Hedge fund replication strategies: implications for investors and regulators

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Over the past decade, academic research has identified a number of replication strategies capable of capturing between 40% to 80% of the average return of many popular hedge fund strategies. Investors are beginning to take notice of these replication strategies, especially because of their rule based, transparent features and the fact that they can be executed at low cost. Armed with this alternative way of accessing passive hedge fund returns, investors can effectively structure incentive fee contracts to reward skill-based returns (i.e., alternative alpha) differently from passive index-liked returns (i.e., alternative beta). This can raise the barrier to entry for new funds to the industry in that hedge fund managers must demonstrate skill in order to participate in profit sharing. This should reduce the risk of herding by hedge fund managers who may otherwise be enticed by incentive fee contracts that rewards them for taking popular factor bets.

The hedge fund industry has grown rapidly over the past ten years. Asset under management increased from under USD 100 billion in 1995 to nearly USD 1 trillion by mid 2006, according to Tremont Capital Management (2006). US pension plans and university endowments have steadily increased their allocation to hedge funds. According to National Association of College and University Business Officers (NACUBO), endowments in the US invested 17% of their assets in hedge funds in 2005, up from 5% in 1999. Pensions & Investments found that the largest 200 US defined benefit plans increased their allocation to hedge funds from 0.1% in 2000 to 0.8% in 2005.

A decline in performance, however, has accompanied this rapid growth of hedge funds. Chart 1 displays the rolling 4-year average of annual returns. The return of the average hedge fund is the solid line, and the return of funds-of-hedge funds ("FoFs") the broken line. Both started with double digit returns in the mid 1990s, and dropped to single digits in the current decade. However, it is possible that risk exposures of hedge funds have also declined in respond to the response rising dominance of institutional investors replacing family offices and private individuals as the primary source of investor capital. Therefore, it is important to investigate whether risk-adjusted return, or alpha, has declined. The key question is: In the search for alpha, have all the low-hanging fruits been picked? In order to answer this question, one must first acknowledge that the search for alpha properly begins with the identification of betas. Section two of this paper traces the historical attempts to quantify the systematic risk factors inherent in hedge fund strategies –the separation of hedge fund alphas from betas.

Armed with these results, Fung *et al.* (2006) estimated the alpha of funds-of-hedge funds ("FoFs") from the merged TASS, HFR, and CISDM databases using the seven-factor model from Fung and Hsieh (2004b).[1] Separating the sample of FoFs into *have-alpha* and *beta-only* funds, Fung *et al* (2006) find that the average FoF does not deliver statistically significant alpha, and about 21 percent of the total sample of FoFs have positive alpha over the sample period 1995 to 2003. Even for the have-alpha FoFs, alpha has declined in the recent period (April 2000 to December 2004) relative to earlier periods. More recent results indicate that for the 2004-2005 period, only 5 percent of FoFs delivered alpha to their investors. This decline coincides with the large inflow of money into the hedge fund industry and is consistent with the prediction of Berk and Green (2004) that large capital inflows to funds will drive down the net-of-fee excess returns to zero so that in equilibrium there should be no excess return to investors.

Although the Fung *et al.* (2006) findings confirm some long-held suspicion of hedge fund industry professionals, this begs the question as to: *Why do investors not simply withdraw from hedge funds?* Unlike the mutual fund industry, there is no consistent negative alpha in net-of-fee returns in hedge funds. This is consistent with the view that hedge fund managers are able to find alpha (before fees), but the alpha is consumed by fees, as Berk and Green (2004) predicts. It is this combination of high fees and declining risk-adjusted performance in the industry that drives the quest for passive, rule-based hedge fund products or "HF Clones" –a low cost alternative to conventional hedge fund investing. Section three of this paper examines the potential applications of HF Clones. Concluding remarks and conjectures on this auspicious development in the hedge fund industry are presented in section four.

1| The origin of rule-based replication strategies

The origin of passive rule-based replication strategies can be traced back to the first academic study on the risk and return of hedge funds. Fung and Hsieh (1997) used principal components to analyze hedge funds, and found that the first five components accounted for nearly 45% of the cross-sectional variation in hedge funds. Using self-described strategies of hedge funds,[2] these five components were identified as two "trend following" strategies, "value", "global/macro", and "distressed securities".

