hedge fund simply does not exist. Timing and leverage differences need to be part of the strategy applied by a hedge fund to a group of assets. Furthermore, hedge funds commonly use derivative securities that are traded only in the OTC market, and some may have occasion to include private investment interests in their portfolio. Consequently, the classification of hedge funds into style categories that have similar performance characteristics is much more complex than the classification of mutual funds.

The challenge is to define style factors from underlying hedge fund strategies whose return can be replicated by observable asset prices. In the example of a long–short equity style, one approach is to define the first style as "long–short/value" and the second style as "long–short/growth." In this way, a fund that uses a long/value together with a short/growth style can be expressed as a linear combination of value and growth stocks.[16]

For trend-following funds, Fung and Hsieh (2001) created the rates of return of lookback straddles and showed that these lookback options' returns are strongly correlated with the returns of trend-following funds. Thus, we were able to relate a complex group of trading strategies to observable asset returns without having to exact the detailed workings of the strategies themselves. In other words, this approach has the benefit of creating transparency from otherwise opaque investments, and it overcomes data limitations through the use of observable market prices. These attractive features are the primary motivation for developing asset-based style factors beyond our results for trend-following hedge funds.

The Study

Since the publication of Fung and Hsieh (2001), nearly four more years of data (January 1998 to September 2001) have become available, so we can now provide an out-of-sample validation of our finding that trend followers have return characteristics that mimic the payout of a lookback option on traditional assets. This examination will illustrate the benefit of modeling hedge fund strategies with asset-based style factors.

Instead of constructing our own trend-following index from commodity funds, as in Fung and Hsieh (1997b, 2001), we used the Zurich Capital Markets Trend-Follower index,[17] which is the median return of trend-following trading advisors tracked by Zurich since 1983. For the observation period 1989–1997, the two methods for indexing trend followers' performance are highly correlated, with a monthly return correlation coefficient of 0.971. Therefore, in the study reported here, we used only the Zurich Trend-Follower index to depict the unusual return characteristics of trend followers. The first two rows of **Table 1** update Fung and Hsieh (1997b) by covering the period January 1983 through September 2001.

To construct Table 1, we divided the monthly returns of the S&P 500 Index for January 1983 through September 2001 into five "states" of the world. State 1 consists of the worst months of the S&P 500 (as determined by returns being more than 1.8 standard deviations below the mean return). State 2 consists of the next worst months of the S&P 500 (1.8 to 0.33 standard deviations below the mean return). State 3 consists of the normal months of the S&P 500 (–0.33 to +0.33 standard deviations). State 4 has the better months of the S&P 500 (+0.33 to 1.8 standard deviations). And State 5 has the best months of the S&P 500 (more than 1.8 standard deviations above the mean return). Table 1 provides for these states the mean monthly return of the S&P 500, Zurich Trend-Follower funds, and the asset-based trend-following (TF) style factor (the construction of which is explained later in this section). Note the average positive performance of the trend-following funds in States 1 and 2.

The positive returns of trend-following funds are even more pronounced during periods of large declines in the equity market, as shown in **Table 2**. The last four periods (starting with July–August 1998) represent out-of-sample validation of the pattern initially recognized in Fung and Hsieh (1997b)—namely, that trend-following funds perform well during extreme movements, particularly declines, in equity markets.

To extend the analysis beyond simply recognizing this pattern as an empirical phenomenon and to overcome the well-known data deficiencies of peer-group averages, such as survivorship bias and potential nonstationarity in style grouping, we applied the methodology in Fung and Hsieh (2001) to construct an asset-based style factor of trend-following strategies.

In essence, our approach uses the structured options called lookback straddles to create a basic trend-following strategy called "the primitive trend-following strategy" (PTFS). Recall that a lookback straddle has a payoff equal to the difference

Table 1. Average Returns in Five Stock Market Environments Based on the S&P 500, January 1983–September 2001

Grouping	1	2	3	4	5
S&P 500	–10.4%	–2.1%	1.4%	5.1%	11.1%
Zurich Trend-Follower	4.6	0.9	0.2	1.7	2.4
Asset-based TF factor	4.8	1.3	0.4	0.7	1.4

Source: Data from Barra and Zurich; compiled by authors.

