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Asset-Based Hedge-Fund Styles and Portfolio Diversification

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1. Introduction

It is a well-documented stylized fact that hedge fund returns differ from the returns of traditional asset classes. Investors looking for alternative return characteristics in hedge funds must be concerned about the question of consistency. To go beyond relying on historical hedge fund performance repeating itself, one needs to answer the key question on hedge fund performance: "What is the wind behind this sail?" After all, hedge fund managers typically transact in similar asset markets to traditional managers. How then do they deliver different return characteristics to the very asset classes they trade? We believe the answer to these questions lies in understanding the value of hedge-fund strategies and how they can be directly related to traditional asset classes.

In a recent paper, Fung and Hsieh (2001a) modeled the unusual return characteristics of trend-following hedge funds. It was first reported in Fung and Hsieh (1997a) that these funds have performance characteristics that resemble straddles on the equity market. They deliver positive returns when the equity markets are at extremes—both up and down. This is an attractive return profile for diversification purposes. In order to verify that this phenomenon is not merely an empirical regularity, Fung and Hsieh (2001a) explicitly modeled trend-following strategies using traded options. It was shown that the returns from trend-following strategies can be replicated by a dynamically managed option-based strategy known as a *lookback* option.

The intuition is as follows. 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 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] Viewed this way, we can capture the essence of a trend-following strategy's return characteristics without having to delve into the details of the models used to generate the returns.[2] More importantly, this approach allows us to focus on the source of value that investors can derive from trend-following strategies in a broader asset allocation context.

The return of this option-based replication strategy is shown to have a high degree of explanatory power on hedge funds that adopt a trend-following style. These results demonstrate that the unusual return characteristic of trend-following funds is a systematic consequence of a broad class of trend-following strategies. 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.

The Fung and Hsieh (2001a) paper illustrates the advantage of providing an explicit description of a class of commonly used hedge-fund strategies known as *trend following*. Modeled this way, the economics underlying this class of strategies is transparent to investors. The performance characteristics of this class of strategies can be computed using observable market prices with a long history spanning several market cycles. These are necessary properties of investment class benchmarks that are of institutional quality. We call this an *asset-based* hedge-fund style factor.

In this paper, we recount some of the results in an early paper by Fung and Hsieh (1997a) in order to motivate the development of the research we undertook in Fung and Hsieh (2001a). In addition, by casting the analysis in a broader framework, we hope to

[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.

persuade readers that there are systematic reasons why hedge-fund strategies offer unusual and diversifying return characteristics to a portfolio of traditional assets. Our research on trend-following strategies and the recent paper by Mitchell and Pulvino (2001) on merger-arbitrage strategies are beginning to provide explicit links between hedge-fund strategies and observable asset returns. Through these links, the myriad of hedge-fund styles may eventually be expressed as a simple, unifying model of familiar asset classes in the spirit of Sharpe's (1992) style model for mutual funds. Asset-based style factors directly relate hedge-fund returns to the returns of trading strategies applied to familiar asset classes with readily observable market prices. They provide an explicit description of how various styles of hedge funds add to portfolio diversification rather than relying on peer group averages of historical hedge-funds returns.

2. The Starting Point: Sharpe's Style Model

Let us begin with the basic premise behind Sharpe's (1992) innovative work on investment styles. It was intended to be an asset-class model that reduces the myriad of mutual fund styles to a model involving only a limited number of major asset classes. The elegance of Sharpe's solution lies in its simplicity. But more importantly, it provides an explicit link between investment styles and traditional asset classes. This is the key connection between the way investment strategies are implemented (styles) and how they relate to overall portfolio efficiency (optimal asset allocation).

In Fung and Hsieh (1997a), we took a step towards extending this concept by asking the question "Can we discern the return characteristics of hedge-fund strategies by looking at how hedge-fund returns are statistically clustered together?" Although we

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[2] Which is generally not observable.

were able to capture a significant portion of return variations among the hedge funds in our universe, our results represent only one piece of a large jigsaw puzzle. Other pieces remain to be uncovered.

It is helpful to frame the puzzle before we search for the missing pieces. Ideally, a fully specified style model should look like the following:

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

where R_t is a fund's return, $\{ SF_{k,t} \}$ are the style factors, and $\{ b_k \}$ are the factor loadings.

How Hedge-fund Style Factors help in performance evaluation and portfolio construction

With a model like equation (1), the manager's alpha is expressed relative to a set of hedge-fund style factors $\{ SF_{k,t} \}$. The respective betas tell us the capital allocation to each style factor, which in the case of hedge funds also reflects the degree of leverage the fund employs.

An application of a model like this is in the case of Long Term Capital Management ("LTCM"). It is clear form the numerous reported accounts on the LTCM episode that it was the betas (or leverage) that led to their demise. There was nothing inherently unsound about the strategies like- bond basis, long/short equity, risk arbitrage, and volatility mean reversion -- that LTCM employed.[3] According to the reported accounts, LTCM could easily have had double-digit betas with respect to the underlying style factors. This is a good example on clarifying where the bets were placed. Was the bet on an unusual set of hedge-fund trades or was it a highly levered bet on familiar trades? The key point here is that the failure of LTCM did not imply the failure of the strategies they employed and certainly not a systemic failure of all hedge-fund styles. It was a failure of what was an overly leveraged investment style. A model like equation (1) above makes this point explicit.

Another commonly used concept in managing hedge fund portfolio is that of manager diversification. Frequently, portfolio investors invest in more than one manager employing similar styles. A model like equation (1) helps to quantify this type of portfolio construction. Two managers employing an identical set of strategies can differ in important ways. First, they can be different in their use of leverage. This will lead to differences in their betas. Second, the efficiency of their trade execution can differ.[4] This will show up in their alphas. Third, the choice of securities each manager apply the strategy to can be different. For example, some funds may specialize in mergers and acquisitions in a specific industry group. This will affect both the manager's alpha and beta. Overall, equation (1) provides a framework for quantifying the degree of diversification in a hedge fund portfolio in terms of its exposure to various classes of hedge-fund style factors.