1 *Here the choice of FoF returns as the empirical subject stems from the observation made in Fung and Hsieh (2002c) in which they advanced the proposition that FoF returns represent a source of data on diversified portfolios of hedge funds with minimal measurement errors.*

2 *The Fung and Hsieh (1997) work pre-dated the emergence of electronically available hedge fund data bases. The, somewhat, crude qualitative classification scheme they used was derived from manual inspection of hedge fund documents. Subsequent work by Brown and Goetzmann (2003) reached broadly similar conclusions.*

In an attempt to model the risk and returns of these strategies, Fung and Hsieh (1997) noted that any investment fund's return is a function of *where* it trades (asset class), *how* it trades (strategy), and *how much* it trades (leverage). Performance attribution, risk management, and replication of the systematic part of the strategy's return can be achieved if one can link returns of a fund to returns of rule-based trading strategies. For mutual funds, performance attribution turns out to be a comparatively straight-forward exercise. The typical mutual fund employs relatively static, long-only, strategies, and seldom uses leverage. Thus, indices of standard asset class returns are eminently suitable benchmarks for mutual funds, as shown in Sharpe (1992), but they can be woefully inadequate for hedge funds.

When it comes to hedge funds, the search for alpha is complicated by the dynamic use of long and short positions. This in turn generates nonlinear returns that require customized benchmarks –see for example Glosten and Jagannathan (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 can be highly nonlinear in the returns of underlying assets. In the ensuing decade, the development of a number of these rule-based trading strategies have allowed researchers to model a diversified portfolio of hedge funds, such as indices of hedge funds and FoFs. This resulted in Fung and Hsieh (2003) coining the term "alternative beta" to describe the exposure of hedge funds to these rule-based trading strategies, analogous to the traditional "beta" concept that measure the exposure of mutual funds to standard asset benchmarks. Similarly, the term "alternative alpha" refers to the incremental return over and above the return based on alternative beta exposure.

At this point, a minor digression on two parallel but related concepts helps to put the ensuing developments in the proper context. 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 nonlinearity 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. We begin by tracing the development path of the first separation property –separating hedge fund alphas from betas.

A path to uncover betas from a hedge fund's total returns was first proposed in Fung and Hsieh (2001) in which they advanced the concept of *primitive trading strategies* (PTS) designed to capture the essence of dynamic trading strategies using passive, rule-based algorithms. The simplest way to think about a PTS is to begin with the insight in Merton (1981) that the payoff of a perfect market timer should be identical to the payoff 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. 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 PTS used by market timers –the *how they trade* part of the dynamic trading strategy model in Fung and Hsieh (1997). Isolating the PTS part of the strategy helps to highlight the skill required to apply the strategy to the appropriate security (the *where they trade* part of the dynamic trading strategy model) as well as the leverage decision –all of which contribute to the overall success of a given strategy.

In this context, the Merton market timing PTS can be expressed 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, along with the price of the underlying security. Before turning to the more general problem of dynamically combining different PTSs to represent a diversified portfolio of evolving hedge fund styles, we briefly review the library of reported research on PTS.

1|1 Examples of PTS– the fundamental building blocks of HF Clones

TREND FOLLOWERS AND MANAGED FUTURES

Fung and Hsieh (2001) used lookback straddles to replicate the returns of trend followers. The majority of commodity trading advisers (CTAs), or managed futures funds, follow a strategy called "trend following". These funds tend to use mechanical rules, such as moving averages of asset prices, to capture "trends" in markets. While it may be easy to identify a trend ex-post, it is difficult to do so ex-ante. To circumvent this problem, Fung and Hsieh (2001) used an extension of the elegant insight of Merton (1981). Unlike the market timer in Merton (1981) who can only go long the market, the trend follower in Fung and Hsieh (2001) can go long or short. In that case, the perfect trend follower should buy at the low and sell at the high, which is exactly the payoff of a lookback straddle.

A lookback straddle consists of a lookback call option and a lookback put option. The lookback call option allows the owner to buy an asset at the lowest price over the life of the option. The lookback put option allows the owner to sell an asset at the highest price of the life of the option. The lookback straddle therefore allows the owner to buy at the low and sell at the high. Based on the method described in Goldman *et al* (1979), Fung and Hsieh (2001) was able to replicate the payout of lookback straddles using exchange traded options from 26 markets. They demonstrated that the portfolios of lookback straddles can replicate the returns of trend followers much better than the typical long-only commodity benchmarks.

