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Hedge Fund Benchmarks: A Risk Based Approach
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Abstract

This paper reviews the data and methodological difficulties in applying conventional models of constructing asset-class indices to hedge funds and argues against the conventional approach. Extending the work of Fung and Hsieh (2002a) on asset-based style (ABS) factors, an APT-like model of hedge fund returns with dynamic risk factor coefficients is proposed. For diversified hedge fund portfolios, the seven ABS style factors explain up to 90% of monthly return variations. As ABS factors are directly observable using market prices, our model provides a standardized framework for identifying differences among major hedge fund indices free of biases inherent in hedge fund databases. An ABS factor model distinguishes between hedge fund alphas (alternative alphas) from returns that are derived from bearing systematic, albeit alternative sources of, risks (alternative betas). Time-varying behavior of alternative alphas and betas reveals important insight on how funds-of-hedge funds alter their bets over time.

1. Introduction

The new millennium marked the end to the *Internet bubble* and closed another investment cycle where the simple *buy-them and hold-them* strategy dominated all other strategies on the way up. Investors' search for alternative investments intensified naturally in the ensuing market decline. As a result, hedge funds have received their share of increase interest from a broad base of investors. The opaqueness of hedge fund operations and the lack of performance reporting standard make it hard to formulate expectations of hedge fund performance that reflect current economic outlook. This lack of performance reporting standard and the relatively short history of hedge fund returns further make it hard to assess their long-term performance pattern. It is simply not easy for investors to determine the role of hedge funds in their portfolio and the appropriate amount of exposure to hedge fund strategies. Existing hedge fund indices, while helpful in providing investors with an idea on the current progress of the industry on average, offer little clues to the above questions.

Conventional models for constructing asset-class indices rest on the assumption that the underlying assets are reasonably homogenous and that the dominant investment strategy used is to buy-and-hold. In contrast, performance characteristics of hedge funds are diverse, the investment styles are dynamic, and, bets are highly levered. This, together with the lack of standardized reporting of historical performance greatly limits the information content of hedge fund indices constructed using conventional methods and at times, even lead to misleading results. Section two of this paper reviews the flaws of existing hedge fund indices.

Section three of the paper proposes an alternative approach to benchmarking hedge fund returns by using a model of hedge fund risks. This approach is based on some simple observations. Hedge fund managers typically transact in the same markets as traditional fund managers. Yet evidence shows that hedge fund returns have different characteristics than those of traditional fund managers. For example, Fung and Hsieh (1997a) found that hedge fund returns have much lower correlation to standard asset returns than mutual fund returns. One interpretation is that hedge fund managers have more skills than traditional fund managers. However, this view is inconsistent with the evidence that hedge funds typically perform poorly when asset markets perform very poorly. An alternative interpretation is that hedge funds, like mutual funds, are exposed to risks, except that hedge fund risks are different from mutual fund risks. In this paper, we employ a different method to create hedge fund benchmarks that captures the common risk factors in hedge funds, using the asset-based style (“ABS”) factors in Fung and Hsieh (2002b).

The process works as follows. First, we extract common sources of risk in hedge fund returns. Second, we link these common sources of risk to observable market prices. We call these explicitly identified risk factors ABS factor. These ABS factors are used to construct an APT-like (Arbitrage Pricing Theory) hedge fund risk-factor model where the factor loadings (betas) are permitted to vary over time. The payoff of this model can be significant. Consider the analogy with equities. Equity risk factors can be modeled using the Capital Asset Pricing Model (CAPM) or the Arbitrage Pricing Theory (APT). These models separate the return of an equity investment into two parts: systematic and idiosyncratic. The systematic part is the common source of return. In the CAPM, it is

simply the market portfolio; with the APT it is typically the market portfolio together with a few other risk factors such as interest rate spreads. The idiosyncratic part of the return is unique to the equity and unrelated to other equities. This decomposition allows investors to diversify away from idiosyncratic risk by holding a large portfolio of equities. At the portfolio level, investors need to be concerned with the common sources of equity risk. This type of risk model was successfully developed in Sharpe (1992) for equity mutual funds. In the same way, our hedge fund risk-factor model helps investors identify the common sources of risk expressed in a familiar setting using conventional asset prices—hence the notion of ABS factors. This creates the critical link between hedge fund investments and conventional asset classes and allows them to be managed within the framework of an overall portfolio.