Finally, asset-based style factors can be applied to manage the risk of hedge-fund portfolios. Take the example of calculating the value-at-risk (VaR) 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 are fraught with difficulties. This is because hedge-fund returns tend to be reported at monthly intervals and generally do not have long histories. The asset-based style factors allow us to make use of data sets with

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[3] See Dunbar (2000) and Lowenstein (2000) for a vivid account of the events and description of the strategies involved.

much longer histories. Beyond VaRs, asset-based style factors can be used to conduct *what if* scenario analyses. Suppose we want to know the effect on a portfolio of hedge funds if credit spreads widen and market volatility collapses. This can be readily answered if we know to which asset-based style factors the portfolio is sensitive. Generally, the asset-based style factors help to *qualify* the nature of the risk a hedge-fund investment is exposed to beyond just a *quantity* risk measure that conventional statistical tools provide. Constructed from observable asset 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.

Extending Sharpe's (1992) model to hedge funds

Applying equation (1) to hedge funds is less than straightforward. An immediate problem is that hedge-fund style factors are likely to be substantially different from those used in Sharpe (1992). For example, we know that traditional asset class models would not work for hedge funds. Hedge-fund returns are supposed 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).[5] In order to extend Sharpe's (1992) model, we need to establish a set of hedge-fund style factors that explains hedge-fund performance and have return characteristics that can be directly related to the returns of traditional asset classes. To attain the clarity of Sharpe's (1992) model and to maximize the practical value of the model, the number

[4] Differences such as transactions costs, funding costs of shorts, etc.

of factors should be kept to a minimum. Put differently, we wish to establish a small set of factors { $SF_{k,t}$ } whose returns can be measured using observed prices of traditional assets (and their derivatives). For notional convenience, we refer to these factors as asset-based style factors. Several issues need to be resolved in order to identify the style factors and to reach an intuitively appealing form of equation (1) that affords empirical content.

3. Strategy, Location, Style, and Style Factors

We start by making a distinction between four terms: *strategy*, *location*, *style* and *style factor*. A hedge-fund investment style consists of three elements: *strategy* (short for investment strategy) *location* and *risk management*. *Strategy* tells us how long and short security positions[6] are combined to reflect the strategy's objective. *Location* tells us which assets the strategy is applied to. *Style* refers to how these positions are levered and managed. *Style factor* refers to a main style whose characteristics are common to many similar styles. A comparison to familiar mutual fund styles helps to explain the differences between these terms.

In the mutual fund literature, a standard style would be something like small cap value stocks, small cap growth stocks, large cap value stocks, and large cap growth stocks. Here, the concept of strategy is not relevant because implicit in this categorization is a buy-and-hold, long-only strategy.

Typically assets are passively held as long positions, with minimal or no leverage, for a substantial length of time (e.g., months or years). For these passive mutual funds

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[5] Not to mention the low R^2 that is likely to be observed when only standard stocks, bonds and commodity

stylistic differences involve only the location variable. In other words, *where* a passive mutual fund invests encapsulates its investment strategy, location, and style. Often, this is referred to as the fund's style for simplicity.

With active mutual funds, performance can be related to their passive counterpart via the usual manager's alpha and a beta coefficient to reflect systematic risk differences due to timing and security selection.

An individual mutual fund's style often carries a description like small cap financial stocks, while another's style may be large cap telecommunication stocks. The number of possible permutations is large. Yet, the essence of these stylistic differences may be quite small and can be captured by four simple style factors: small cap value, small cap growth, large cap value, and large cap growth. Sharpe's (1992) model was able to distill the proliferation of qualitative styles to a reduced set of essential style factors that can be expressed as functions of familiar asset classes.

The situation is different with hedge-fund strategies and hedge-fund styles. A good example is the well-known long/short hedge-fund strategy[7] that utilizes both long and short positions. Like the mutual example, assume that the location in this case is the U.S. equity market. The dramatic change in market sentiment for value stocks towards the end of the recent growth-stock-led rally gave rise to some striking illustrations of our point.

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indices are used as regressors.

[6] Including their derivatives.

[7] Throughout the paper, we use the strategy description long/short to indicate a fund's ability to trade from both the long as well as the short side. It is meant to include long-only and short-only portfolios as special cases. With dynamic trading styles like hedge funds, it is quite possible for managers to switch from one extreme to another. This is especially the case with those funds that employ market-timing strategies.

For long/short-equity hedge funds that apply their strategy only to value stocks, the pain they have to endure during the growth-stock rally was limited. Presumably, losses from long positions would have been offset by gains on short positions even if all value stocks lost value. For long/short-equity hedge funds that were long value stocks and short growth stocks, the pain they have to endure during the growth-stock rally could be substantial. This is so even if the fund was dollar-neutral or beta-neutral.[8]

This example makes two important points. First, unlike the case of mutual funds, the details of a hedge-fund strategy matter. Obviously, having a long bias in a given asset will have diametrically opposite results to having a short bias on an asset. The above example shows that a long/short strategy, which amounts to spread trading, will yield yet different return characteristics, especially when the spread position involves different segments of the equity market. In other words, strategy and location can combine in different ways to yield significant performance differences.

Second, unlike mutual funds, the concept of a *passive* hedge fund simply does not exist. Timing and leverage differences need to be part of the style in which a strategy is applied to a group of assets. Furthermore, hedge funds commonly employ derivative securities that are only traded in the over-the-counter markets ("OTC") and some may have occasion to include private investment interests in their portfolio. Consequently, the

[8] It was widely rumored that the former Tiger Fund favored value stocks on the long side and was negative on "tech stocks." In February of 2000, Julian Robertson announced the dissolution of the fund. 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 index showed positive returns yet there were dramatic performance differences between value stocks and growth stocks going from February to March of that year. Our point is that the *spread risk* inherent in a long/short portfolio often overwhelms the market directional component of the portfolio's exposure. Consequently a beta-neutral position with respect to a broad-based index may not be effective in controlling spread risk.

classification of hedge funds into style categories that have similar performance characteristics is a much more complex proposition than the case of mutual funds.

The overall goal is to catalogue all hedge-fund styles (i.e., pairs of strategy and location), and to distill them down to a small number of key hedge-fund style factors where individual hedge fund manger's alpha can be determined on a risk-adjusted basis. Ideally, these style factors should satisfy the properties of asset-based style factors and, therefore, possess the quality that make them useful as performance benchmarks.

