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Will Hedge Funds Regress towards Index-like Products?

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I. Introduction

Hedge funds have grown substantially in the past few years. According to estimates by Tremont Capital Management (2006), the industry's assets under management increased from just over $200b in 2000 to over $800b by the end of 2005. Along with the rapid inflow of capital, hedge fund performance has declined. According to HFR, the average fund of hedge funds returned 10.5% per annum during 1996-2000, but only 5.8% during 2001-5. This development is consistent with the prediction of Berk and Green (2004) that unchecked inflow of funds will ultimately erode performance due to diminishing returns to scale. There is a sense of *deja vu* among hedge fund investors that many hedge fund managers are beginning to resemble active managers in the mutual fund industry of the past—failing to deliver returns commensurate to the fees and expenses they imposed on investors. History tells us that over-priced active managers will be replaced by low-cost passive index-liked alternatives. Could the same process be taking place in the hedge fund industry? Against this background, it is not surprising that investors are demanding more cost efficient hedge fund products. But, is existing technology capable of support the creation of rule-based, low-cost, passive hedge funds?

The term "alternative beta" refers to the returns achievable from low-cost replication of rule-based trading strategies that capture return characteristics common across hedge funds, while "alternative alpha" refers to the returns that are not easily replicated. The introduction of this terminology was partly motivated by the need to stress that the search for hedge fund alpha properly begins with the identification of beta exposure to systematic risk factors which can go beyond conventional asset-class factors. This in turn points to the need for new technology if alternative beta factors are to be replicated successfully—a new tool kit is needed.

This paper reviews the development of the tool kit used to distinguish "alternative alpha" from "alternative beta." In particular, we review the development of various primitive trading strategies (PTSs) that captures the essence of hedge fund strategies and extends the well-known approach of Sharpe (1992) for mutual funds. In addition, we discuss some potential pitfalls in applying the existing technology to replicate hedge fund returns.

II. From Passive Benchmarks to Replicating Hedge Funds

It has long been recognized that the search for alpha begins with the proper identification of the systematic drivers of returns ("betas"). For mutual funds, this search has been satisfactorily dealt with in Sharpe (1992). For hedge funds, the search for alpha is complicated by their dynamic use of long and short positions. This in turn generates nonlinear returns that require customized benchmarks—see for example Golsten and Jaganathan (1994). Fung and Hsieh (1997) explored this issue in their extension of the Sharpe (1992) model on mutual fund styles to hedge funds. They proposed to model hedge fund styles using linear combinations of rule-based trading strategies, some of which are highly nonlinear in the returns of underlying assets. In the ensuing decade, a number of these rule-based trading strategies have been developed to allow researchers to model a diversified portfolio of hedge funds, such as indices of hedge funds and funds-of-funds.

Embodied in this simple idea are two important separation properties. First, there is the familiar alpha-beta separation in attributing hedge fund performance. The second, less obvious, concept is the separation of strategy-driven nonlinearity in observed returns from the nonlinearity caused by dynamic asset allocation. Empirically, it is a challenge to untangle these two sources of return linearity given the opaqueness of hedge fund operations. While the first separation property pertains mainly to ex-post performance evaluation models, the second separation property is critical to successful replication of a diversified portfolio of hedge fund strategies. One way forward is to separate, as much as possible, one source of modeling error from the other in designing replication portfolios of hedge fund returns. In this section, we highlight some of the potential pitfalls in applying standard econometric techniques to model hedge fund returns

It is useful to start with the Sharpe (1992) model for alpha/beta separation for mutual funds. Start with a standard factor model for asset i:

$$r_{i,t} = b_{i1} f_{1t} + b_{i2} f_{2t} + \ldots + b_{iN} f_{Nt} + e_{it} \qquad (1)$$

Here the r's are asset returns, f's factor returns, b's factor loadings, where all returns are measured in excess of the riskfree return.

We can write the (excess) return of an investment fund as:

$$R_t = \sum_i w_{it} r_{it} \qquad (2)$$

where the w's are weights allocated to each asset. We can then express the fund's excess returns in terms of the factor model:

$$R_t = \left[\sum_i w_{it} b_{i1}\right] f_{1t} + \left[\sum_i w_{it} b_{i2}\right] f_{1t} + \ldots + \left[\sum_i w_{it} b_{iN}\right] f_{Nt} + \left[\sum_i w_{it} e_{it}\right], \text{ or}$$

$$R_t = B_{1t} f_{1t} + B_{2t} f_{2t} + \ldots + B_{Nt} f_{Nt} + E_t, \text{ where}$$

$$B_{jt} = \left[\sum_i w_{it} b_{ij}\right], \text{ and } E_t = \left[\sum_i w_{it} e_{it}\right] \qquad (3)$$

It is easy to see from the above equations that an "accidental alpha" can arise from using the wrong benchmark. Take the simple case of a passive mutual fund, where the allocations to assets are constant over time:

$$R_t = \sum_i w_t r_{it} \qquad (2a)$$

In this correctly specified model, the fund has constant exposures to the factors, and has no alpha relative to these factors:

$$R_t = B_1 f_{1t} + B_2 f_{2t} + \ldots + B_N f_{Nt} + E_t \,,$$
$$B_j = \left[\sum_i w_i b_{ij}\right], \text{ and } E_t = \left[\sum_i w_i e_{it}\right] \qquad (3a)$$

Now let us assume that the researcher selected a style that has allocation to only the first two factors:

$$S_t = X_1 f_{1t} + X_2 f_{2t} \qquad (4)$$

Note that a style is essentially a well-diversified portfolio of assets.

We can express R_t in terms of style returns S_t as:

$$R_t = \left[(B_1 - X_1) f_{1t} + (B_2 - X_2) f_{2t} + B_3 f_{3t} + \ldots + B_N f_{Nt}\right] + S_t + E_t \qquad (5)$$

However, when the researcher regresses R_t on S_t, the constant term of the regression will pick up the average of the term in the square brackets in equation (5):

$$\alpha = \left[(B_1 - X_1)\overline{f_1} + (B_2 - X_2)\overline{f_2} + B_3 \overline{f_3} + \ldots + B_N \overline{f_N}\right], \text{ where the expression } \overline{Z} = \frac{1}{T}\sum_t z_t$$

The constant term will include factor "tilts", i.e., $(B_1 - X_1)$, as well as average of the returns due to missing factors, i.e., $B_3 \overline{f_3}$. Even when there are no factor tilts (or $B_1 = X_1$ and $B_2 = X_2$), an accidental alpha results if the missing factors have positive premia.

We can extend these standard observations on benchmarking in mutual funds to the case of hedge funds. Using Sharpe (1992) as a starting point, Fung and Hsieh (1997) put forward a simplified model of hedge fund returns (in gross terms):

R= f (leverage, location, strategy) (6)

This embodies the notion that performance is a function of how they trade (strategy), where they trade (location, or markets), and how much they trade (leverage, or sizing of positions). The key difference between hedge fund strategies and mutual fund strategies is that "strategy" for hedge funds is typically different from the long-only strategy used by the majority of mutual funds.