Thus far, seven risk factors have been identified. Equity long/short hedge funds are exposed to two equity risk factors. Fixed income hedge funds are exposed to two interest rate-related risk factors. Trend-following funds are exposed to three portfolios of options. Empirical evidence shows that these seven risk factors can jointly explain a major portion of return movements in hedge fund portfolios, as proxied by funds-of-hedge funds, as shown in section four.

Section five is devoted to an analysis of existing hedge fund indices. The primary difficulty in comparing existing hedge fund indices is the lack of a common standard. In general, existing hedge fund indices not only differ in their construction method but are also drawn from widely different data universes. Historical measurement errors in the data like those discussed in section two of the paper cannot be easily rectified by statistical means alone. Here, we circumvent some of these difficulties by asking the

question: *what do different hedge fund indices tell us about hedge fund risk and return?*

We show that our risk factor model can identify differences between hedge fund indices and helps to explain anomalous return differences among them.

Section six provides an out-of-sample check on the usefulness of the risk factor model in its ability to explain significant return differences among major hedge fund indices. Limitations and possible direction for future research are in section seven. A summary of our findings and conclusions are presented in section eight.

2. Data Biases in Peer-Group Averages

A standard method to model hedge fund risk is to use broad-based indices of hedge funds as risk factors.¹ However, indices constructed from averaging individual hedge funds can inherit errors in hedge fund databases. These problems have been noted in previous papers, e.g., Brown, Goetzmann, and Ibbotson (1999), Fung and Hsieh (2000), and Liang (2000). The remainder of this section provides a summary of these problems.

Selection Bias:

Unlike mutual funds, hedge funds are not required to make public disclosure of their activities. In addition, there is no hedge fund industry association comparable to the Investment Company Institute for mutual funds that acts as a depository of fund information. Hedge fund data are generally collected by data vendors and sold to accredited investors, with the consent of the hedge fund manager. Selection bias can arise

¹ For example, hedge fund indices are available from CFSB/Tremont, Hedge Fund Research (HFR), and Zurich Capital.

if the sample of funds in the database is not a representative sample of the universe of hedge funds. This can happen because entry to a database is a voluntary decision. As hedge funds are prohibited from public solicitation, they can only be marketed through word of mouth. This can be accomplished by belonging to a database purchased by interested investors. To the extent that the performance of funds seeking investors are different from the performance of funds not seeking investors, there will be selection bias.

Survivorship Bias:

Most hedge fund databases only provide information on operating (or live) funds. Funds that have stopped reporting information or ceased operation are regarded as uninteresting to investors, and are purged from the database. This creates a survivorship bias, since the performance of disappearing funds is typically worse than the performance of surviving funds. This type of bias is well known in mutual funds, see for example, Brown, Goetzmann, Ibbotson, and Ross (1992).

Instant History Bias:

When a fund enters a database, its past performance history (prior to the entry date) is appended to the database. This creates “instant history bias”. Many new funds start with an incubation period to accumulate a track record. If the performance is “good”, they enter into a database to seek new investors. Otherwise they cease operation. When a data vendor backfills the fund’s performance, the average return in the database is biased (upwards).

When hedge fund indices are created from hedge fund databases, they inherit all these biases. Some hedge fund index providers do take care to correct these errors to the extent possible. However, to what extent these errors can be mitigated through data manipulation techniques alone is unclear.

Fund-of-Hedge Funds Indices:

One method to reduce some of these data biases is to use the returns of funds-of-hedge funds. Fung and Hsieh (2000) argued that fund-of-hedge fund data are less prone to these three data biases. If a fund-of-hedge fund invests in a fund that does not report to any database, the performance of that fund is still reflected in the performance of the fund-of-hedge funds. Thus, returns of funds-of-hedge funds have less selection bias than those of individual funds. If a fund-of-hedge fund invested in a fund that ceased operation, the performance of that fund remains in the historical return of the fund-of-hedge funds. This reduces survivorship bias. When a fund-of-hedge fund invests in a hedge fund, the previous history of the hedge fund is not included in the historical return of the fund-of-hedge funds. This reduces instant history bias.

Sampling Differences:

Sampling differences exist across the various hedge fund databases. For example, the Centre for Hedge Fund Education and Research has access to the TASS, HFR, and Zurich Capital databases. As of December 2000, TASS has 1061 funds that are in operation, HFR 1151, and Zurich Capital 909. However, only 315 funds are in all 3

databases. TASS contains 396 funds that are not in the other two databases. Similar HFR (Zurich Capital) has 446 (292) funds that are not in the other databases.