4. Peer-Group Style Factors and Return-Based Style Factors

We begin by reviewing existing methods for defining hedge-fund styles.

Peer-Group Style Factors

To help investors understand hedge funds, consultants and database vendors group hedge funds into *categories* of funds based on the managers' self-disclosed strategies and location. We refer to these as peer-group style factors.

The search for performance similarity: The apparent objective of the peer-group approach is to capture the performance characteristics of funds operating similar strategies. While this is a useful first step to understanding the myriad of different styles (i.e. strategy and location pairs) in the hedge fund universe, 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, at times, ad hoc. Periodically, curious performance differences emerge between similar sounding hedge-fund style groups.[9] In other words, database vendors' interpretations of what fund managers say they do may not be borne out by what managers actually do. There is a need to verify that similar sounding strategies do indeed deliver similar performance characteristics.

The proliferation of styles: Without a model to discern meaningful differences in performance, when confronted with inconsistent performance results there is a tendency for suppliers of peer-group style factors to increase the number of style groups in order to compensate. This has been a major cause for the proliferation of hedge-fund styles.[10]

Style diversification and market dynamics: Over the years, there has been an increasing tendency for hedge-fund mangers to employ multiple strategies. Leaving aside the economy of scale in R&D to support *similar* strategies, the sheer value of creating a more stable stream of returns over different market cycles has attracted hedge-fund managers to adopt a multi-strategies approach. This has created further problems for peer-group type of style factors. Homogeneous peer-groups are easier to verify if the number of strategies involved in the group is small. When different funds employ different combinations of strategies dynamically over time, the precise level of aggregation among *peers* that would capture the essence of both the strategies employed and the dynamical allocation of capital to these strategies over time becomes almost an impossible task.

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[9] Except for the rare occasion when there is complete homogeneity in both the strategies employed and the way they are managed among the funds constituting the group inconsistencies are likely to arise. For example, in early February 2001, the HFR index for Equity Market Neutral hedge funds was reported to return –1.61% for the month of January 2001 whereas the CSFB/Tremont index for Equity Market Neutral hedge funds returned 2.13% for the same month. Inconsistencies of this magnitude highlight the need for better standardization of hedge fund benchmarks. See Fung and Hsieh (2001b) and Brittain (2001) for other measurement and interpretation problems with existing hedge fund indices.

Consequently, the risk of erroneously asserting that a hedge-fund manager has changed style with respect to a broadly defined peer group is high. The converse of this problem is to have too few peer groups with uninformative descriptions.

Lack of transparency and measurement errors: With peer-group based style factors, only two types of information on the hedge funds in each group are available. They are respectively, a qualitative description of the strategies used and the historical return characteristics of the group. In other words, there is a brief statement from providers of the peer-group style factors (or indices) of "here's what they do," and "this is what you get" over a given historical period. The lack of an analytical framework to support the construction of peer-groups leaves open a number of unanswered questions; see for example Brittain (2001). Basically, the lack of disclosure on how returns are generated is unsatisfactory to investors. In addition, without a model to relate the criteria used to form groups of hedge funds and the reported return characteristics, a number of biases in measuring returns can occur; see for example, Fung and Hsieh (2000b, 2000c) and Liang (2000).

Comparison to mutual funds: Forming homogeneous peer-groups of mutual funds is less problematic because mutual-fund strategies are predominantly long only. Where mutual funds invest dictates their respective style.[11] However, there is no unique method for defining the location variable and style proliferation can occur. Sharpe's (1992) paper addresses precisely this issue. Because mutual-fund strategies tend to follow a buy-and-

[10] Not to mention the lack of standardization in the qualitative descriptions of hedge fund styles.
[11] Security selection and market timing activities are captured by the "alpha" term.

hold pattern, the problem of managers changing their investment style over time is less pronounced. Similarly, as leverage is not an integral component of mutual-fund strategies, the impact of dynamic allocation across different styles over time is also less pronounced. As mutual fund positions are a matter of public record, the question of transparency is less problematic.[12] Although the returns of mutual-fund peer-groups do inherit *survivorship bias*, there is a large body of research literature that aids investors in dealing with this, as in Malkiel (1995). Finally mutual funds rarely transact in OTC or private markets, their returns can normally be directly related to observable market prices. In summary, although there are a few caveats to be considered when assessing the returns from peer-groups of mutual funds, the problem is much more manageable than that of hedge funds.

Return-based Style Factors

An asset-class model for analyzing mutual fund investment styles was first proposed in Sharpe (1992). Mutual fund strategies are directly related to asset-classes (in the form of published indices) by comparing a fund's historical return to that of indices of traditional asset classes. This provides a mean for verifying whether a fund manager's performance has been in line with the fund's mandate. Through this process, funds with highly correlated returns can be assigned to the same group based on their return characteristics.[13] Sharpe (1992) was able to explain a significant amount of cross-sectional variation of mutual fund returns using only a limited number of asset-class indices. Although the debate on the usefulness of return-based style factors in detecting

[12] Investment positions in-between reporting periods are generally not available.

style drifts among mutual fund managers has not reached its conclusion, Sharpe's (1992) model remains an excellent platform for building models that can analyze an investment manager's style. [14]

Fung and Hsieh (1997a) used the idea that managers with the same style (i.e., strategy and location pairs) will generate correlated returns to generalize Sharpe's (1992) model to hedge funds. They applied principal components and factor analysis on hedge-fund returns to extract style factors.

The methodology adopted by Fung and Hsieh (1997a) is motivated by four reasons. First, statistical clustering of funds' returns should approximate the common risk return characteristics of the strategies they employ. Second, in order to arrive at a linear style model like Sharpe (1992), the inherent return nonlinearity from hedge-fund strategies are subsumed in the returns of the estimated factors.[15] This, in turn, allows for a linear combination of these factors to be used to explain hedge-fund styles. Third, the estimated return factor proxies the return commonality among hedge funds statistically which can then be compared to the out of sample qualitative self-description of their respective strategies in order to interpret the factors. This way there is a consistency check on not only what hedge funds say they do, but also what they did compared to

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[13] Conversely, funds that were incorrectly assigned to a peer-group are likely to have radically different betas with respect to the asset class indices from their "peers."