Table 2. Returns During Extreme Declines in the S&P 500, January 1983–September 2001

Period of Large Decline	S&P 500	Zurich Trend-Follower	Asset-Based TF Factor
September–November 1987	–29.6%	11.7%	12.9%
June–October 1990	–14.7	23.5	28.5
July–August 1998	–15.4	9.4	5.6
September–November 2000	–13.1	6.5	–5.0
February–March 2001	–14.9	9.3	3.6
August–September 2001	–13.8	9.3	3.9

Source: Data from Barra and Zurich; compiled by the authors.

between the maximum price and the minimum price of the underlying asset during the life of the option. In Fung and Hsieh (2001), we used exchange-traded options to replicate lookback straddles and then formed five PTFS portfolios of lookback straddles on stocks, bonds, three-month interest rates, currencies, and commodities. We showed that these PTFS portfolios have high explanatory power for the returns of trend-following commodity trading advisors (CTAs) over the 1989–97 sample period.[18] Here, we provide an out-of-sample validation of those results using three additional years of data, from January 1998 through September 2001, by comparing the PTFS returns with the Zurich Trend-Follower index returns.[19]

For the same period tested in Fung and Hsieh (2001), 1989–1997, we found that the regression of the trend-following index returns on the five PTFS portfolios' returns has an R^2 of 0.44. The data for three of the PTFS portfolios (bonds, currencies, and commodities) are statistically significant. These results are very similar to the findings of Fung and Hsieh (2001) for an equally weighted portfolio of trend-following CTAs instead of the Zurich Trend-Follower index. We removed the two PTFS portfolios that were not statistically significant (stocks and three-month interest rates) and used the average return of the remaining three PTFS portfolios as the return to our asset-based style factor of trend-following strategies.

The out-of-sample comparison of this asset-based style factor with the Zurich Trend-Follower index was performed as follows: We forecasted the Zurich Trend-Follower index from January 1998 through September 2001 by using the coefficients from the 1989–97 regression and the actual values of the PTFS portfolios. **Figure 1** graphs the actual and forecasted Zurich Trend-Follower index. The graph speaks for itself. The forecasts derived from the asset-based trend-following index are reasonably correlated with the actual outcomes. The major discrepancy occurs in September 1999, when gold spiked up dramatically for one month. Additionally, we found that the forecasts were virtually identical when we estimated the regression through 1998 (for forecasting 1999–2000) and through 1999 (for forecasting the year 2000).

These results provide an explicit link between the returns of the peer-group-based Zurich Trend-Follower index and the asset-based TF style factor. By construction, this style factor—based purely on observable market prices—is a transparent, rule-based description of the return characteristics of trend-following strategies.

Next, we compared the state-dependent returns of the asset-based TF index with returns to the S&P 500. The results, shown in the last line of Table 1, indicate that this asset-based TF style factor exhibits return behavior similar to that of the Zurich Trend-Follower index. It produced larger positive returns during the extreme declines in the S&P 500 (State 1) than during the middle states (2 and 3) but had much less pronounced positive returns during the extreme positive states (4 and 5).

Because institutional investors are more interested in using trend followers to provide diversifying performance during extreme downturns in the stock market, we examined the behavior of the asset-based TF style factor specifically during these times; the results are given in the last column of Table 2. The returns of the asset-based TF style factor had characteristics similar to those of the Zurich Trend-Follower index in four of the five large declines in the S&P 500 during the past 15 years.

We carried out another out-of-sample test of the Fung and Hsieh (2001) model by using the Nasdaq Composite Index instead of the S&P 500. The results for the states based on the Nasdaq are shown in **Table 3**. **Table 4** presents the results for the worst periods suffered by the Nasdaq. Note that since the peak of the Nasdaq in February 2000, the index declined 68 percent by September 2001. During that time, the Zurich Trend-Follower index gained 20 percent and the asset-based TF style factor gained 5.5 percent.