To implement this extension to hedge funds, we first construct "primitive trading strategies" (PTS) to capture the essence of dynamic hedge fund strategies. Leaving specific examples aside, the simplest way to think about a PTS is to refer to the insight in Merton (1981) that the return of a perfect market timer should be identical to the return from owning a call option on the market. This reduces the problem of designing complex, and often unobservable, trading rules to a simple option position. It also transfers the strategy return from complex (possibly nonlinear) functions of the underlying asset return to a series of familiar option returns. In the terminology put forward by Fung and Hsieh (2001), this simple option-based characterization of market-timing strategies can be referred to as the primitive trading strategy ("PTS") used by market timers.

At a general level, we define a PTS as a dynamic allocation to risk factors:

$$g_{it} = \sum_j x_{ijt} f_{jt} \tag{7}$$

The linearity in the factors reflects the intuition that the PTS is constructed using conventional asset factors with familiar statistical properties. When the weights (x's) are constant, we obtain the style factors in Sharpe (1992). By putting time subscripts in the weights (x's), we allow for nonlinear, dynamic combination of these factors that makes the PTS return nonlinear—the way hedge funds trade, in the language of Fung and Hsieh (1997). In this context, the Merton market timing PTS can be written as a dynamic linear combination of the underlying asset and the riskfree rate depending on the delta position of the option. Standard option theory tells us that the weighting scheme of the risky and riskfree assets in turn depends on the familiar factors that drive option prices such as volatility and time to expiration.

By allowing arbitrary weights (x's) in Equation (7), we open up the proliferation of PTSs, as pointed out in Fung and Hsieh (1997). For a PTS to be a useful part of the replication tool kit, it must be a low-cost, rule-based trading strategy that generates returns similar to those found in common hedge fund strategies. In the next section, we illustrate some of these useful PTSs.

We can represent the return from a portfolio of hedge fund strategies as the linear combination of an exhaustive set of all possible PTSs used by the fund:

$$R_t = \sum_i w_{it} g_{it} \tag{8}$$

Here, if the allocation of risk capital (w's) to each PTS is constant over time, then all of the nonlinearity in the observed hedge fund returns is captured by the set of PTS.

At this point, it is worthwhile to step back and discuss the philosophy behind this setup. Nonlinearity in returns enters in two ways: through the trading strategy (the x's in Equation 7) and through dynamic allocation across strategies (the w's in Equation 8). We use the PTSs to capture the nonlinearity in hedge fund returns that result from specific trading strategies (such as Merger Arbitrage and Trend Following, discussed in the next section). This allows us to study the nonlinearity in dynamic allocation across these strategies.

Returning from this slight digression, notice that Equation (8) for hedge funds resembles Equation (2) for mutual funds, where security returns are replace by PTS returns. This allows us to extend the results from the mutual fund literature to hedge funds: accidental alpha can arise from a missing or mispecified PTS, or from a misspecification of dynamic allocation of risk capital to the PTSs.

To illustrate the first point, take the case of a hedge fund that has fixed allocation to only two PTSs:

$$R_t = w_1 g_{1t} + w_2 g_{2t} \qquad (9)$$

This hedge fund has no alpha relative to the properly specified set of PTSs. Suppose the researcher knows about the first PTS but not the second and proceeds to regress the hedge fund's return on the first PTS. What happens?

$$R_t = \left(w_2 \overline{g_2}\right) + w_1 g_{1t} + \left[w_2 \left(g_{2t} - \overline{g_2}\right)\right] \qquad (10)$$

The first term in parentheses is the "accidental alpha" that captures the average return to the unknown second PTS.

To illustrate the second point, consider a multi-strategy hedge fund with dynamic allocation to the two PTSs:

$$R_t = w_{1t} g_{1t} + w_{2t} g_{2t} \qquad (11)$$

What happens when we regress the fund's return on the first PTS?

$$R_t = \left(\overline{w_1 g_1} + \overline{w_2 g_2}\right) + \overline{w_1} g_{1t} + \left[\left(w_{1t} - \overline{w_1}\right) g_{1t} + w_{2t} g_{2t} - \overline{w_2 g_2}\right] \qquad (12)$$

Here the constant term absorbs the average return from timing the PTSs leaving the beta term to capture the average exposure to the first PTS.

Note that the calculations in (10) and (12) assume that the two PTSs returns are uncorrelated. If the two PTSs returns are correlated, then the slope coefficient, or "beta", of the first PTS will be biased, capturing the portion of the fund's exposure to the second PTS that is correlated with the regressor.

These examples point out that alpha in hedge funds can arise "accidentally" from exposure to unknown PTSs, and/or from difficult-to-observe market timing in PTSs. What the examples do not explore is the additional error that occurs from potential measurement errors in the PTS returns. The proper identification of PTS is an important step in the modeling exercise because it is the PTS that link hedge fund strategy returns to conventional asset factors. In the next section we provide an overview of known PTSs and explore some of the pros and cons in alternative approaches to complete the "PTS" tool box needed by researchers.

III. Primitive Trading Strategies—a powerful but incomplete tool kit

Since PTSs are the critical building blocks needed to successfully replicate hedged funds, we provide specific examples of these primitive trading strategies (PTS) and explore the intuition underlying different construction methods.

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Merger Arbitrage

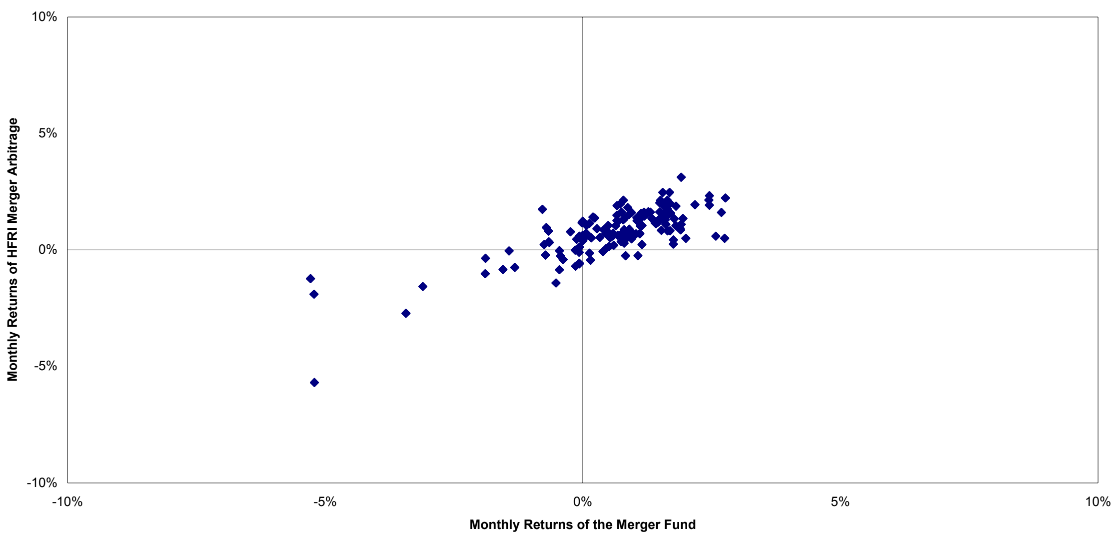
One of the oldest examples of a hedge fund strategy available to mutual fund investors is merger arbitrage. Merger arbitrage (or risk arbitrage) is a strategy that typically bets on the successful completion of merger/takeover (business combination) transactions. On average, the strategy rewards the arbitrageur with a risk premium for betting on deals going through. It follows that, on average, the return to merger arbitrage is a beta-like return and alpha in this context refers to an arbitrageurs' ability to select better deals and/or manage the entry/exit points on deals they bet on—the analogy of security selection in Sharpe's (1992) language.