[14] Another school of thought is that past returns are not as effective in assessing a manager's style and its dynamics over time as direct observations on the invested positions; see for example Christopherson (1995). Other authors have suggested that the truth may lie somewhere in between; see Buetow, Johnson and Runkle (2000). With hedge funds, the luxury of observing actual positions of each manager is generally not available. In addition, it is hard to extract information from hedge-fund positions that are highly dynamic. It is probably just as hard to discern a pattern of changes in investment style by directly tracking a hedge-fund's positions as oppose to detecting the change from daily changes in portfolio value. The exception is of course with cases where there is a complete violation of the investment mandate where a manager invests in securities that are excluded by the fund's charter.

[15] See Fung and Hsieh (1997a) and Fung and Hsieh (2001a) for discussions on the nonlinear properties of hedge-fund returns, and Glosten and Jagannathan (1994) for a summary on the nonlinear properties of traditional fund manager's returns.

other funds within the same cluster. Fourth, a principal component analysis is most likely to reduce the number of factors down to a more manageable and orthogonal set. This helps to ease the problem of style proliferation and double counting.

A few caveat on the results in Fung and Hsieh (1997a) needs to be noted. First, their methodology is targeted at explaining cross-sectional variation of hedge fund returns therefore, little insight is offered on the dynamic of hedge-fund returns over time. Second, there is still a substantial amount of cross-sectional return variation of the hedge funds sample used in Fung and Hsieh (1997a) that the main factors cannot explain.[16] Third, a formal model for identifying the empirically generated style factors needs to be developed.[17]

For a style-factor to attain the level of information content as traditional-asset indices, two properties are essential. First, there must be complete transparency in the way the factor returns are derived. Second, there must be a sufficiently long performance history in order to generate reliable statistics. Neither property is present in peer group-based and return-based hedge-fund style factors.

To address these concerns, attempts to relate the style factors in Fung and Hsieh (1997a) to traditional asset classes (and their derivatives) have been proposed in Agarwal

[16] On average, the Fung and Hsieh (1997a) model could only capture about half of the cross-sectional return variations with five major factors type of analysis opens up complicated issues of selection bias. This illustrates some of the conflicting issues in constructing peer-group based style factors.

[17] One way to gain further insight on the estimated style factors is to replicate the factor returns by portfolios of hedge funds. Unfortunately, this 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 rather than a failure of the strategies themselves. This makes a peer-group estimate of style factor that includes LTCM a poor descriptor of the underlying hedge-fund strategies' return characteristics. However, to exclude LTCM from a peer-group type of analysis opens up complicated issues of selection bias.

and Naik (2000a, 2000b). While these are useful contributions, further developments are required in order to establish transparent, rule-based hedge-fund style factors that are based on observable market prices with an adequate history.

5. Asset-Based Style Factors: Transparent, Rule-Based and Long Return History

We believe the way forward is to develop explicit models of hedge-fund strategies applied to traditional assets such as those in Fung and Hsieh (2001a) and Mitchell-Pulvino (2001). In both these papers, the authors constructed the return of classes of hedge-fund strategies based on explicitly specified investment rules using long histories of traditional asset prices. We call these asset-based style factors.

Generally stated, the challenge here is to define a set of style factors whose return can be replicated by observable asset prices in accordance with the underlying hedge-fund strategies. Continuing with the example of long/short equity style, one approach is to define the first style as long/short-value stocks. A long/short-growth stocks style can be similarly defined. This way, a fund that employs a long value, short growth style can be expressed as a linear combination of value and growth stocks. What remains is to develop a model that captures the essence of the long/short-equity style using explicitly specified investment-rules. For example, the work on "Pairs Trading" by Gatev, Goetzmann and Rouwenhorst (1999) can be extended to achieve this goal.

Merger arbitrage is another specific, but common, example of long/short-equity style. Here, long positions in the target firms and short positions in the acquiring firms after a merger transaction is announced. The bet is that the mergers will be completed. Mitchell and Pulvino (2001) constructed returns of a specific form of merger-arbitrage strategy from 1963 to 1998. They showed that the return profile of the simulated trades is similar to the profile of merger-arbitrage hedge funds from 1990 to 1998. However, to complete the analysis, variations to the basic merger strategy modeled in Mitchell and Pulvino (2000) needs to be extended.[18]

Both of the above examples are partial developments of asset-based style factors. A more complete example can be found in Fung and Hsieh (2001a). It was shown that trend-following strategies have returns similar to a dynamically managed option-based strategy called a lookback straddle. This gives rise to an option-based trend-following strategy. Using only exchange-traded options, the pricing and construction of this option-based trend-following strategy are totally transparent to investors. In Fung and Hsieh (2001a) the rates of return of these lookback straddles are created using all of the major futures and options contracts worldwide and covers the period 1985-1997.[19]

It is shown in Fung and Hsieh (2001a) that these lookback options' returns are strongly correlated to the returns of trend-following funds. By modeling a family of hedge-fund strategies this way we were able to relate a complex group of trading strategies (trend-following in this case) to observable asset returns without having to exact the detailed workings of the strategies themselves. In other words, this type of approach has the benefit of creating transparency from otherwise opaque investments and overcomes data limitations through the use of observable market prices.

To illustrate the benefit of modeling hedge-fund strategies in an asset allocation framework, we provide a summary of the empirical findings in Fung and Hsieh (2001a).