Picking up from when the Fung and Hsieh (2001) sample ended in 1997, Chart 2 provides a static out-of-sample verification of their results spanning the January 1998 to June 2006 period. The graph shows that lookback straddles do mimic many of the peaks and troughs in the return pattern of trend followers. This empirical regularity persisted despite the fact that the capital allocated to each market (weights) were held constant at the 1997 level where the Fung and Hsieh (2001) study ended. The first row in Table 1 illustrates a more realistic replication strategy that allows for time-varying weights. Using a rolling 24-month regression to estimate the portfolio weights (time-varying alternative betas), we can construct a replication portfolio that delivers 41 basis points per month, from 1998 to the end of 2006. This is slightly more than two-thirds of the actual managed futures return of 62 bp per month.

MERGER ARBITRAGE

Mitchell and Pulvino (2001) created a passive trading strategy that mimics the activities of merger arbitrageurs. Despite placing a number of restrictions on their replicating strategy –such as position limits to insure diversification– Mitchell and Pulvino (2001) showed simulated returns that are very similar to those of merger arbitrage funds.

Unfortunately, the return of the passive merger arbitrage strategy in Mitchell and Pulvino (2001) ended in 1998. However, there is a US mutual fund, called the Merger Fund, that describes in its prospectus an investment strategy similar to the one in Mitchell and Pulvino (2001). Chart 3 shows the higher correlation between the return of the Merger Fund and the HFR Merger Arbitrage Index. To create a passive, replicating portfolio to Merger Arbitrage hedge funds, we use a 24-month rolling regression of the Merger Arbitrage Index on the Merger Fund to estimate the portfolio weight (time-varying alternative beta) of the Merger Fund, with the rest of the portfolio invested in cash. The second row in Table 1 shows that this replication strategy generates an average of 44 bp per month from 1998 to 2006 which represents two-thirds of the average return of the Merger Arbitrage Index of 66 bp per month.

FIXED INCOME HEDGE FUNDS

Fung and Hsieh (2002) showed that the typical fixed income hedge fund is exposed to increases in credit spreads. Chart 4 updates their analysis, graphing the negative relation between monthly returns of the HFR Fixed Income Index and the change in the credit spread, as proxied by the yield difference between Moody's Baa corporate bonds and the 10-year constant maturity interest rate, provided by the Board of Governors of the Federal Reserve System.

The third row in Table 1 reports the result of a simple replication strategy –long Baa corporate bonds and short 10 year treasuries. The size (time-varying alternative beta) of this dollar-neutral position is determined by a 24-month rolling regression of the returns of fixed income hedge funds on this long/short portfolio. This replication strategy leads to a return of 33 bp per month from 1998 until 2006, nearly 60% of the return of 57 bp per month of fixed income hedge funds.

Duarte *et al* (2005) analyzed several additional passive fixed income strategies. These include trading strategies using the swap spread, the yield-curve spread, mortgage spread, among others. The swap spread trade bets on the movement in the difference between the swap rate and the yield of a treasury security with the same maturity. The yield-curve spread trade bets on relative movements between the yields of treasury securities with different maturities. The mortgage spread trade bets on the movement in the difference between mortgage yields and the yield of treasury securities with comparable maturities. Duarte *et al* (2005) showed that these strategies can also explain the returns of fixed income hedge funds.

Other passive hedge fund strategies-equity long/short, convertible arbitrage and emerging markets

Agarwal and Naik (2004) studied the general equity hedge funds, while Fung and Hsieh (2006a) focused on the subset of long-short equity hedge funds. Both articles showed that equity hedge funds tend to have positive exposure to US stock market plus an exposure to the relative performance between small cap and large cap stocks. The simulated returns from a portfolio replicating these exposures are reported in the fourth row of Table 1. The time-varying alternative beta of this portfolio is determined by a 24-month rolling regression. Between 1998 and 2006, this replication strategy delivers 38 bp per month, nearly 40% of the average return of 99 bp per month of long-short equity hedge funds.

Agarwal *et al* (2006) created a passive convertible arbitrage strategy using US and Japanese convertible bonds, which they label as a buy-and-hedge strategy. As the description suggests, this replicating strategy calls for the purchase of a portfolio of convertible bonds and simultaneously hedging the equity, interest rate and credit risk of the portfolio following pre-specified rules. The authors show that the buy-and-hedge strategy can generate 81% of the average return of convertible arbitrage hedge funds, as reported in the fifth row of Table 1.