Mitchell and Pulvino (2001) created such a rule-based merger arbitrage strategy. For specific types of announced mergers (such as stock for stock), the strategy goes long the target and short the acquirer. Although the construction of this passive merger arbitrage portfolio is specific to the Mitchell and Pulvino (2001) study, nonetheless it represents the best available definition of a primitive merger arbitrage strategy—or the PTS for this style. They show that this primitive trading strategy generates returns whose distribution is similar to that of actual merger arbitrage funds.

Unfortunately, the Mitchell and Pulvino (2001) published PTS returns ended in 1998. Instead of trying to extend their PTS, we use a mutual fund, called the Merger Fund (ticker: MERFX), that has been in existence since 1989 and follows a comparable rule-based merger arbitrage strategy described in its prospectus. As a mutual fund is required to file quarterly positions (Form N-Q) with the SEC, the holdings of the Merger Fund are observable. Verification of its trading strategy is straight-forward. We obtained the returns for the Merger Fund from the Morningstar mutual fund CD. This set of data has the advantage of reflecting the actual investing experience into a passive, rule-based hedge fund-like strategy at mutual fund fees.

Figure 1 graphs the monthly returns of the HFRI Merger Arbitrage Index versus the returns of the Merger Fund from Jan 1994 until Jun 2006. It shows a high degree of correlation between them—the correlation coefficient is 0.77. However, it is important to note the HFRI Merger Arbitrage Index is basically a statistical construct that cannot be easily replicated in practice—see Fung and Hsieh (2004) for a discussion on using peer group averages to benchmark hedge fund performance.

Figure 1. Merger Arbitrage Vs The Merger Fund (Jan 1994 - Jun 2006)



An alternative PTS is an investable portfolio of merger arbitrage funds such as the HFRX Merger Arbitrage Investable Index. While this index satisfies the criterion of investability of a PTS, we are not able to verify if it is a low-cost replication strategy. Since the creation of the HFRX Merger Arbitrage Investable Index in April 2003, up through June 2006, this investable index returned 0.42% per month, which is net of the fees charged by the underlying merger arbitrage hedge fund fees but before HFR's fee for managing the product. Once we subtract the second (undisclosed) layer of fees, the index return would likely be much worse than that of the Merger Fund. Over the same time period, the Merger Fund returned 0.52% per month, which is net of all fees and expenses. This makes the Merger Fund a better choice as the PTS to represent the systematic return to this passive strategy. However, there is a caveat—the Merger Fund is mostly betting on US deals. It may result in an accidental alpha when used as a benchmark for merger arbitrage managers with a global mandate.

Managed Futures (Trend Followers)

Managed Futures funds are operated by commodity trading advisors, the majority of whom describe themselves as trend followers. Fung and Hsieh (2001) developed a model for trend followers using lookback straddles. The motivation behind using lookback straddles to mimic trend followers is to establish a rule-based, executable replication of the essence of the trend following strategy, similar to the motivation in Mitchell and Pulvino (2001) for the merger arbitrage strategy.

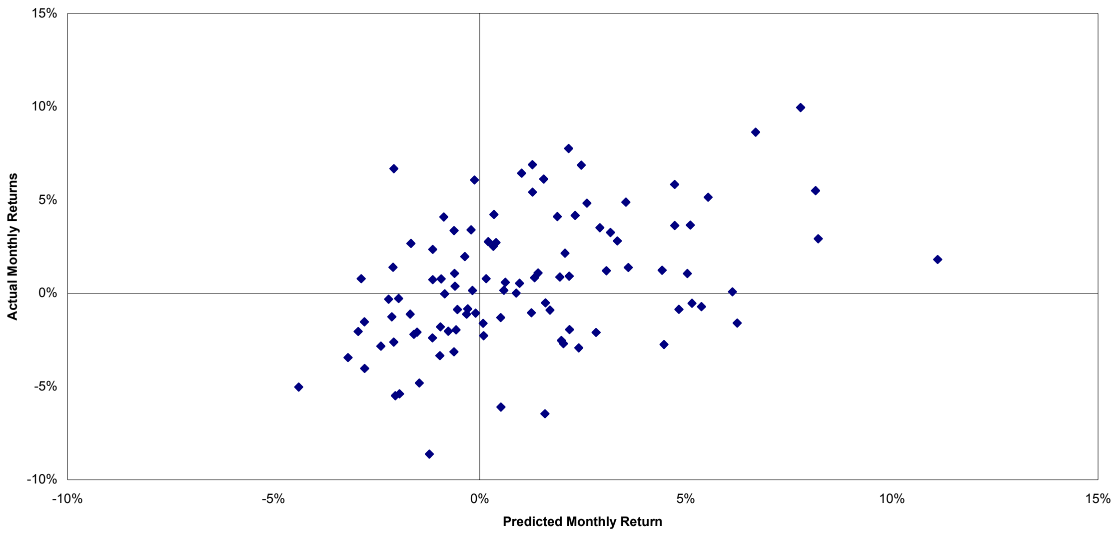
The essence of a trend following strategy is to derive the maximum benefit from large, directional moves in a variety of asset markets. The lookback straddle ensures that over any given time period, a buyer of the straddle on a particular asset always enjoys the difference between the highest and lowest price realized. This exposes the seller of the straddle to the risk of capturing the peaks and troughs of price moves. Such a risk premium can be directly observed using the publicly traded options market on that asset. When the risk of large moves in any given asset is high, this risk premium will rise and vice versa. Therefore, a trend follower (or buyer of the lookback straddle) is essentially betting on large, not well anticipated, moves in asset prices where the payout of the straddle exceeds the risk premium demanded by the seller. In other words, the performance of the lookback straddle mimics the market conditions under which trend followers are likely to do well despite that fact that few, if any, trend followers actually purchase the lookback straddles. Intuitively, we can think of the delta of the lookback straddle mimicking what a trend follower does in order to capture the final pay out of a large market move. The cost of such a strategy is being caught in rapid price reversals in which the lookback straddle's premium exceeds the final pay out.

This is the basic methodological difference between a PTS based on the Mitchell and Pulvino (2001) approach that replicates the actual transactions undertaken by merger aribitrageurs and a PTS based on lookback straddles which mimics the market conditions that are conducive to trend followers. It is important to note that neither Mitchell and Pulvino (2001) nor Fung and Hsieh (2001) addresses the dynamic asset allocation decision in their respectively replicating portfolios in that both are essentially equally weighted portfolios of the underlying transactions.