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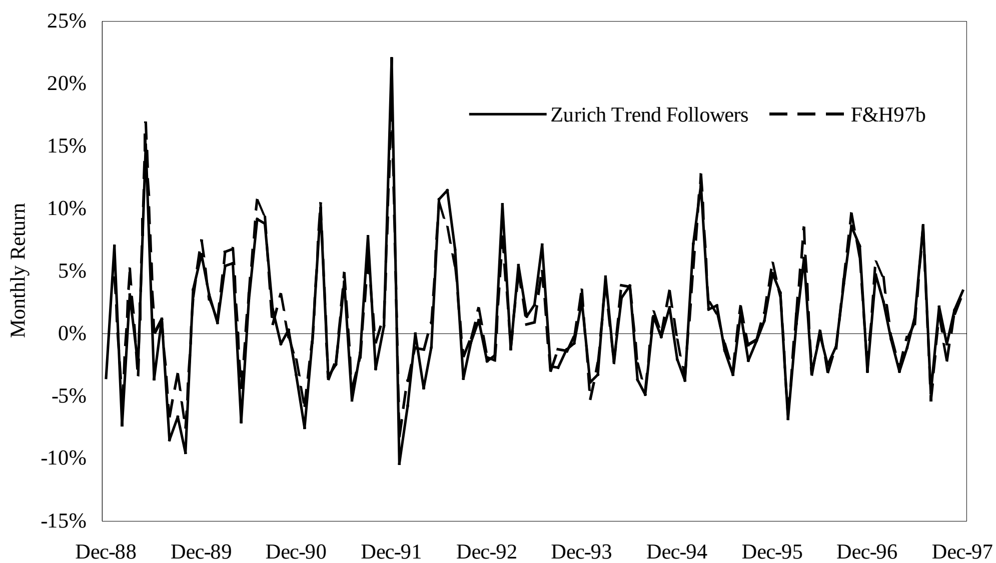
[18] Mitchell and Pulvino (2001) include only cash and stock-for-stock merger transactions. Specifically, they exclude any transactions involving bonds, hybrid securities, etc.

[19] In majority of the cases, the historical price series used dated back to the inception of the contracts. The idea is to be as exhaustive in the use of data as possible. See Fung and Hsieh (2001a) for details.

It was first noted in Fung and Hsieh (1997b) that trend followers have return characteristics that mimic the payout of an option on traditional assets like stocks and bonds. They tend to do well in extreme markets (both up and down) but do poorly when asset markets are in a trading range around their respective mean returns.

Since the publication of that article we now have three additional years of data (from 1998 to 2000). This allows us to provide an out-of-sample validation of this observation which we accomplish in several steps.

First, instead of constructing our own trend-following index from commodity funds as in Fung & Hsieh (1997b), we use the Zurich trend-following index, which is the median return of trend-following trading advisors tracked by Zurich since 1983. Over the common observation period from 1989 to 1997, the two methods for indexing trend followers' performance are highly correlated with a monthly return correlation coefficient of 0.971. The following figure illustrates that the two series are virtually identical.



Second, we depict the unusual return characteristics of trend followers using the Zurich trend-following index. Exhibit 2 in Fung and Hsieh (1997b) is updated using the Zurich-trend-following index returns over the period January 1983 to December 2000 as Table 1 below. Here we divided the monthly returns of the S&P500 from January 1983 to December 2000 into five "states" of the world. State 1 has the worst months of the S&P (as determined by being more than 1.8 standard deviations below the mean return). State 2 has the next worst months of the S&P (between 1.8 and 0.33 standard deviations below the mean return). State 3 has the normal months of the S&P (between -0.33 and +0.33 standard deviations from the mean return). State 4 has the better months of the S&P (between +0.33 and 1.8 standard deviations from the mean return). State 5 has the best months of the S&P500 (more than 1.8 standard deviations above the mean return). The mean monthly return of the S&P500 and the corresponding mean monthly return of Zurich trend-following funds in these five states are in Table 1 as follow:

Table 1.
Average Return in Five Stock Market Environments

States	1	2	3	4	5
S&P 500	-10.9%	-2.2%	1.5%	5.2%	11.1%
Zurich trend-followers	4.9%	1.0%	0.2%	2.0%	2.4%

Sources: BARRA, Zurich/Hedge.

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.

Table 2.
Returns During Extreme Declines in the Stock Market

Periods of Large Decline	S&P500	Zurich trend-followers
Sep-Nov of 1987	-29.6%	11.7%
Jun-Oct 1990	-14.7%	23.5%
Jul-Aug of 1998*	-15.4%	9.4%
Sep-Nov 2000*	-13.1%	6.5%
Feb-Mar 2001*	-15.45%	9.3%
Aug-Sep 2001*	-13.83%	6.8%

Sources: BARRA, Zurich/Hedge.
* Out-of-sample confirmation on the pattern first recognized in Fung and Hsieh (1997b).

The last 4 periods (Jul-Aug 1998, Sep-Nov 2000, Feb-Mar 2001, and Aug-Sep 2001) are out-of-sample validation of the pattern initially recognized in Fung and Hsieh (1997b): that trend-following funds perform well during extreme movements in equity markets, particularly during declines.

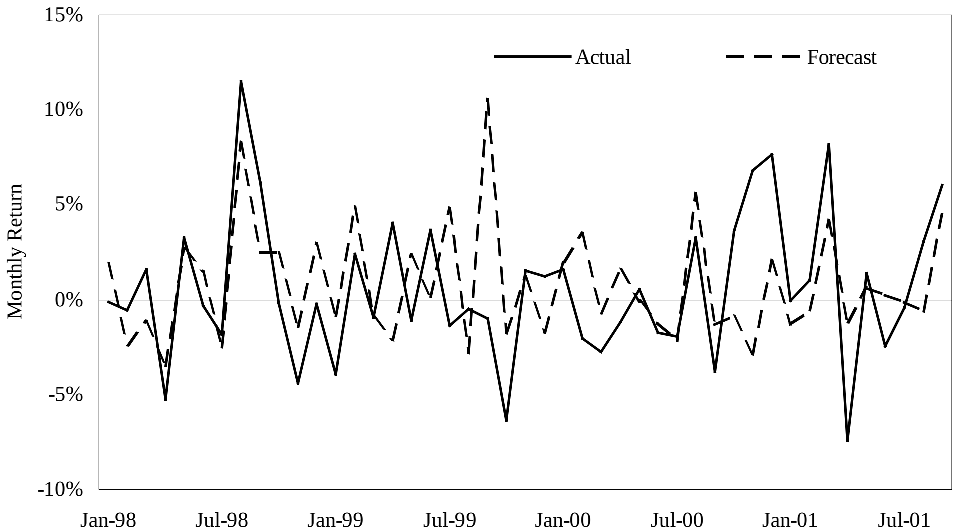
Third, to go beyond recognizing this purely as an empirical phenomenon and to overcome well-known data deficiencies of peer-group averages such as survivorship bias and potential non-stationarity in style grouping, we apply the methodology in Fung and Hsieh (2001a) to construct an asset-based style factor of trend-following strategies.