Fung and Hsieh (2006b) showed that emerging market hedge funds have strong exposure to the IFC Emerging Market Index. The resulting replication strategy, in the sixth row of Table 1, can deliver more than 60% of the return of Emerging Market Hedge funds. Finally, distressed securities hedge fund have strong exposure to the CSFB High Yield Bond Index. Their replication strategy (in the seventh row of Table 1) can generate about 40% of the returns of distressed securities hedge funds.

1|2 Replicating the alternative beta return of diversified hedge fund portfolios

In an early application of PTS to classify hedge fund styles, Fung and Hsieh (2002) put forward the concept of Asset-Based Style ("ABS") factors. ABS factors were intended to link qualitatively constructed hedge fund styles commonly found in hedge fund data bases to market prices. By recognizing the PTS implicit in the relevant trading strategies used in each qualitatively defined hedge fund style, ABS factors can be expressed as static, linear combinations of PTS which captures the passive component of different hedge fund styles. From this one can express the total return from a given qualitatively defined hedge fund style as:

$$\{\text{Alternative}\}\text{ alpha} + \Sigma\,(\{\text{Alternative}\}\text{ beta(s)} * \text{ABS factor(s)})$$

thereby giving birth to the concept of alternative alphas and alternative betas in Fung and Hsieh (2003). Here three seemingly disparate concepts can be linked –the total return of qualitatively defined hedge fund styles, their alpha, and their beta with respect to the strategy's passive component expressed in market prices. From here, it was all but a small step to construct synthetic versions of hedge fund strategies, or HF Clones using ABS factors.

However, developments in the hedge fund industry over the past few years have accentuated the need to properly model the second separation property-return nonlinearity emanating from dynamic allocation of risk capital across strategies as distinct from the nonlinear return properties of the strategies themselves. Responding to the unrelenting capital inflow into the industry over different economic cycles, it is natural to find hedge fund managers exhibiting dynamic exposures to factor bets (beta bets). This phenomenon naturally arises from the hedge fund managers' desire to diversify their income stream– thereby motivating the growth of multi-strategy hedge funds employing a wide range of strategies (from 0.5 percent to 12–14 percent of total capacity).

As different strategies are introduced into the portfolio mix, different risk factors will emerge and evolve over time in response to changes in the market environment. This evolving trend has reached a point at which qualitative hedge fund style classifications have to be broaden to such an extent that linking qualitative style returns to static combinations of strategies is no longer a meaningful exercise. Consequently, a more explicit link between hedge fund portfolio returns and its underlying PTS that admits time-varying alternative betas needs to be established.

A simple risk factor model for diversified portfolios of hedge hunds

Over the past decade a library of passive hedge fund strategies capable of replicating the majority of popular hedge fund strategies. For example, four of the five popular styles in Fung and Hsieh (1997) –trend following, value, and distressed securities– have replication strategies. Another way to check the coverage of available replicating strategies is to look at the share of hedge fund assets allocated across different styles. According to Tremont Capital Management (2006), 73% of hedge fund assets in 2005 are allocated to long-short equity, distressed securities, merger arbitrage, fixed income arbitrage, emerging markets, convertible arbitrage, and managed futures. In addition, as a strategy matures its idiosyncratic features are often eroded away by competition leaving behind a systematic strategy core. Put differently, over time hedge fund strategies regress towards its systemic risk factors and their returns become primary beta returns. Putting these two observations together, it would be reasonable to conjecture that 75% of hedge fund strategies are amenable to cloning.

Drawing from the past decade's research on replicating different hedge fund styles and the tendency for aging strategies to be accepted as beta-like risk factors, Fung and Hsieh (2004) proposed a simplified seven-factor model for replicating diversified portfolios of hedge funds. Two equity factors (the market, and small cap-large cap) come from equity hedge funds. Two bond factors (change in the ten-year constant maturity rate, and change in the spread spread) come from fixed income hedge funds. Three lookback straddles come from managed futures. Fung and Hsieh (2006b) show that these seven factors explain up to 85% of the return variation of the average hedge fund, through 2004.

Table 2 updates the regressions in Fung and Hsieh (2006b) that estimated the alternative alpha and alternative beta of various hedge fund indices. For example, the first column provides the excess return regression of the HFR fund-of-fund index against the 7 factors. The alternative alpha is estimated to be 6 bp per month, not statistically different from zero. Standard errors were calculated using the Newey-West (1987) covariance estimator with 6 lags. There is statistically significant exposure to 6 risk factors. Using a 24-month rolling regression to estimate the exposure of Global/Macro funds to the seven risk factors, Fung and Hsieh (2006b) can replicate 64% of their returns (see the eighth row of Table 1). The same method can replicate 60% of the average returns of funds-of-funds (see the ninth row of Table 1).