Sample differences can lead to divergent returns across different hedge fund subindices. For example, the HFR index for Equity Market Neutral hedge funds was reported to return -1.57% for the month of January 2001 whereas the CSFB/Tremont index for Equity Market Neutral hedge funds returned 2.13% for the same month. However, the high degree of return correlation between broad-based peer group averages from different databases indicate that there may only be a small number of common hedge fund risk factors.

Short History:

Another drawback of hedge fund indices, either based on individual funds or funds-of-hedge funds, is that reliable data on hedge funds start in the 1990s. This sample coincides with one of the greatest bull markets in history, and with only a few years of market decline. It does not provide a sufficiently long history to allow us to determine how hedge funds would perform over a variety of market environments not witnessed in the 1990s. Below, we propose a method to constructing hedge fund risk factors that can circumvent this problem.

Lack of Transparency:

Another disadvantage of using hedge fund indices is the lack of transparency. As private investment vehicles, hedge funds do not disclose their activities. Consequently, other than historical return statistics that are of dubious quality, there are only limited

avenues to determine the equity content, or bond content, of a hedge fund portfolio and to assess its impact in an overall asset allocation framework.

Issues on the Choice of Index Weights:

Typically, conventional asset classes transact in different markets and can easily be distinguished by the way in which an asset is securitized. An index of a conventional asset class is usually an average (equally-weighted, price-weighted or value-weighted) of the underlying assets in that class. Consequently, an asset-class index resembles a broad-based index for the market in which the constituent assets are traded. As an investment portfolio, an investable asset-class index is passive and its constituents change only according to explicitly defined rules governing index rebalance. However, the rebalancing rules themselves implicitly assume particular portfolio strategies. For instance, an equally-weighted index implicitly assumes a contrarian approach where the better performing assets are sold in exchange for the under-performing assets at index rebalancing points in order to maintain equal weighting. A value-weighting scheme, on the other hand, assumes a momentum strategy where winners are permitted to exert increasing influence on the portfolio's (index's) total return. When these assumptions are applied to hedge funds, certain problems occur.

It is well known that the distribution of assets among hedge fund managers is skewed towards the top funds. Easily, less than twenty-five percent of the funds manage in aggregate more than seventy-five percent of the industry's capital. Therefore, an equally weighted index's returns will not reflect this phenomenon. Also, an equally

weighted scheme biases the index towards newly minted funds where the instant history bias is at its maximum.

Using asset under management as weights in a hedge fund index also has its problems. First, the quality of historical series of assets managed by hedge fund managers is much less reliable than historical series of returns. Second, most hedge fund strategies have finite capacity. This could result in a situation where a large, successful hedge fund manager may choose to close the fund to new capital and stop reporting performance to index providers resulting in distortions to the index return series. Third, an index of hedge funds should reflect the return experience of risk capital used to generate the performance. Leverage can distort this. The dollar return of any strategy, and of the hedge fund industry, is ultimately dependent on the market environment. The rate of return, on the other hand, involves one more factor—the degree of leverage used by the hedge fund managers. It may be unreasonable to assume that all hedge fund managers operate at optimal leverage at any given point in time. Using an asset-under-management weighting scheme will bias the index return towards under-levered managers, and at an extreme, overemphasize the performance of asset-gatherers.

In the absence of explicitly specified portfolio objectives, there is no optimal way to determine how hedge fund managers should be combined to form an index that will be suitable to all investors. A more flexible method for constructing hedge fund benchmark is clearly called for.

3. Return-Based and Asset-Based Style Factors

In order to avoid the data biases in hedge fund databases, we construct benchmarks based on asset returns rather than hedge fund returns. The approach we advocate is to link common components of hedge fund returns to observable market risk factors. We extract common components of hedge fund returns using a statistical procedure called principal components, and call these common components “return-based” style factors. Whenever return-based style factors can be linked to models involving only observable market risk factors, we call the latter “asset-based” style factors.