In essence, the Fung and Hsieh (2001a) approach creates a basic trend-following strategy called the primitive trend-following strategy (PTFS) using structured options called lookback straddles. A lookback straddle has a payoff equal to the difference between the maximum price and the minimum price of the underlying asset during the life of the option. Fung and Hsieh (2001a) 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. The paper showed that these PTFS portfolios have high explanatory power on the returns of trend-following CTAs, over the sample period from 1989 to 1997. Here, we provide an out-of-sample validation of their results using three additional years of data, from 1998 to 2000, by comparing the PTFS returns to the Zurich trend-following index's returns[20]

Over the same time period: 1989 to 1997, the regression of the Zurich trend-following index returns on the five PTFS portfolios' returns has an R^2 of 0.44. Three of the PTFS portfolios (bonds, currencies, and commodities) are statistically significant. These results are very similar to those in Panel B of Table 5 in Fung and Hsieh (2001a) which was based on using an equally-weighted portfolio of trend-following CTAs instead of the Zurich trend-following index. When we remove the two PTFS portfolios that were not statistically significant (stocks and three-month interest rates), the results are very similar to those in Panel C of Table 5 in Fung and Hsieh (2001a). This leaves us with three PTFS portfolios applied to bonds, currencies and commodities. We then use the average return of these three PTFS portfolios as the return of our asset-based style factor of trend-following strategies.

The out-of-sample comparison of this asset-based style factor of trend-following strategies to the Zurich trend-following index is performed as follows. We forecast the Zurich trend-following index from 1998 through 2000 with the coefficients from the 1989-1997 regression and the actual values of the PTFS portfolios. The figure below graphs the actual and forecasted Zurich trend-following index.

[20] We were able to update all of the option data in Fung and Hsieh (2001a), with the exception of the options on the DAX and the Nikkei which were unavailable due to data changes.



The graph speaks for itself. It suggests that the forecasts using the asset-based trend-following index are reasonably correlated to the actual outcomes. The major discrepancy was in Sep 1999, when gold spiked up dramatically for 1 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-following index to our asset-based trend-following style factor. By construction, this asset-based style factor is a transparent, rule-based description of the return characteristics of trend-following strategies based purely on observable market prices.

Fourth, we compare the state-dependent returns of the asset-based trend following index to the S&P 500 in the same manner as in tables 1 and 2 above.

Table 3.
Average Return in Five Stock Market Environments

States	1	2	3	4	5
S&P 500	-10.9%	-2.2%	1.5%	5.2%	11.1%

Zurich Trend followers	4.9%	1.0%	0.2%	1.8%	2.4%
Asset-based TF style factor	5.6%	1.2%	0.6%	0.4%	0.3%

Table 3 shows that this asset-based trend-following style factor has similar return behavior to that of the Zurich trend following index. It has larger positive returns during the extreme declines in the S&P (State 1) than the middle states (2 and 3), but has much less pronounced positive returns during the extreme positive states (4 and 5). As institutional investors are more interested in using trend followers to provide diversifying performance during extreme downturns in the stock market, we examine the behavior of the asset-based trend-following style factor in the following table:

Table 4.
Returns During Extreme Declines in the Stock Market

Periods of Large Decline	S&P 500	Zurich Trend Followers	Asset-Based Style Factor
Sep-Nov of 1987	-29.6%	11.7%	12.9%
Jun-Oct 1990	-14.7%	23.5%	28.5%
Jul-Aug of 1998*	-15.4%	9.4%	5.6%
Sep-Nov 2000*	-13.1%	6.5%	-5.0%
Feb-Mar 2001*	-14.9%	9.3%	3.6%
Aug-Sep 2001*	-13.8%	9.2%	3.9%

This table shows that the returns of the asset-based style factor of trend-following strategies have similar characteristics to those of the Zurich trend followers in 4 of the 5 large declines in the S&P during the past 15 years.

Another out-of-sample test of the Fung and Hsieh (2001a) model can be performed using the NASDAQ Composite Index instead of the S&P500. The results are tabulated as Tables 5 and 6 below.

Table 5.
Average Return in Five Stock Market Environments Based on the Nasdaq

States	1	2	3	4	5
Nasdaq Composite Index	-17.6%	-1.1%	1.6%	6.8%	17.0%
Zurich trend followers	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 6.
Returns During Extreme Declines in the Nasdaq

Periods of Large Decline	S&P 500	Zurich Trend Followers	Asset-Based Style Factor
Jun 83-Jul 84	-27.9%	36.1%	-2.5%
Jul-Nov 87	-29.8%	6.2%	12.0%
Sep 89-Oct 90*	-30.3%	32.5%	34.9%
Jun-Aug 98*	-20.9%	9.4%	5.6%
Feb-May 00*	-27.6%	-3.3%	0.7%
Aug-Dec 00*	-41.3%	14.6%	-3.0%
Jan-Mar 01*	-33.6%	9.3%	2.2%
Jul-Sep 01*	-30.7%	8.8%	3.7%

Note that, since the peak of the Nasdaq in February 2000, the index has declined 68% by September 2001. During that time, Zurich trend followers gained 18.1% while the asset-based trend-following style factor gained 5.5%.

Given the transparency of the asset-based trend-following 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 of the asset-based trend-following style factor. During periods of high volatility, asset price movements are often amplified in magnitude. In addition, other studies have reported concurrent rise in price volatility across other asset classes when the equity market is under stress. Although the direction of price movement in other asset classes need not coincide with that of the stock market, the magnitude of price movements are often commensurate. It is the emergence of large price movements that provide trend followers with profitable opportunities.

In reverse, during steady periods in the stock market, the cost of being long options in periods of low volatility will lead to unfavorable performance of the asset-based trend-following style factor. By the same token, low volatility periods imply price movements of limited magnitude. This is an unfavorable environment to trend followers.