Modeling the effect of style drift and the life cycle of strategies

There are three opposing forces affecting the way in which diversified portfolios of hedge funds can be replicated. On the one hand, individual hedge fund manager's desire to diversify their business is likely to lead to a decline of niche hedge funds in favor of multi-strategy mega funds. In time, this will make PTS harder to construct as niche strategies are increasing being subsumed into broad-based hedge fund offerings. This makes replicating strategies harder to construct. On the other hand, as hedge fund strategies mature, the systematic shell that is left behind can easily be replicated by rule-based models. Finally new strategies will be given birth with new attendant risk factors. All these development trends imply time-varying betas and dynamic emergence of risk factors.

Empirical results reported in Fung and Hsieh (2004) and Fung *et al* (2006) point to structural shifts in the way diversified portfolios of hedge funds are exposed to the underlying risk factors. Thus far, these shifts tend to correspond to major market dislocations such as the LTCM crisis and the burst of the Dotcom bubble which all have profound effect on the way the market prices risk. Recent work by Agarwal *et al* (2006) and Fung and Hsieh (2006a) uncovered non-price variables that impact hedge fund strategy returns. Agarwal *et al* (2006) showed that the issuance pattern of convertible bonds can affect the profitability of convertible arbitrage. Fung and Hsieh (2006a) reported results where Long/Short Equity hedge fund managers profit is affected by the level of stock market activities. All of these point to the importance of incorporating variables exogenous to hedge fund returns in order to capture environmental shifts that can affect the structure of replicating hedge fund portfolios.

2| POTENTIAL APPLICATIONS OF HEDGE FUND CLONING TECHNOLOGY

The advantage of identifying PTS goes beyond the fact that their component risk factors are readily observable (transparent) but that they are also investable (liquid). The immediate application is clear. For investors, alpha buyers now have a way to measure the quality of their hedge fund investment. Beta buyers (investors who prefer leveraged factor bets) can assess whether their capital is exposed to the desired risk; and both can evaluate whether the fees they paid are appropriate. For counterparties, measuring the exposure to key risk factors offers a market-price-driven metric that aggregates hedge fund risk in capital-at-risk calculations. For regulators, it provides a barometer to gauge potential convergence of systemic risk exposures from hedge funds, proprietary desks, and conventional money managers.

PAYING THE RIGHT PRICE FOR TALENT

Since the early days of AW Jones, circa 1949, numerous innovative trading strategies have been created and applied successfully by hedge fund managers. The diversity of approaches and performance characteristics have caught the attention of investors. Despite the differences in risk taken by hedge fund managers to generate profit for their investors, their compensation structures remained remarkably similar across a broad range of investment styles. There is practically a "one-size fits all" formula where hedge fund managers are paid a fixed fee proportional to the capital they manage and participates in the trading profits they generate without any reference to risk. One plausible explanation is that, unlike conventional long-only strategies, the absence of suitable benchmarks –against which the manager's skill, alpha, can be separated from passive beta bets– makes it difficult to establish suitable performance hurdles that properly reflect the passive component of hedge fund returns. The arrival of HF clones could have a profound influence on how hedge fund managers are compensated. Armed with this alternative way of accessing passive hedge fund returns, investors can point to investable performance benchmarks that separate alpha returns from passive beta bets. Incentive fee contract can now be structured to reward skill, or alpha, differently from passive index-like returns.

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.

REDUCING THE RISK OF HERDING AND SMOOTHING THE FLOW OF CAPITAL

Brown and Goetzmann (2003) pointed out the impact of incentive fees on managers' risk taking behavior. An incentive fee contract which does not carry a hurdle that reflects the return of passive factor exposures encourages managers to herd. Betting on factors that are currently in vogue rewards a manager for simply being a free rider betting alongside the crowd. Using HF Clones to construct performance benchmarks mitigates this problem. By the same token, using low-cost HF Clones as performance benchmarks can also act as a barrier to entry to new hedge funds. The bottom line is unless there is alternative alpha (skill-based returns), profit participation by hedge fund managers does not begin. In turn this should slow down the rush to become hedge fund managers and reduce the high attrition rate of the hedge fund industry.