We have extracted common components of hedge fund returns in two ways. In Fung and Hsieh (1997a), we analyzed all hedge funds and commodity funds with two years of monthly performance data. We used the idea that, if two funds traded similar assets in a similar manner, their returns would be highly correlated. The correlated part of their return is therefore a common return component. By grouping funds with correlated returns, we can extract their common component. In that article, we found that the five most important common components accounted for roughly 50% of the covariation among these funds. This method is very similar to the way the CAPM and the APT were empirically implemented.

Applying a variation of this method allows us to extract common return components from subgroups of hedge funds that have been classified by data vendors to have similar styles without having to verify their classification method. This is in line with the philosophy of checking what hedge managers do instead of interpreting at face value what they say they do. This was done in Fung and Hsieh (2001, 2002a).

The next phase of our approach is to explicitly identify these common return components using observable market risk factors. This process is illustrated for four subgroups of hedge funds and commodity funds below.

Trend-Following Funds:

In Fung and Hsieh (1997b), we extracted a common return component from trend-following funds. In Fung and Hsieh (2001), this common return component was modeled as portfolios of lookback options. The model extends the insight from the pioneering work of Merton (1981) and asserts that trend followers are betting on big moves. They make money when markets are volatile similar to option buyers. We therefore constructed five portfolios of lookback options from exchange-traded options. We showed that these option portfolios have very similar return characteristics, and high correlation, with the returns of trend-following funds. Subsequently, Fung and Hsieh (2002b) showed that this analysis continues to hold beyond the sample period of the original analysis.

[insert Figure 1 here]

The out-of-sample results are from Jan 1998 to the end of 2002 in Figure 1. The solid line is the average monthly return of trend-following funds, as measured by the Zurich Trend-Following Index. This is the return-based style factor for trend-following funds. The broken line is the monthly return of the portfolio of lookback options, based on the parameter estimates in Fung and Hsieh (2001) that used data through the end of 1997. This is the asset-based style factor for trend-following funds. The figure shows that the replicating portfolio of straddles can mimic the returns of the average trend-

following fund. Modeled this way, the trend-following ABS factor highlights an interesting feature of the strategy. Trend-following strategies thrive when conventional asset markets are distressed, which provides a valuable diversifying source of return to portfolios of conventional assets.²

Merger Arbitrage Funds:

Mitchell and Pulvino (2001) created an asset-based style factor for merger arbitrage funds. Merger arbitrage (also known as risk arbitrage) is a strategy that buys the stock of the target and shorts the stock of the acquirer. The bet is that the announced merger transaction will be completed. Mitchell and Pulvino simulated the return of a rule-based merger arbitrage strategy using all announced stock and cash merger transactions from 1968 to 1998. They showed that this asset-based style factor for merger arbitrage has similar return characteristic as merger arbitrage funds.

[insert Figure 2 here]

They also discovered a very interesting result, illustrated in Figure 2. The horizontal axis is the monthly return of the S&P index, from 1990 until 2002. The vertical axis is the corresponding monthly return of the HFR Merger Arbitrage Index, which is an average of the returns of merger arbitrage funds in the HFR database. This figure shows that returns of merger arbitrage funds have low correlation with the S&P, except when the S&P experiences large declines. In those months, a sharp decline of the S&P coincides with the worst performance of merger arbitrage funds. In other words, the deal risk that merger arbitrageurs are exposed to can be proxied by a short position in an out-of-the-money put option on the S&P.

² Agarwal and Naik (2004) also find option-like behavior in hedge fund returns.

This is a reasonable conclusion. The systemic risk in merger arbitrage is that many transactions are cancelled at the same time. Under normal market conditions, individual deal risks are idiosyncratic and can be diversified. However, if the market declines sharply, merger transactions can be called off or postponed irrespective of their individual merit, creating a loss for merger arbitrage funds. Here, the ABS factor, in the form of a short put, helps to highlight a systemic source of risk beyond the individual deal risk of merger arbitrage.

Fixed-Income Hedge Funds:

In Fung and Hsieh (2002a), we analyzed fixed-income hedge funds. We found that these funds are typically exposed to interest rate spreads. The reason is that many fixed-income funds buy bonds that typically have lower credit rating and/or less liquidity and hedge the interest rate risk by shorting treasuries that have the highest credit rating and are more liquidity. The difference between the yields on the two bonds is the interest rate spread.