In other words, the unusual return characteristic of trend-following strategies is a systematic consequence of large price volatility and not just an empirical regularity we found among trend-following funds. One immediate consequence of this is that trend-following funds contribute to portfolio diversification in a very specific way. Our theoretical model 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.[21]

At the individual fund level, a trend-following fund's performance can be assessed using equation (1). In essence, if a trend-following fund failed to capture the volatility value of the markets in which it operates, then investors would be been better off replicating the characteristics of trend-following strategies directly using traded options.[22] In addition, equation (1) allows portfolio investors to design option-like exposures to a broad range of commodity markets. By just observing the returns of a given group of trend-following funds, it is unclear as to how much diversification is being achieved by investing in them.

[21] It was shown in Fung and Hsieh (1997b) and in Billingsley and Chance (1996) that majority of the CTA funds employ trend-following strategies.
[22] In Fung and Hsieh (2001a), we found that generally, CTAs have positive alphas versus the strategy factors of about 1% per month.

Lastly, this method of asset-based style factors can generate long time series to simulate the behavior of hedge fund trading strategies. For example, Mitchell and Pulvino (2001) are 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 further back in time, by simulating option returns based on a theoretical option pricing model such as the Black-Scholes model.

6. Can Asset-Based Style Factors be Developed to Cover the Myriad of Hedge-Fund Strategies?

Just how practical a proposition is it to develop these complex models of hedge-fund strategies and present them as asset-based style factors? More importantly, can these asset-based style factors be easily maintained and placed in the public domain? Already, there is a US mutual fund called the "Merger Fund" that runs a passive merger arbitrage-strategy in a manner similar to the Mitchell-Pulvino model. The basic point is that not only can the returns be computed using market prices as in Mitchell and Pulvino (2001), an operational fund using this approach exists. In fact, the correlation between merger arbitrage hedge funds (as proxied by the HFR Merger Arbitrage index) and the Merger Fund is 0.85 over the period Jan 1990 to Dec 2000.

In terms of the trend-following model of Fung and Hsieh (2001a), institutional investors have told the authors that they have adopted the portfolio strategy of using trend-following funds to provide return during extreme market conditions.[23] Other than

[23] A number of multi-strategy hedge funds have also added a "systematic" component to their portfolio of strategies. This is often done with the expressed objective of capturing some of the option-liked downside protection these strategies offer.

the tedious data collection effort required, the Fung and Hsieh (2001a) model can be computed 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. This raises the question "Given the myriad of hedge-fund styles (i.e., strategy and location pairs) and the dynamic ways they evolve, can this be accomplished?"

The answer will not be known until we have developed a sufficient number of asset-based style factors to model the majority of the hedge fund strategies. By some measures, however, we may be more than half way there. Consider, for example, the HFR Composite Index, which is an equally weighted portfolio of hedge funds in the HFR database and the CSFB/Tremont (CT) Hedge Fund Index, which is an asset-weighted portfolio of large hedge funds in the TASS database. It turns out that these aggregate indices have strong market exposures, as in the following regressions (from 1994 until 2000)[24]:

Table 7
Market Exposures of Hedge Fund Indices

Hedge Fund Indices	Constant	Small Cap	High Yield Bd	IFC Composite	R-sq
HFR Composite index	0.0074 *	0.287 *	0.184 *	0.104 *	0.892
Standard errors	0.0009	0.022	0.072	0.017	
CT Hedge Fund Index	0.0062 *	0.225 *	0.372	0.074	0.463
Standard errors	0.0025	0.065	0.243	0.049	

[24] Including the Wilshire Small Cap index makes the S&P 500 and its lags statistically significant. This raises an interesting alternative interpretation to the results reported by Asness et al (2001). Are there more suitable risk factors that explain hedge fund returns than the one used by Asness et al (2001)? We believe that 'hedge-fund alphas' come from bearing unconventional risk rather than being a consequence of measurement errors due to omitted lagged terms in a standard linear risk model.

Undoubtedly, differences in the index construction methodologies of different hedge-fund index suppliers affected the reported results; see for example Fung and Hsieh (2001b). However, there is little doubt that nearly half of the volatility of these indices can be explained by readily observable "long-only" asset-based style factors in the form of conventional indices.

Two caveats remain. What do we do with the unexplained variance? With a large and significant "alpha" and beta coefficients that sum to much less than one; what other factors are at work?

To further increase the explanatory power of using readily available style factors, the work by Aggrawal and Naik (2000b) provides valuable clues. They showed that simulated option returns (using the Black-Scholes option model) 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 are selected based purely on goodness of fit) to specific hedge fund strategy.

In terms of the large market exposures, further clues can be gleamed by analyzing the subindices that comprise these broad-based hedge-fund indices.

Out of 16 HFR subindices of peer-group based hedge-fund t styles, 9 have R^2s above 0.50 (see Appendix A for details). They are Distressed Securities, Emerging Markets (Total), Equity Hedge, Equity Non-Hedge, Event Driven, Fixed Income (Total), Relative Value, Sector (Total), and Short Selling. Many of these styles have significant market exposures. For example, the Distressed Securities style is strongly correlated to high yield bonds. The Emerging Markets style is strongly correlated with the IFC

Composite index. Equity Hedge, Equity Non-Hedge, Short Selling, and Sector (Total) are strongly correlated to small cap stocks.

We estimate the weights of the 16 component styles by regressing the HFRI composite index on the 16 component styles. The 9 styles that have significant exposure to the three market factors combine to account for roughly 80% of the HFRI composite index.

Interestingly, nearly half (7 out of 16) of the component styles have much lower correlation with the three market factors. They are Convertible Arbitrage, Equity Market Neutral, Marco, Market Timing, Merger Arbitrage, Statistical Arbitrage, and Regulation D. These styles are generally regarded as have little or no directional exposure. However, their combined weight in the HFRI composite index is estimated to be only 20%. This explains why the HFRI composite index is so strongly correlated to market factors. It also suggests that the observed alpha from the regression is in part due to the average returns of these non-directional strategies.