Empirically, lookback straddles are not traded on organized exchanges. However, Goldman, Sosin and Gatto (1979) showed how to replicate the payout of lookback options using standard options. Based on this replication strategy, Fung and Hsieh (2001) constructed executable portfolios of lookback straddles using exchange-traded options in twenty eight markets. They found that three portfolios (bond options, currency options, and commodity options) generate returns that mimic those of the average trend follower.

Figure 2 provides an out-of-sample verification of this method. We graph the return of the CSFB/Tremont Managed Futures Index on the vertical axis, against the conditional forecast on the horizon axis, using the regression coefficients reported in Table 5 Panel C of Fung and Hsieh (2001)—which is based on data ending 1997—as the weights for the lookback portfolios. We feed in the observed lookback portfolio returns from January 1998 until June 2006.

Figure 2. CSFB/Tremont Managed Futures Index: Actual Vs Predicted (Jan 1998 - Jun 2006)



The correlation between the forecasted values and the actual values is only 0.43. This seems rather low, compared to the much tighter correlation between the Merger Arbitrage Index and its corresponding PTS. However, for the trend following style, we cannot hope to get much better results. The regression in the Fung and Hsieh (2001, Table 5 Panel C) had an R^2 of 0.48, which translates to an in-sample correlation of 0.69 between the returns of trend followers and their PTS.

In this updating exercise, we had to replace or discard some of the original straddles used in Fung and Hsieh (2001). To account for the European Currency Union in 1999, we replaced the Deutsche Mark with the Euro FX. We also replaced the French Notional Bond and the German Bunds with the Euro Bund. This is an example in which the conventional asset factors used to construct a PTS can change in response to changes in the market environment.

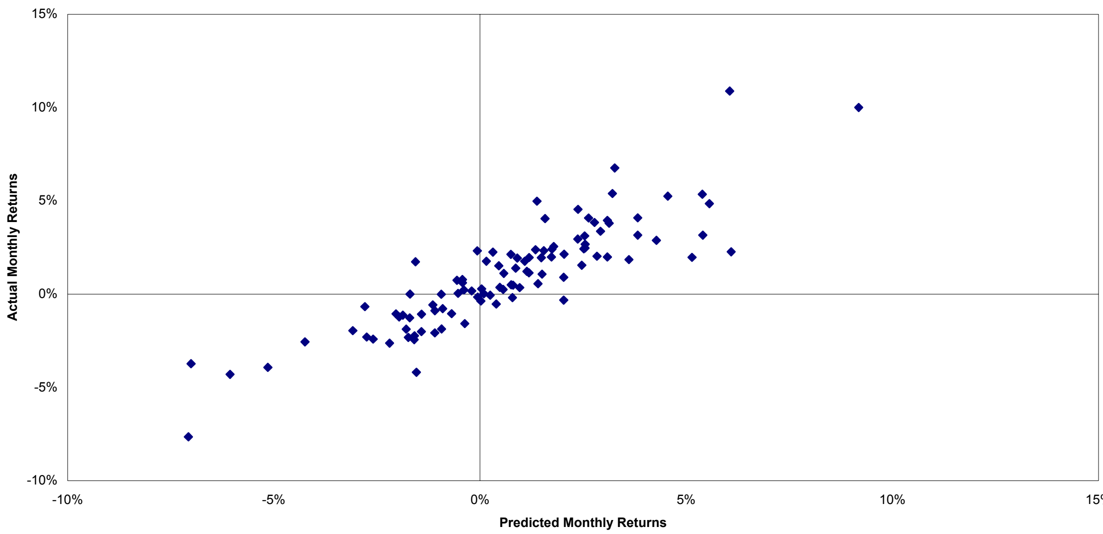
Long/Short Equity

Long/Short Equity is perhaps the most commonly found hedge fund style which consistently accounts for some 30 percent of the hedge fund industry. The first hedge fund, started by A.W. Jones, was a long/short equity fund. He used long and short positions in stocks. Historically, these funds tended to exhibit a long bias in the equity market(s).

Agarwal and Naik (2004) and Fung and Hsieh (2006) show that two major PTS can account for over 80 percent of the return variation in the average long/short equity fund. One PTS is simply a long position in the US stock market reflecting the long-bias of these funds. The other PTS can be modeled as a static spread position between long small cap/short large cap stocks, represented by the spread between the Russell 2000 and the S&P 500 returns. While Agarwal and Naik (2004) find evidence of option-like returns in individual equity funds, Fung and Hsieh (2006) find little evidence of option-like returns in the average long/short equity fund. This leaves us with a very simply representation of the average L/S Equity hedge fund as a linear combination of two PTS each of which can be expressed as static combinations of familiar equity market factors.

Figure 3 shows the predictive power of the two PTSs, using a rolling 24 month regression. For each month, we regress the returns of the average long/short equity fund on the two PTSs using the previous 24 monthly returns. We form conditional one-step-ahead forecasts, using the estimated coefficients and the realized values of the PTSs. The graph shows a strong correlation between the actual and predicted values.

Figure 3. HFRI Equity Hedge Index: Actual Vs Predicted (Jan 1998 - Jun 2006)



On the face of it, these results hint at the existence of a static combination of two simple, familiar equity-related factors capturing most of the return characteristics of this sector of hedge funds. It is important to bear in mind that both Agarwal-Naik (2004) and Fung-Hsieh (2006) point to substantially cross-sectional return variations among L/S equity hedge funds. These cross-sectional return characteristics can be important factors to consider when replicating the return behavior of hedge funds in this sector. When younger emerging equity markets mature and begin to figure more prominently in the opportunity set of hedge fund managers, it may be important to see if a new PTS in some form of an emerging market stock index is needed.

Beyond the above PTSs, others are emerging as the academic literature on this subject grows. For example, Agarwal, Fung, Loon and Naik (2006) developed a PTS for convertible arbitrage hedge funds. Durate, Longstaff and Yu (2005) constructed synthetic fixed-income arbitrage strategy returns that can be used to construct PTSs to mimic hedge funds in this general category. Other potentially useful PTSs are discussed in Fung and Hsieh (2007).

Overall, the academic literature has gone a long way towards creating low-cost, rule-based, executable and transparent representations of hedge funds strategies—PTSs. But this is still an incomplete set. Useful PTSs remain to be developed for Equity Market

Neutral and Statistical Arbitrage strategies. Researchers are constantly challenged to keep pace with market developments. In this respect, we still have a long way to go. Against this observation is the puzzling empirical regularity that large portfolios of hedge funds, such as hedge fund indexes, can apparently be modeled with a high degree of accuracy via only a limited set of PTSs, as in Fung and Hsieh (2004). Before tackling this puzzle, the next section offers a few examples of how errors can emerge when replicating hedge fund returns with incomplete data.

IV. Replicating hedge fund strategies in an econometric minefield

In this section, we employ a few simulated hedge fund replication examples to illustrate the issues raised in section II. These examples are constructed using the standard four factor model for equity returns.