Given the transparency of the asset-based TF style factor, we can now provide the economic intuition behind the unusual return characteristics of trend-following strategies. When the stock market is at an extreme, which tends to coincide with periods of high volatility, option prices rise, resulting in the high positive returns to the asset-based TF style factor. During periods of high volatility, movements of asset prices are often amplified. In

Figure 1. Actual and Forecasted Zurich Trend-Follower Index, January 1998–September 2001

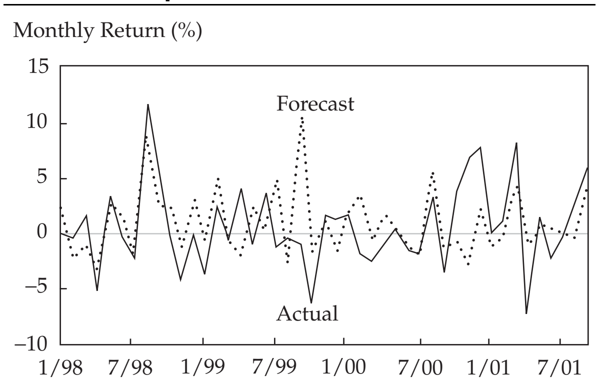

Table 3. Average Returns in Five Stock Market Environments Based on the Nasdaq, January 1983–September 2001

Grouping	1	2	3	4	5
Nasdaq	–17.6%	–1.1%	1.6%	6.8%	17.0%
Zurich Trend-Follower	3.5	1.0	0.1	1.4	–0.1
Asset-based TF style factor	3.6	0.8	0.2	0.7	0.4

Table 4. Returns During Extreme Declines in the Nasdaq, January 1983–September 2001

Period of Large Decline	Nasdaq	Zurich Trend-Follower	Asset-Based TF Style Factor
June 1983–July 1984	–27.9%	36.1%	–2.5%
July–November 1987	–29.8	6.2	12.0
October 1989–October 1990[a]	–30.3	32.5	34.9
July–August 1998[a]	–20.9	9.4	5.6
March–May 2000[a]	–27.6	–3.3	0.7
September–December 2000[a]	–41.3	14.6	–3.0
February–March 2001[a]	–33.6	9.3	2.2
August–September 2001[a]	–30.7	8.8	3.7

[a]Out-of-sample confirmation of the pattern found in Fung and Hsieh (1997b).

addition, other studies have reported concurrent rises in price volatility for other asset classes when the equity market is under stress (e.g., Loretan and English 2000). Although the direction of price movement in other asset classes need not coincide with that of the stock market, the magnitude of the price movements is often commensurate. It is this emergence of large price movements that provides trend followers with profitable opportunities.

In contrast, during steady periods of low volatility in the stock market, the cost to the asset-based TF style factor of being long options is unfavorable performance. By the same token, low-volatility periods imply price movements of limited magnitude, which is an unfavorable environment for trend followers. In short, the unusual return characteristic of trend-following strategies is a systematic consequence of large price volatility, not simply an empirical regularity we found among trend-following funds.

An immediate consequence of this characteristic is that trend-following funds contribute to portfolio diversification in a very specific way. Our theoretical model for trend followers shows that it would be a mistake to withdraw from trend-following funds because of losses during a period when the stock market is in a trading range (i.e., State 3).

At the individual-fund level, a trend-following fund's performance can be assessed by using Equation 1.[20] In essence, if a trend-following fund failed to capture the volatility value of the markets in which it operates, investors would have been better off replicating the characteristics of trend-following strategies directly by using traded options. In addition, Equation 1 allows portfolio investors to design option-like exposures to a broad range of commodity markets. Judging how much diversification is being achieved by investing in a given group of trend-following funds will not be clear by simply observing their returns.