Since interest rate spreads tend to move together, especially during times of market distress, fixed-income funds can be modeled as being exposed to credit spreads. In addition, fixed-income arbitrage positions are often highly levered. The cost of financing the positions will also depend on the overall liquidity of the market place, which is reflected in the credit spread variable. Therefore, both the nature of the bets and the way positions are funded are sensitive to credit spread as the common risk factor. The following regression of the HFR Fixed Income Arbitrage Index on changes in the

credit spread is a good illustration. Here, the credit spread is measured as the difference between the yield on Moody's Baa bonds and the yield on the ten-year constant maturity treasury.

$$\text{HFR Fixed Income Arb} = 0.0096 - 5.37 \times [\text{change in credit spread}]$$

The R^2 of this regression is 0.30, using data from 1990 until 1997. The regression tells us that a 1% increase (decrease) in the credit spread will lead to a 5.37 decline (increase) in the return of the average fixed-income arbitrage fund.

[insert Figure 3 here]

This regression is useful when we examine the history of the credit spread in Figure 3. The hedge fund data we have, starting in 1990, covers a relative benign period for the credit spread: it had generally declined, and remained low relative to the 1970s or 1930s. As a result, it is not possible to answer the question: "How would fixed-income arbitrage hedge funds perform in the credit market conditions of the 1970s?" based on their returns alone, as they did not experience the less benign market environment in our data sample. However, the beta of these funds with respect to the credit spread will give us a good idea of what might happen. A rise of 2% in the spread, which has not been experienced in the 1990s, would lead to a loss of 10.7% for these funds. That conclusion cannot be drawn from the hedge fund data alone. By identifying and using the relevant ABS factors, it is now possible to assess the risk of a given hedge fund strategy over a much longer histories spanning different economic cycles.

Equity Long/Short Hedge Funds:

The original concept of a hedge fund, due to A.W. Jones, had long and short positions in equities. As a result, this strategy is called Equity Long/Short. Fung and Hsieh (2003) showed that equity long/short hedge funds have exposure to the stock market and the spread between large cap and small cap stocks. The risk factors of these funds can be seen in the following regression:

$$\text{HFR Equity Hedge Index} = 0.0097 + 0.46 \times [\text{S\&P 500}] + 0.44 \times [\text{SC-LC}]$$

where “SC” denotes the Wilshire 1750 Small Cap index, and “LC” the Wilshire 750 Large Cap index. The sample period is 1994-2002, and the R^2 of this regression is 0.77. This is consistent with the observation that equity long/short funds tend to have a small positive exposure to stocks, and that they tend to be long lower capitalization stocks and short higher capitalization stocks. Therefore, long/short equity hedge funds are generally not an alternative source of investment to a conventional portfolio with a significant equity content. There will be an overlap of directional exposure to the US equity market and may be increasing a portfolio’s tilt to small cap stocks. An interesting application from the ABS factor analysis is whether these systemic risk factors can be separately managed to modify the return profile of long/short equity hedge funds so as to enhance their diversifying attribute to conventional asset portfolios.

A Seven-Factor ABS Model:

Thus far, research has found seven risk factors. The market (as proxied by the S&P 500) and the SC-LC spread are found in Equity Long/Short hedge funds. We refer to these two ABS factors as the Equity ABS factors. The two equity ABS factors are the

major risk factors for a sizable portion of the industry. In the TASS database, out of 1824 operating funds as of March 2003, 795 (44%) are classified as Equity Long/Short funds. In the HFR database, out of 1911 operating funds as of July 2003, 550 (29%) are classified as Equity Hedge funds.³

The change in 10-year treasury yields and the change in the yield spread between 10-year treasury and Moody's Baa bonds are significant return drivers in Fixed Income Arbitrage funds. We refer to these as the Fixed-Income ABS factors, and they are the major risk factors for a small portion of the hedge funds. For example, there are 88 such funds (5%) in the TASS database as of March 2003, and 34 (2%) in the HFR database as of July 2003.

The portfolios of lookback options on bonds, currencies, and commodities are significant return drivers in trend-following funds. We refer to these as Trend-Following ABS factors. They are the major risk factors for 5-10% of hedge funds. For example, there are 161 (9%) Managed Futures funds in the TASS database as of March 2003, and 121 (6%) in the HFR database as of July 2003.⁴

In summary, these seven risk factors are found in 57% of the hedge funds in TASS, and 37% in HFR. Research on additional hedge fund styles will likely discover other risk factors. However, some of the yet-to-be-discovered risk factors can be correlated to the existing seven risk factors. For example, Fung and Hsieh (2002b) found that fixed income hedge funds (such as Convertible Bonds, Mortgage-Back Securities)

³ The incremental ability of the two Equity ABS factors to explain returns of Equity long/short hedge funds, over and above that of the market factor, was shown in Fung and Hsieh (2003).