IV.1. Factor Definitions

The first three factors (RMRF, SMB, VMG) are the Fama-French (1993) three factor model. RMRF is the value-weighted CRSP index minus the one-month treasury bill rate. SMB is the return of small cap stocks minus the return of large cap stocks. VMG is the return of value stocks minus the return of growth stocks. The fourth factor (UMD) is the momentum factor in Jagadeesh and Titman (1993), which is the return of stocks with the best performance in the prior 12 months minus the return of stocks with the worst performance over the same period.

In subsection IV.2, we show that we can accidentally find an alpha if we incorrectly specify the benchmark.

IV.2. Simulated Strategy 1: An Index Fund in Wolf Clothing.

Skeptics of hedge funds often refer to the large static exposure to conventional asset classes as a mockery to the fees hedge funds demand. However, taking these objections at face value implies that some hedge fund strategies can be replicated by low-fee index-like alternatives. The truth, on the other hand, has a way of surprising us.

Suppose a researcher estimates the CAPM for the HFR Equity Non-Hedge index with RMRF as the proxy for the market portfolio. Using monthly returns during 2000-2005, we get the following regression:

$$\underset{}{R-r_f} = \underset{(2.34)}{0.0046} + \underset{(18.3)}{0.84}\ \mathrm{RMRF},\quad R^2 = 0.84$$

The t-statistics are in parentheses. A hedge fund advocate will point to a positive and significant alpha of 46 basis points per month net of all fees as adding value to a passive index-like alternative. However the following regression shows that may be just a simple case of accidental alpha:

$$R\text{-}r_f = 0.0021 + 0.77\ RMRF + 0.31\ SMB + 0.03\ VMG + 0.01\ UMD,\ R^2 = 0.95$$
$$\quad (1.56) \quad (18.4) \quad\quad (6.2) \quad\quad (0.9) \quad\quad (0.03)$$

A hedge fund skeptic will note that the 46 basis points of alpha relative to RMRF is accidental, due largely to the missing SMB factor. Does this mean that the hedge fund skeptics are right that on average long-biased equity hedge fund managers only out-performed a passive index fund by taking on alternative beta (factor) risk?

While the skeptics may be right that, on a net-of-fee basis, long-biased equity managers do not add value on average, it would be incorrect to imply that there is no skill in the sense of Sharpe's (1992) style model. The possibility remains that these managers are generating returns in excess of risk exposure to these four factors, but the average excess returns are insufficient to overcome the hefty fees hedge fund managers charge—an observation that is consistent with the Berk and Green (2004) model of active management.

This discussion raises the general question of the hedge fund fee contract. Currently, most hedge funds charge incentive fees based on the total return of their portfolio without any hurdle that differentiates skill from return for bearing systemic risks. From this perspective, it is important for investors to properly identify the set of PTSs that drives performance in order to avoid paying for accidental alternative alphas. The next step is for low cost replication of the PTSs to be made available, paving the way to better risk/return sharing between hedge fund managers and investors. The treatment of hedge fund fees will be taken up at a future date. We continue in subsection IV.3 to show that a missing PTS can give rise to accidental alpha.

IV.3. Strategy 2: The Constant Bet that Moves

Consider a strategy that invests 70% of capital in the HFR Equity Non-Hedge index, and adds a short position in the S&P 500 index put struck at 95% with a premium equal to 2% of the portfolio to spice up the returns. This leaves 32% of the portfolio's value in cash. To keep things simple, the portfolio is rebalanced at the end of each month to maintain these proportions.

Note that the put option does not add a new asset factor. As shown in section IV.2, the HFR Equity Non-Hedge Index is a linear combination of four standard equity factors. The put option is merely a nonlinear exposure to the market factor, since the option can be replicated dynamically. In the context of our previous discussion, the put option is a PTS. By construction, the fund in this example has a static allocation to this PTS.

If our regression model includes all the component strategies (PTSs in our language), we get the correct replicating equation as follows:

$$R\text{-}r_f = 0.0023 + 0.54\ RMRF + 0.21\ SMB + 0.02\ HML + 0.006\ UMD - 0.02\ PUT,$$
$$\quad (1.92) \quad (12.7) \quad\quad (5.9) \quad\quad (0.97) \quad\quad (0.23) \quad\quad (-11.7)$$

$R^2 = 0.97$.

Notice what happens if a researcher knows only the exposure to the HFRI Equity Non-Hedge Index but not the exposure to the option PTS and runs the four-factor regression model:

$$
\begin{array}{llllll}
R\text{-}r_f = 0.0071 & + 0.80\ \text{RMRF} & + 0.19\ \text{SMB} & - 0.01\ \text{HML} & - 0.003\ \text{UMD}, & R^2 = 0.94 \\
\quad (5.22) & (24.3) & (4.5) & (-0.2) & (-0.12) &
\end{array}
$$

He finds an accidental alpha that is positive and significant, due to the missing option PTS. Moreover, the beta of 0.80 on the market factor (RMRF) in his misspecified model is quite different from true beta of 0.54 in the correct model. The reason is that the put option's delta changes with the market factor (RMRF), resulting in nonlinear correlation with RMRF. The misspecified regression captures the average nonlinear correlation in the beta of the market factor. The "Constant Bet" model relative to the 5 correctly specified PTSs turns into in a "time-varying bet" model relative to the 4 PTSs.

This example points to the problem of unknown PTSs in hedge fund replication. If the researcher were to use the misspecified four-factor model to replicate the "Constant Bet" strategy, keeping a constant exposure to RMRF, then he would end up replicating Strategy 1 in IV.2. He would have missed the dynamic adjustments of the exposure to RMRF needed to mimic the changing delta of the missing option PTS. This leads us to subsection IV.4, that dynamic allocation to PTS can also lead to accidental alpha.

IV.4. Strategy 3: Going with the (Deal) Flow—and Event-Driven Strategy

In this simulation we synthesize an actively managed strategy that invests in the two main event-driven hedge fund styles—Merger Arbitrage and Distressed Securities—according to the prevailing market conditions. To mimic the component style returns we use the CS-Tremont Risk Arbitrage Index and the Distressed Index. The exposure to the Distressed Securities Index is rebalanced each month to maintain a constant 50% weighting. In contrast the exposure to the Risk Arbitrage Index is managed actively following a pre-specified decision rule.

The decision rule works as follows. Monitor the dollar volume of quarterly merger activity compiled by Securities Data Corp. Our data came from various annual reports of the Merger Fund. Express this as a fraction of the market value of the US equity market proxied by the Wilshire 5000 index—call this the M&A Activity indicator. Whenever the previous quarter's M&A Activity indicator exceeds the lowest quartile then invest the remaining 50% of the portfolio into the Risk Arbitrage Index, otherwise stay in cash earning the risk free rate.

To a researcher replicating the performance of this strategy, it is tempting to simply run the following regression:

$$R\text{-}r_f = 0.0009 + 0.61 \text{ Event Driven}, \quad R^2 = 0.83$$
$$(2.11) \qquad (19.7)$$

where R is the monthly return of "Going with the (Deal) Flow" strategy and Event Driven refers to the CS-Tremont Event-Driven index returns which is a combination of the Risk Arbitrage and Distressed Securities styles.