Finally, using asset-based style factors can generate long time series to simulate the behavior of hedge fund trading strategies. For example, Mitchell and Pulvino were able to go back to 1963 to simulate returns of the merger arbitrage style. In the case of trend-following styles, our results can be extended farther back in time by simulating option returns based on a theoretical option-pricing model, such as the Black–Scholes model.

The Future of Asset-Based Style Factors

How practical would it be to develop these complex models of hedge fund strategies for use as asset-based style factors? More importantly, can the asset-based style factors be easily maintained and placed in the public domain? The answer is that not only can the returns be computed from market prices, as in Mitchell and Pulvino, but an operational fund using this approach also exists. A U.S.

mutual fund called the "Merger Fund" already runs a passive merger arbitrage strategy in a manner similar to the Mitchell–Pulvino model. The correlation between merger arbitrage hedge funds [as proxied by the Merger Arbitrage Index maintained by Hedge Fund Research (HFR) Asset Management] and the Merger Fund is 0.86 for the period January 1990 through September 2001.

In terms of our trend-following model, institutional investors have told us that they have adopted the portfolio strategy of using trend-following funds to provide returns during extreme market conditions.[21] Other than the tedious data collection required, the model can be computed by using exchange-traded futures and option prices.

Beyond these two groups of hedge fund strategies, more research is required to develop similar asset-based style factors for other hedge fund styles. The question is: Given the myriad of hedge fund styles (i.e., strategy and location pairs) and the dynamic ways they evolve, can similar factors be found for other hedge fund strategies? The answer will not be known until a sufficient number of asset-based style factors have been developed to model the majority of hedge fund strategies. By some measures, however, we may be more than halfway there. Consider, for example, the HFR Fund Weighted Composite Index, which is an equally weighted portfolio of hedge funds in the HFR database, and the CSFB/Tremont Hedge Fund Index (CTI), which is an asset-weighted portfolio of large hedge funds in the TASS database. As the regressions for January 1994 to September 2001 in **Table 5** show, these aggregate indexes have strong market exposures.[22]

Although differences in the index construction methodologies of different suppliers of hedge fund indexes undoubtedly affected the results reported in Table 5 (see Fung and Hsieh 2002), there is little doubt that nearly half of the volatility of these indexes can be explained by readily observable "long-only" asset-based style factors in the form of conventional indexes.

Two questions remain: What should be done with the unexplained variance? In addition, with a large and significant "alpha" and beta coefficients that sum to much less than 1.0, what other factors are at work?

For increasing the explanatory power of readily available style factors, the work by Agarwal and Naik (2000b) provides valuable clues. They showed that S&P 500 option returns can add substantial explanatory power to long-only benchmarks in explaining hedge fund style returns. What is needed is a theoretical model linking the option returns (which were selected purely on the basis of goodness of fit) to a specific hedge fund strategy.

In terms of the large market exposures, further clues can be gleaned by analyzing the subindexes that compose the broad-based hedge fund indexes. As **Table 6** indicates, out of 16 HFR subindexes of peer-group-based hedge fund styles, 9 (those not shaded) have R^2s above 0.50. Many of these styles have statistically significant market exposures, as indicated by the asterisks following the regression coefficients. For example, the distressed securities style is strongly correlated with high-yield bonds. The emerging markets style is strongly correlated with the IFC (International Finance Corporation) Composite Index. Equity hedge, equity nonhedge, short selling, and sector (total) are strongly correlated with small-cap stocks.

The last column in Table 6 shows our findings when we estimated the weights of the 16 component styles by regressing the HFR Composite on the 16 styles. The 9 styles that have significant exposure to the three market factors combine to account for roughly 80 percent of the HFR Composite.