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, it will require new technological innovations that are likely to come at ever increasing price tags and replication risk.

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 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.

A tool kit of passive, rule-based, replication strategies has been developed over the last ten years. It now covers roughly 75% of capital invested in hedge funds. This tool kit allows investors to benchmark many of the popular hedge fund strategies. It provides long histories for risk assessment. Funds that employ these replication strategies can have the transparency and liquidity sought by many investors. In addition, aggregate bet sizes can be monitored by regulators for over crowded situations, to develop measures to prevent systemic risk.

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Table 1
Average monthly performance of actual and replication strategies
1998-2006

(%)

Hedge fund strategy	Actual return	Replication return
Managed futures	0.62	0.41
Merger arbitrage	0.66	0.44
Fixed income	0.57	0.33
Long-short equity	0.99	0.38
Convertible arbitrage[a)]	0.94	0.76
Emerging market	1.00	0.63
Distressed securities	0.92	0.37
Global macro	0.73	0.46
Funds-of-funds	0.58	0.35

a) 1998-2003

Table 2
Alternative alpha and alternative beta of hedge fund indices
April 2000-December 2005

Index	HFR Eq Wt FoF	HFR Eq Wt Composite	CSFB Asset Wt Composite	MSCI Eq Wt Composite
Constant	0.0003	**0.0019**	**0.0024**	**0.0031**
SNP-RF	**0.1575**	**0.3031**	**0.1755**	**0.1632**
RUT-SNP	**0.1528**	**0.2178**	**0.1688**	**0.1680**
BD10-RF	**0.1217**	**0.1066**	**0.1649**	**0.1288**
BAA-BD10	**0.1766**	**0.1700**	0.1015	0.0734
PTFSBD-RF	-0.0030	0.0009	-0.0038	0.0030
PTFSFX-RF	**0.0098**	**0.0090**	**0.0117**	**0.0155**
PTFSCOM-RF	**0.0197**	**0.0185**	**0.0182**	**0.0144**
Rsq	0.67	0.87	0.63	0.73
Durbin-Watson	1.49	1.66	1.55	1.59

Bold coefficients are statistically significant at the 1% significance level, based on Newey-West standard errors using 6 lags.

Chart 1
Rolling 4-year average of returns for hedge funds and funds-of-funds
(%)

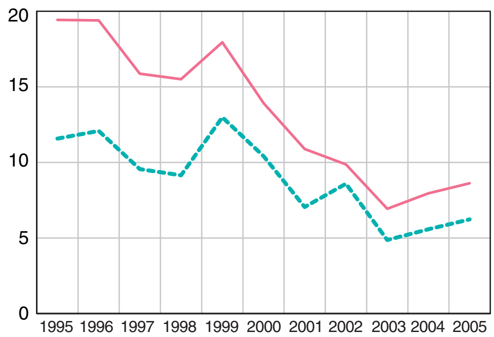

Chart 2
Average return of trend followers: actual and predicted
(%)

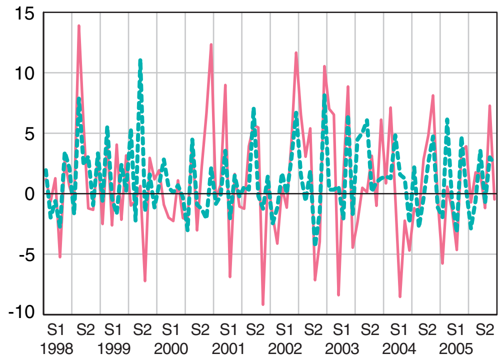

Chart 3
Average return of merger arbitrage hedge funds vs the merger fund
(%)

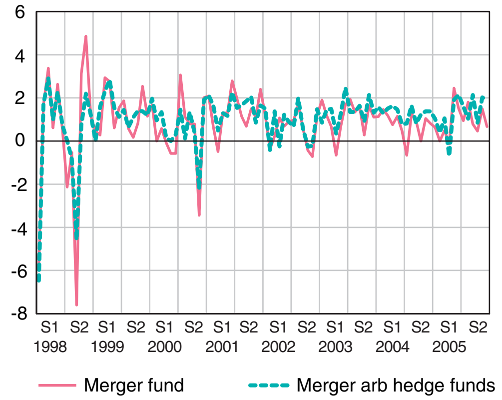

Chart 4
Change in credit spread vs fixed income hedge funds
1990-2005
(fixed income hedge fund monthly return, %)