This replication equation shows an accidental alpha of 9 basis points per month. Yet the returns are derived from substantially similar underlying hedge fund styles. The question here is what does this accidental alpha represents?

Note that the CS-Tremont Event-Driven index follows its own index-rebalancing rules that are different from the decision rule used in the Going with the (Deal) Flow strategy. It therefore follows from equation (12) that the accidental alpha term in the above replication equation simply reflects the differences between the time-varying betas with respect to the component styles of the dependent variable and the regressor. In short, there is no deal selection skill involved. It could be argued that the 9 bp accidental alpha reflects the timing advantage of the Going with the (Deal) Flow decision rule *relative* to the index construction of the CS-Tremont Event-Driven Index for a given sample of data. It is likely that the results will change with a different data sample. In the next simulation we elaborate further on this stability issue of replicating strategies.

IV.5. Strategy 4: The Stationary Observer

It is widely accepted that hedge funds are nimble speculators operating a myriad of dynamic trading strategies with highly nonlinear return characteristics. For example some hedge fund strategies that rely on asset prices to mean revert (such as statistical arbitrage) tend to work well when markets are range bound. However, the same set of market conditions can have the opposite effect on momentum-dependent strategies such as trend following which exhibit straddle-like return characteristics as shown in Fung and Hsieh (2001). It is precisely these diverse and cyclical characteristics of different hedge fund strategies that offer an investor the opportunity to construct a diversified portfolio with stable returns.

Fung and Hsieh (1997, 2001, 2004) argued that a substantial amount of the nonlinear return characteristics can be directly modeled using primitive trading strategies. For this to succeed, we need to accomplish two essential steps in modeling the returns of a diversified hedge fund portfolio. First, we need to identify, as much as possible, the complete set of PTS. Second, we need to model the asset allocation process that aligns the capital at risk with the cyclical nature of the PTS.

The interesting question is whether there are enough PTSs in our tool kit to be able to reduce the typical diversified hedge fund portfolio to *static, linear combinations* of these PTSs. The two previous examples in IV.3 and IV.4 raise some doubts. In the next simulation, we confirm that standard econometric techniques applied to commonly know risk factors are insufficient to achieve this task.

Consider a broad-based hedge fund index like the HFRI Fund Composite Index (HFRI for short). Take a set of commonly used risk factors such as the S&P500 index (SNP), the Russell 2000 Index (RUS), the MSCI EAFE Index (EAFE), the MSCE Emerging Markets Index (EMG), and US Dollar Trade-Weighted Index (DOLLAR). Choose a less eventful period in the market such as April 2000 to June 2006 (post Dotcom bubble) and fit a simple linear model of the HFRI using these factors:

$$R_t = a + b_1 SNP_t + b_2 RUS_t + b_3 EAFE_t + b_4 EMG_t + b_5 DOLLAR_t + e_t$$

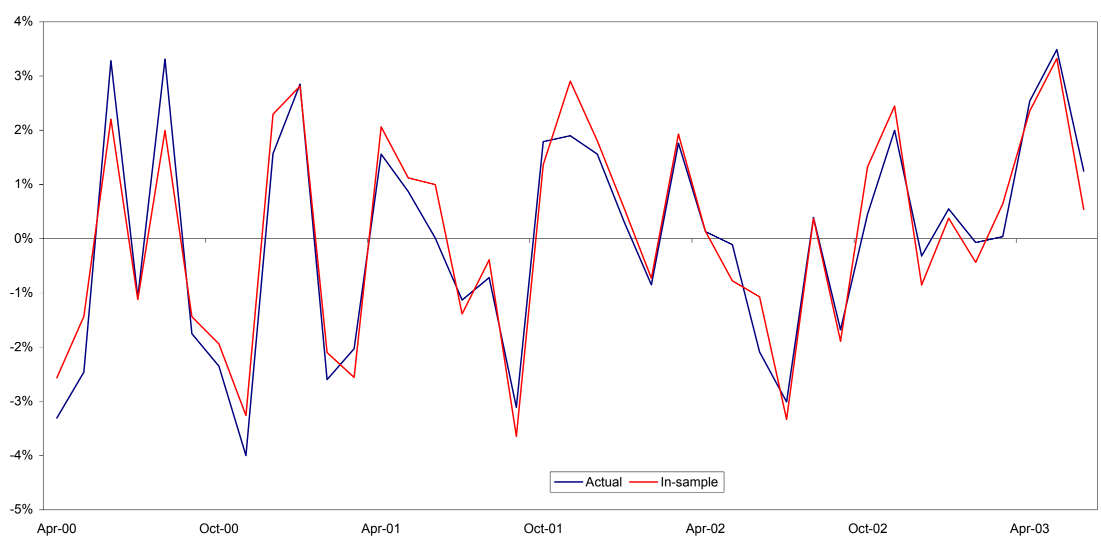
where returns are expressed in excess of the riskfree asset (1 month treasury bill). This yields:

Regression results: April 2000-March 2003

	Coeff	S.e.
Constant	-0.0009	0.0012
SNP	0.1011	0.0493
RUS	0.2216	0.0345
EAFE	-0.1995	0.0603
EMG	0.1105	0.0308
DOLLAR	-0.2418	0.0733
R^2	0.915	

Figure 4 depicts the in-sample fit of this model from April 2000 until March 2003:

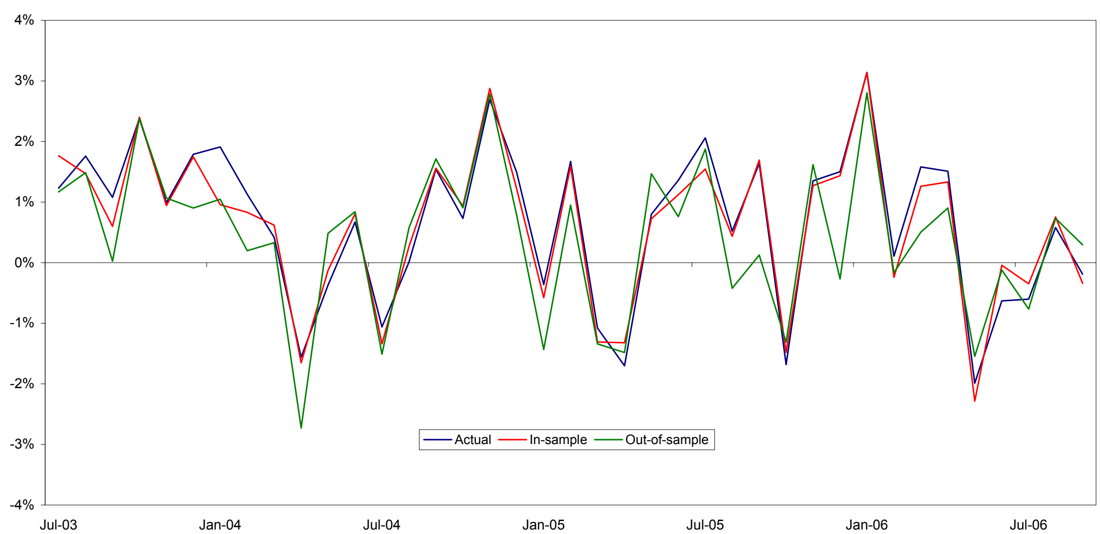
Figure 4: HFRI Composite Index: Actual & In-sample (Apr 2000 - Jun 2003)



The blue line is the actual index. The red line is the fitted values. The high R^2 and good in-sample fit make it tempting to conclude that a static combination of these five factors can capture the performance characteristics of this broad-based hedge fund index such as the HFRI. This works in spite of the fact that the composition of the HFRI index changes as new funds are included and non-reporting funds exit the data universe.