Interestingly, nearly half (7 out of 16) of the component styles have low correlations with the three market factors. These styles (shaded in Table 6)—convertible arbitrage, for example—are gen-

Table 5. Market Exposures of Hedge Fund Indexes, January 1994–September 2001
(heteroscedasticity-consistent standard errors in parentheses)

Index	Constant Term	Wilshire 1750 Small Cap	CSFB High-Yield Bond	IFC Composite	R^2
HFR Composite	0.0077*	0.278*	0.112	0.101*	0.876
	(0.0010)	(0.022)	(0.081)	(0.017)	
CTI Composite	0.0072*	0.219*	0.205	0.062	0.414
	(0.0025)	(0.056)	(0.201)	(0.050)	

*Statistically significant in a one-tailed test at the 99 percent level.

Table 6. Market Exposures of HFR Style Indexes: January 1994–September 2001 (heteroscedasticity-consistent standard errors in parentheses)

HFR Subindex	Constant Term	Wilshire 1750 Small Cap	CSFB High-Yield Bond	IFC Composite	R^2	Estimated Weight in Composite Index
Convertible arbitrage	0.0080*	0.023	0.272*	0.012	0.341	0.04
	(0.0010)	(0.020)	(0.077)	(0.017)		
Distressed securities	0.0066*	0.095*	0.354*	0.046	0.563	0.01
	(0.0014)	(0.032)	(0.121)	(0.022)		
Emerging markets (total)	0.0051	0.088	0.229	0.574*	0.799	0.12
	(0.0027)	(0.063)	(0.207)	(0.051)		
Equity hedge	0.0104*	0.461*	–0.054	0.033	0.819	0.17
	(0.0014)	(0.037)	(0.098)	(0.028)		
Equity market neutral	0.0073*	0.091*	0.043	–0.065*	0.174	0.12
	(0.0010)	(0.028)	(0.085)	(0.022)		
Equity nonhedge	0.0058*	0.650*	0.121	0.099*	0.890	0.16
	(0.0017)	(0.040)	(0.119)	(0.030)		
Event driven	0.0088*	0.185*	0.333*	0.047	0.758	0.07
	(0.0010)	(0.023)	(0.076)	(0.021)		
Fixed income (total)	0.0052*	0.033	0.317*	0.012	0.546	0.06
	(0.0009)	(0.015)	(0.085)	(0.020)		
Macro	0.0067*	0.146*	0.144	0.080*	0.350	0.06
	(0.0022)	(0.041)	(0.149)	(0.036)		
Market timing	0.0094*	0.266*	–0.258	0.068	0.532	0.05
	(0.0018)	(0.036)	(0.140)	(0.033)		
Merger arbitrage	0.0088*	0.074*	0.174	0.015	0.427	0.04
	(0.0011)	(0.021)	(0.086)	(0.010)		
Relative-value arbitrage	0.0074*	0.058*	0.251*	0.003	0.461	0.10
	(0.0010)	(0.018)	(0.080)	(0.019)		
Sector (total)	0.0082*	0.707*	-0.019	0.072	0.768	0.08
	(0.0028)	(0.085)	(0.191)	(0.054)		
Short selling	0.0130*	–1.179*	0.437	–0.047	0.765	0.02
	(0.0040)	(0.101)	(0.262)	(0.074)		
Statistical arbitrage	0.0064*	0.051	0.156	–0.026	0.134	–0.03
	(0.0015)	(0.033)	(0.083)	(0.029)		
Regulation D (1996–2000)	0.0126*	0.109	–0.030	0.041	0.149	0.01
	(0.0023)	(0.063)	(0.154)	(0.042)		

*Statistically significant in a one-tailed test at the 99 percent level.

erally regarded as having little or no directional exposure. Their combined weight in the HFR Composite, however, is estimated to be only 20 percent. This weighting explains why the HFR Composite is so strongly correlated with market factors. It also suggests that the observed alpha from the regression can be partly ascribed to the average returns of these nondirectional strategies.

Another possibility must be noted. The tendency for hedge funds to use more than one strategy has been growing. Therefore, nondirectional strategies may exist within the subindexes that showed significant market exposures, which would be another source of alpha.[23]

Table 7 indicates that we found similar results when using the CSFB/Tremont peer-group-based subindexes. Four of the nine CTI subindexes have significant market exposures. As in the case of the HFR indexes, we estimated the weights of the component styles by regressing the composite index on the nine component styles.[24] The four with significant market exposures represent roughly 45 percent of the weight of the composite index.