Another possibility must be noted. Over the past years, there has been a growing tendency for hedge funds to employ more than one strategy. Given this tendency, it is plausible that there are non-directional strategies within the subindices that showed significant market exposures. This is another potential source of alpha. In fact, the tendency for hedge funds to employ several strategies is another reason why peer-group based style indices are inherently problematic.

Similar results can be obtained using the CT indices, see appendix B for details. Four of the nine CT component styles have significant market exposures. They represent roughly 45% of the weight of the composite index. As in the case of the HFR indices, we estimate the weights of the component styles by regressing the composite index on the nine component styles.

Given these results, the way forward seems much less problematic. Hedge fund strategies with a directional component can be modeled with “long only” asset-based style factors in the form of readily available conventional indices. Our results show that this can account for more than 50% of observed variance in hedge fund returns. To improved upon these results, additional techniques are required to model the nonlinear characteristics of hedge fund returns. These nonlinear characteristics can come from a variety of sources. They can be a result of dynamic allocation of risk capital across markets and the dynamic use of leverage. Both can lead to option-liked return patterns that cannot be captured by using a linear model of conventional indices. Progress has been made but more research is required. For example, trend-following strategies can be modeled using option positions, as in Fung and Hsieh (2001a). This also provides an addition reason why one observes a significantly higher R^2 for the HFR composite index using only conventional indices because, unlike the CSFB/Tremont index, they excluded CTAs in their index composition.

For non-directional (or otherwise referred to as market neutral) hedge-fund strategies, new models are required. For example, Merger Arbitrage has been modeled by extending the work of Mitchell and Pulvino (2001). What we need is to model the returns of the remaining non-directional styles, which account for less than half of the style indices in the HFR and CSFB/Tremont hedge fund indices. Based on our findings, we may be already half way towards having a complete set of asset-based style factors for the hedge fund industry as a whole. We hope more research will be directed to complete this effort to provide a set of transparent, rule-based indices that help investors understand hedge-fund investing.

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Appendix A
Market Exposures of HFR Style Indices

HFR Indices	Constant	Small Cap	High Yield Bd	IFC Composite	R-sq	Weight Est	Weight Actl
Convertible Arbitrage	0.0070 *	0.027	0.355 *	0.013	0.416	0.05	0.05
	0.0010	0.022	0.081	0.017			
Distressed Securities	0.0051 *	0.097 *	0.481 *	0.054 *	0.637	-0.01	0.03
	0.0013	0.035	0.130	0.021			
Emerging Markets (Total)	0.0033	0.086	0.468 *	0.587 *	0.815	0.12	0.10
	0.0025	0.073	0.228	0.049			
Equity Hedge	0.0108 *	0.487 *	-0.075	0.035	0.830	0.17	0.26
	0.0014	0.036	0.099	0.029			
Equity Market Neutral	0.0069 *	0.101 *	0.107	-0.058 *	0.270	0.07	0.04
	0.0010	0.028	0.077	0.021			
Equity Non-Hedge	0.0058 *	0.664 *	0.113	0.089 *	0.887	0.17	0.10
	0.0017	0.041	0.120	0.029			
Event-Driven	0.0083 *	0.202 *	0.344 *	0.047 *	0.748	0.08	0.06
	0.0011	0.026	0.102	0.022			
Fixed Income (Total)	0.0046 *	0.032	0.370 *	0.009	0.541	0.09	0.08
	0.0009	0.019	0.107	0.019			
Macro	0.0058 *	0.155 *	0.298	0.084 *	0.409	0.05	0.04
	0.0023	0.045	0.177	0.037			
Market Timing	0.0099 *	0.244 *	-0.164	0.071	0.492	0.04	0.03
	0.0021	0.042	0.206	0.036			
Merger Arbitrage	0.0097 *	0.078 *	0.118	0.019	0.378	0.06	0.03
	0.0013	0.020	0.117	0.020			
Relative Value Arbitrage	0.0070 *	0.062 *	0.314 *	0.006	0.508	0.08	0.03
	0.0011	0.020	0.102	0.019			
Sector (Total)	0.0082 *	0.702 *	0.150	0.069	0.768	0.08	0.09
	0.0028	0.096	0.210	0.055			
Short Selling	0.0152 *	-1.172 *	0.165	-0.052	0.763	0.02	0.01
	0.0042	0.118	0.302	0.079			
Statistical Arbitrage	0.0080 *	0.025	0.199 *	-0.032	0.100	-0.01	0.03
	0.0015	0.035	0.087	0.030			

Regulation D	0.0145 *	0.091	-0.019	0.045	0.121	0.01	0.02
(1996-2000)	0.0024	0.068	0.181	0.042			

Appendix B
Market Exposures of CSFB/Tremont Style Indices

CSFB/Tremont Indices	Constant	Small Cap	High Yield Bd	IFC Composite	R-sq	Estimated Weight
Hedge Fund Index	0.0062 *	0.225 *	0.372	0.074	0.463	1
	0.0025	0.065	0.243	0.049		
Convertible Arbitrage	0.0065 *	-0.003	0.448 *	-0.007	0.209	0.08
	0.0018	0.043	0.171	0.035		
Dedicated Short Bias	0.0102 *	-0.755 *	-0.198	-0.140 *	0.768	0.00
	0.0033	0.071	0.245	0.062		
Emerging Markets	0.0032	0.070	0.525	0.646 *	0.657	0.05
	0.0041	0.102	0.364	0.077		
Equity Market Neutral	0.0087 *	0.038	0.080	0.026	0.176	-0.02
	0.0011	0.023	0.068	0.022		
Event Driven	0.0064 *	0.079 *	0.530 *	0.090 *	0.648	0.09
	0.0017	0.028	0.167	0.027		
Fixed Income Arbitrage	0.0039 *	-0.050	0.456 *	0.003	0.221	0.05
	0.0017	0.030	0.190	0.037		
Global Macro	0.0076	0.145	0.463	0.026	0.124	0.43
	0.0048	0.109	0.463	0.090		
Long / Short Equity	0.0064 *	0.563 *	0.064	0.045	0.792	0.29
	0.0020	0.057	0.138	0.040		
Managed Futures	0.0076 *	0.004	-0.572 *	0.054	0.056	0.02
	0.0036	0.077	0.273	0.065		