A simple experiment shows that there are subtle changes in the HFRI index not captured by this type of static linear model. If the in-sample static model accurately captures the HFRI's characteristics, then we should be able to use the first half of the data to predict the returns of the second half to yield similar statistical characteristics as the in-sample fit. This is a routine test of model stability. Figure 5 illustrates the difference between the in-sample fit versus the prediction of a model using only data from the first half of the data window.

Figure 5. HFRI Composite Index: Using Regression from First Half to Forecast Second Half (Jul 2003 - Sep 2006)



Here, the green line represents the out-of-sample forecast of the HFRI using the regression coefficients from April 2000-March 2003. It has a correlation of 0.76 with the actual index. In contrast, the red line represents the in-sample fit of the regression. It has a correlation of 0.97 to the actual index.

The poor performance of the out-of-sample forecast can also be seen when we compare the forecast to the fitted values from the regression using the second half of the sample, April 2003 until September 2006:

Regression Result: April 2003-September 2006

	Coeff	S.e.
Constant	0.0006	0.0006
SNP	-0.1814	0.0512
RUS	0.1492	0.0237

EAFE	0.2352	0.0500
EMG	0.0879	0.0218
DOLLAR	0.0198	0.0383
R^2	0.947	

Three of the five coefficients changed sign. This instability in the regression may explain why the in-sample fits are much better than the out-of-sample forecasts.

To further explore this issue, we perform the same exercise in reverse time: fitting the regression using the April 2003-September 2006 period data and use the coefficients to forecast, out-of-sample, the April 2000-March 2003 period. This time the correlation is somewhat higher (0.85) but is still quite a way below what the static in-sample model results imply (0.97).

Figure 6. HFRI Composite Index: Using Regression from Second Half to Forecast Apr 2000 - Mar 2003

Obviously, testing the ability of a model to forecast future returns is limited by the amount of data available as we move forward in time. However, if the model is assumed to be stationary, one can legitimately run the forecasting test backward in time for much longer horizon and therefore be able to observe the model's behavior over different market cycles and events. In this spirit, we took the model fitted using the second half data (April 2003 to September 2006) and examine how well it predicts the HFRI returns going all the way back to 1994.

Figure 7. HFRI Composite Index: Using Regression from Second Half to Forecast Jan 1994 - Mar 2003

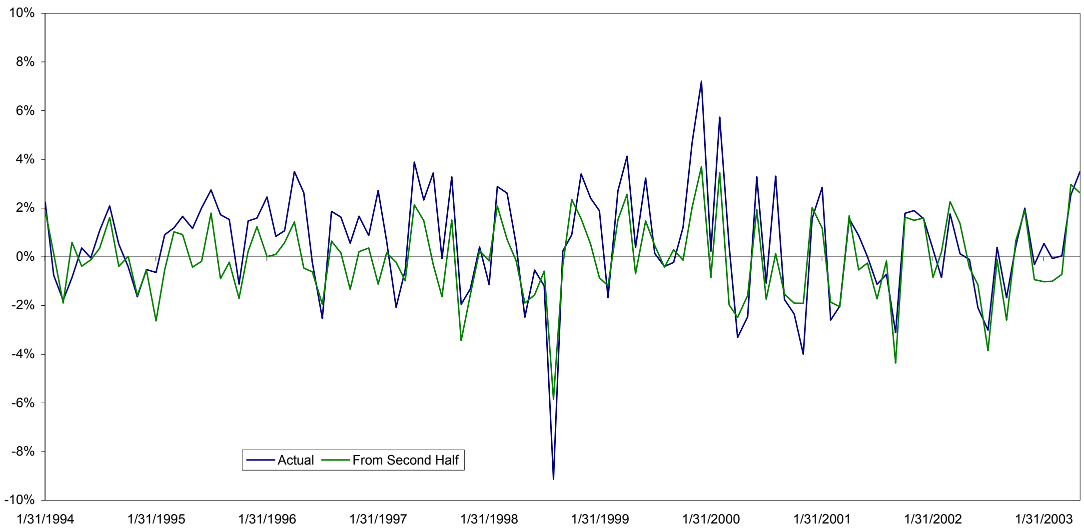


Figure 7 shows that the prediction error gets progressively worse past the Dotcom bubble moving backward in time. This is consistent with the results in Fung, Hsieh, Naik and Ramadori (2006) in which they reported significant sample breaks in the return characteristics using a large sample of funds of hedge funds

Two conclusions stand out. Hedge fund returns, even at the level of a large diversified portfolio like an index, cannot be reasonably modeled as static linear models. Second, changes in return characteristics of diversified hedge fund portfolios may not follow a smooth transition path. Discrete sample breaks consistent with Fung et al (2006) and Fung and Hsieh (2004) cannot be ignored.

The natural question that arises is whether these conclusions are specific to the HFRI index. To answer this question, we ran the same experiment on the CS-Tremont as well as the MSCI hedge fund indexes. Essentially similar conclusions hold; the results are available from the author upon request.

Could the poor performance of a static model be due to missing PTSs? To explore this question, we added the two fixed income PTSs and the three trend following PTSs from the Fung and Hsieh (2004) seven-factor model to the five factors used in the previous exercise and repeated the experiment on the HFRI index. With the additional factors, the in-sample equation is as follows:

Regression result: April 2003-September 2006

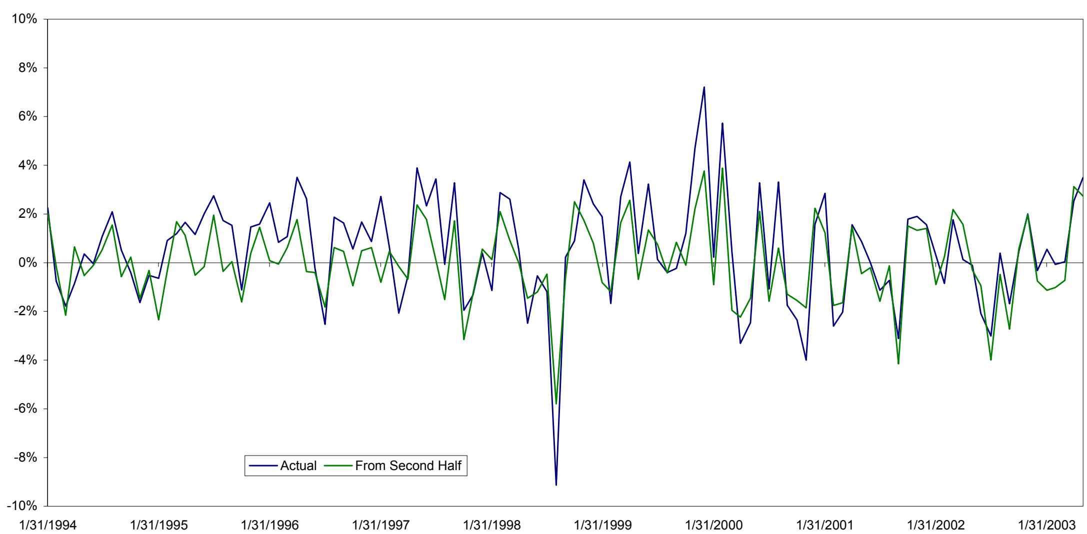
	Coeff	S.e.
Constant	0.0002	0.0012
SNP	-0.1919	0.0555
RUS	0.1693	0.0257

EAFE	0.2365	0.0556
EMG	0.0786	0.0239
DOLLAR	0.0418	0.0484
BD10Y	-0.3375	0.2160
BAAM10Y	-0.0132	0.4061
PTFSBD	0.0007	0.0065
PTFSFX	0.0035	0.0038
PTFSCOM	0.0043	0.0051
R^2	0.950	

Here BD10Y is the change in the 10-year constant maturity yield. BAAM10Y is the change in the spread between Moody's Baa yield and the 10-year constant maturity yield. PTFSBD, PTFSFX, and PTFSCOM are, respectively, portfolios of lookback straddles on bond futures, currency futures, and commodity futures, as constructed in Fung and Hsieh (2001). Note that the extra regressors added little explanatory power to the original model.

To complete this exercise, Figure 8 illustrates the backward prediction error on the expanded model fitted using the data from April 2003 to September 2006. Essentially the same ill-conditioned forecast errors are observed, especially prior to the start of the Dotcom Bubble in October 1998.

Figure 8. HFRI Composite Index: Using Regression from Second Half to Forecast Jan 1994 - Mar 2003 With Additional Bond and PTFS factors



At this point, our examples show that a successful replication of the average hedge fund depends on two key elements. One, our tool kit needs to contain all the key PTSs used by a typical hedge fund. Two, we need to properly model the dynamic allocation to these PTSs by the average hedge fund.

Given the myriad of potential measurement errors reported in numerous academic studies over the past decade, there is no direct reliable way to observe the dynamic allocation of risk capital for the hedge fund industry as a whole. However, monitoring the life cycle of the PTSs can provide important insight to the shifts in the hedge fund industry's risk profile. After all, changes in a portfolio's alternative beta are generally consequences of changes in market conditions and the way they impact the underlying PTSs. This is where econometric techniques need to be augmented by insights on the economics that drive PTS returns. Just like the search for alternative alpha properly begins with the identification of alternative betas, the clues to time-varying alternative betas lie with the understanding of how PTS responds to different market cycles.

In addition, investors may wish to gain direct exposure to specific PTSs. Some PTSs may add diversification to the standard stock and bond portfolios while delivering positive risk premia commensurate for placing capital at risk. For example, over the 2000-5 period, the average return of the market factor (RMRF) was -11 bp per month. In comparison, SMB, HML and the currency lookback straddles, respectively, had average returns of 67 bp, 114 bp and 34 bp per month. They also had low correlation to RMRF: 0.26 for SMB, -0.50 for HML, and -0.12 for the currency lookback straddles.

These same characteristics are often used to illustrate the diversification benefits of certain hedge fund styles—typically proxied by peer group averages of hedge funds. Performance of the investable versions of these hedge fund indices have generally been disappointing—due to large, difficult to explain tracking errors. In about the same time when investable peer group averages were launched, Fung and Hsieh (2004) advanced the concept of Asset-Based Style (ABS) factors as an alternative way of benchmarking hedge fund performance. These ABS factors are constructed from using PTSs based on executable market prices. As such, these PTSs can be thought of as the next generation of investable hedge fund products that can be created in a more efficient manner—liquid, transparent and low-cost. The concept of replicating hedge funds can be trace back to the same line of development. Here it is important to note the original model of hedge fund returns put forward in Fung and Hsieh (1997), knowing where a hedge fund operates and the amount of leverage used at a given point in time may not be sufficient. It is important to know also how they trade, modeling PTSs, that help researchers understand when a replicating model needs to be updated.

V. Concluding remarks

. In doing so, we highlighted the need to construct primitive trading strategies (PTSs) which are dynamic, often nonlinear, functions of conventional asset class factors. As most PTSs can be implemented at a fraction of the cost of prevailing hedge fund products, these PTSs are natural low-cost alternatives to hedge fund products based on similar strategies. Research over the last decade has created a library of rule-based, executable, PTS-like hedge fund replication strategies.

However, investors mostly hold diversified portfolios of different hedge fund strategies. Consequently, there is the additional need to synthesize the dynamic asset allocation process of multi-strategy hedge fund products. A corollary to this observation is that tracking error comes from the two familiar sources—missing PTS (or factors) and misspecification of time-varying alternative betas. The difference here is that these errors are far more pronounced with modeling actively managed hedge funds than passive mutual funds.

The existence of these index-like hedge fund products can also act as catalysts to improve the price discovery process in the hedge fund industry—more efficient fee structure with equitable risk-return sharing between investors and managers. This is in fact a healthy development for the hedge fund industry, one where alpha producers with limited capacity can be sufficiently compensated for their skills and beta-only products will regress to being index-like alternatives at lower fees.

The success of low –cost synthetic hedge funds will inevitably lead to an improvement in the return quality (better performance at lower fees) of the surviving hedge funds. However to replicate these better performing hedge funds, some of which will exhibit skill-based alternative alpha, will require new technological innovations that are likely to come at ever increasing price tags and replication risk. Ultimately the question as to whether hedge funds will become index-like products, will depend on the answer to the fundamental question that precipitated this process, but with a *qualification* —namely do hedge funds add value (have alpha) *that cannot be replicated at a lower cost*? The answer to this question will no doubt emerge over time. In the meantime, low-cost transparent synthetic hedge funds that offer exposures to specific PTSs are likely to become the, index-like, vehicle of choice for delivering the returns of maturing hedge fund strategies. Efficiently priced, dynamically managed combinations of these investable PTSs will challenge inefficient portfolio products such as some over-priced investable hedge fund indexes and funfs-of-hedge funds. Such a development is consistent, as a corollary, with the prediction of Berk and Green (2004) in which investors will earn little excess alpha as a consequence of fees and decreasing return to scales—a phenomenon reported in Fung, Hsieh, Naik and Ramadori (2006) in their study on funds of hedge funds.

Finally, synthetic hedge funds that are liquid and transparent can go a long way toward alleviating regulators' concerns—perhaps we are witnessing the "invisible hand" at work in a maturing, competitive hedge fund industry.

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