Given these results, we can suggest a way forward. Hedge fund strategies with a directional component can be modeled with "long-only" asset-based style factors in the form of readily available conventional indexes. Our results show that this directional component can account for more than 50 percent of the observed variance in hedge fund returns. To improve these results, additional techniques are required to model the nonlinear characteristics of hedge fund returns. Nonlinear characteristics can come from a variety of sources. They can be a result of dynamic allocation of risk capital among markets or the dynamic use of leverage. Both techniques can lead to option-like return patterns that cannot be captured by using a linear model of conventional indexes.

Based on our findings, the research may be already halfway toward providing a complete set of asset-based style factors for the hedge fund industry as a whole. Thus, progress has been made. But more research is required. For nondirectional (or market-neutral) and other hedge fund strategies, new models are required. We hope more research will be directed to complete this effort to provide a set of transparent, rule-based indexes that help investors understand hedge fund investing.

This article benefited from responses of the participants at a presentation at the Centre for Hedge Fund Research and Education at the London Business School and a forum discussion at Albourne Village (village.albourne.com). We thank Joe Sweeney for helpful comments.

Table 7. Market Exposures of CSFB/Tremont Style Indexes: January 1994–September 2001
(heteroscedasticity-consistent standard errors in parentheses)

CSFB/Tremont Subindex	Constant Term	Wilshire 1750 Small Cap	CSFB High-Yield Bond	IFC Composite	R^2	Estimated Weight in Composite Index
Convertible arbitrage	0.0074*	–0.005	0.359*	–0.009	0.180	0.05
	(0.0017)	(0.036)	(0.133)	(0.035)		
Dedicated short bias	0.0071	–0.760*	0.175	–0.130	0.732	0.003
	(0.0037)	(0.066)	(0.278)	(0.061)		
Emerging markets	0.0052	0.077	0.176	0.621*	0.622	0.05
	(0.0042)	(0.091)	(0.320)	(0.079)		
Equity market neutral	0.0088*	0.033	0.075	0.027	0.193	–0.003
	(0.0010)	(0.020)	(0.051)	(0.021)		
Event driven	0.0075*	0.079*	0.392*	0.080*	0.592	0.09
	(0.0016)	(0.028)	(0.133)	(0.028)		
Fixed-income arbitrage	0.0045*	–0.027	0.321	-0.001	0.171	0.07
	(0.0016)	(0.023)	(0.149)	(0.038)		
Global macro	0.0094	0.127	0.320	0.022	0.100	0.42
	(0.0045)	(0.087)	(0.341)	(0.091)		
Long–short equity	0.0072*	0.527*	-0.069	0.030	0.720	0.31
	(0.0023)	(0.061)	(0.189)	(0.041)		
Managed futures	0.0074*	-0.073	–0.371	0.061	0.055	0.01
	(0.0033)	(0.077)	(0.206)	(0.062)		

*Statistically significant in a one-tailed test at the 99 percent level.

Notes

1. Depending on the way the cost of generating the return is managed, the "rate" of return of individual trend followers can exceed that of this option-based strategy.
2. To motivate the development of the research we undertook in the 2001 study, we recount here some of the results in our 1997a paper.
3. Linear factor models, such as Sharpe's, cannot capture the nonlinear return features commonly found among hedge funds.
4. See Dunbar (2000) and Lowenstein (2000) for vivid accounts of the events surrounding LTCM's failure and descriptions of the strategies involved.
5. Differences could involve, for example, transaction costs or the funding costs of shorting.
6. An additional hindrance is the low R^2 that is likely to be observed when only standard stocks, bonds, and commodity indexes are used as regressors.
7. For example, in early February 2001, the Hedge Fund Research index for equity market-neutral hedge funds reported a return of –1.61 percent for January 2001 whereas the CSFB/Tremont index for equity market-neutral hedge funds returned 2.13 percent for the same month. See Fung and Hsieh (2002) and Brittain (2001) for other measurement and interpretation problems with existing hedge fund indexes.
8. Security selection and market-timing activities are captured by the alpha term.
9. Investment positions in between reporting periods are generally not available.
10. See Fung and Hsieh (1997a) and Fung and Hsieh (2001) for discussions of the nonlinear properties of hedge fund returns, and see Glosten and Jagannathan (1994) for a summary of the nonlinear properties of traditional fund managers' returns.
11. On average, the Fung and Hsieh (1997a) model could capture only about half of the cross-sectional return variations with five major factors.
12. One way to gain further insight into the estimated style factors is to replicate the factor returns by portfolios of hedge funds. Unfortunately, this approach takes us back to approximating the style factors using a peer-group-based method, which is prone to selection biases. For example, if LTCM were included in a particular style group, it would have a significant impact on the return characteristics of that style factor. As mentioned earlier, the LTCM episode was the consequence of a failure to manage the leverage applied to strategies, however, rather than a failure of the strategies themselves. Thus, a peer-group estimate of style factors that includes LTCM is a poor descriptor of the underlying hedge fund strategies' return characteristics. But to exclude LTCM from a peer-group type of analysis opens up complicated issues of selection bias.
13. To address these concerns, Agarwal and Naik (2000a, 2000b) proposed ways to relate the style factors in Fung and Hsieh (1997a) to traditional asset classes (and their derivatives).
14. We use the description "long–short" to indicate a fund's ability to trade from both the long and the short side. The term is meant to include long-only and short-only portfolios as special cases. In the dynamic trading styles of hedge funds, managers are quite likely to switch from one extreme to the other—especially managers who use market-timing strategies.
15. For example, it was widely rumored that the former Tiger Fund favored value stocks on the long side and was negative on technology stocks. In February 2000, the dissolution of the Tiger Fund was announced. During March of the same year, events took an unpleasant turn at the Quantum Group of Funds. According to press reports, the group experienced substantial losses when tech stocks fell out of favor. In both months, the Wilshire 5000 Total Market Index showed positive returns, but dramatic performance differences characterized value stocks versus growth stocks from February to March 2000.
16. What remains is to develop a model that captures the essence of the long–short equity style by using explicitly specified investment rules. The work on "pairs trading" by Gatev, Goetzmann, and Rouwenhorst (1999) could be extended to achieve this goal.
17. Formally, the Zurich Trading Advisor Index: Trend-Follower Subindex.
18. Fung and Hsieh (1997b) and Billingsley and Chance (1996) showed that the majority of the CTA funds they studied use trend-following strategies.
19. We were able to update all of the option data in Fung and Hsieh (2001) with the exception of the options on the DAX and the Nikkei, which were unavailable because of data changes.
20. In Fung and Hsieh (2001), we found that CTAs generally have positive alphas in relation to the strategy factors of about 1 percent a month.
21. A number of multistrategy hedge funds have also added a "systematic" component to their portfolio of strategies—often with the expressed objective of capturing some of the option-like downside protection these strategies offer.
22. Including the Wilshire Small-Cap Index made the S&P 500 and its lags statistically significant, which raises an interesting alternative interpretation of the results reported by Asness, Krail, and Liew (2001). Are some risk factors more suitable for explaining hedge fund returns than the factor Asness et al. used (the S&P 500)? We believe that "hedge fund alphas" come from bearing unconventional risk rather than from measurement errors caused by omitted lagged terms in a standard linear risk model.
23. In fact, the tendency for hedge funds to use several strategies is one reason peer-group-based style indexes are inherently problematic.
24. Our finding also helps explain why Fung and Hsieh (2002) observed significantly higher R^2s for the HFR Composite regressed against conventional indexes than for the CTI Composite. The reason is that CTAs have a very low correlation with conventional assets and HFR excludes CTAs in its index composition whereas CSFB/Tremont does not.

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