⁴ The superior ability of the Trend-Following ABS factors to explain the returns of trend-following funds beyond standard buy-and-hold benchmarks was shown in Fung and Hsieh (2001).

are correlated to the change in credit spread.⁵ This cross-correlation among risk factors is a primary reason why we believe that only seven risk factors are sufficient to explain a large portion of the risk in hedge funds.

4. What Do ABS Factors Tell Us About the Typical Hedge Fund Portfolio?

Up to now, research on ABS factors has been evolved along specific (or group of) hedge fund strategies. However, hedge fund investors tend to diversify their investment over a portfolio of different hedge fund strategies. Having identified a number of ABS factors for the major hedge fund styles—trend following, fixed-income related and equity related, it is important to ask the question: how much of the risk of a typical hedge fund portfolio can be identified using the seven risk factors we have found thus far?

To proxy for a typical hedge fund portfolio, we use the HFR Fund-of-Funds (“HFRFOF” for short) index. We regress its monthly return, from 1994 until 2002, on the following seven hedge fund risk-factors: two equity risk factors (S&P 500, SC-LC), two interest rate risk factors (the change in the yield of the 10 year treasury, and the change in the credit spread), and three trend-following factors (the portfolio returns of options on currencies, commodities, and long term bonds). Data prior to 1994 is excluded from the analysis, as the number of funds of hedge funds in the HFR database was less than 100 prior to 1994. In contrast, the HFRFOF now contains over 500 funds

⁵ For some niche styles, other risk factors may add explanatory power. For example, movements of credit spreads of below investment-grade bonds will help to explain the returns of hedge funds specializing in distressed securities; and emerging market stock indices will help to explain the returns of hedge funds specializing in emerging market securities.

of hedge funds as of July 2003. We adopted this simple rule to select a start date for our analysis.⁶

[insert Table 1 here]

Table 1 reports the summary statistics of the regression. The third column of Table 1 shows the HFRFOF to have significant betas to the two equity ABS factors as well as the two fixed-income ABS factors at the 99% one-tailed level. In contrast, exposures to the trend-following factors were statistically insignificant. The adjusted-R² of the regression is 0.55. There is a statistically significant intercept term of approximately 48 basis points per month. Based on these observations, it is tempting to conclude that on the average hedge fund portfolio has systematic exposures to directional equity and interest rate bets, as well as systematic exposures to long/short equity and credit spread bets. There appears to be an average alpha, adjusting for these risk factors, of approximately 48 basis points per month. However, it is unrealistic to assume that investors' asset allocation has been static over this eight years period. This begs the question: *how stable are these conclusions?*

The period of 1994 to 2002 was marred by a number of stressful market events. During the early part of 1994, US interest rate rose abruptly inflicting substantial losses to a number of hedge funds. The LTCM episode also caused substantial volatility to hedge fund returns during the latter part of 1998. In addition, the Internet bubble ended around March 2000 followed by yet another market disruption event of nine-eleven. In two thousand two, the market has to absorb the events at Enron and Worldcom. With

⁶ There is only one other fund-of-funds index, from CISDM (formerly MAR/Hedge). Instead of the average return, it uses the median return, of funds-of-funds. This index is not designed to capture the performance of a diversified hedge fund portfolio we, therefore, excluded it from our analysis.

such a collection of market disruption events, it is likely that most funds of hedge funds have had to adjust their portfolios accordingly. This in turn, is likely to cause the betas in our risk factor model to shift over time.

Estimating the HFRFOF's time-varying bets during different market conditions:

To test the stability of the ABS factor betas, we devised a novel variation to the standard test on cumulative recursive residuals. We do this by running the regression backwards starting in December 2002, adding observations one month at a time. This is similar to running a Kalman Filter with the time scale reversed. The logic behind this approach runs as follows. Given the tremendous growth in the hedge fund industry over the past decade, both the number of funds of hedge funds and their performance data quality has been rising. It follows that the information content of the return data is likely to decline with the age of the return observations. Looking for a sample break point by running the Kalman Filtering process backwards implicitly allows us to place more credence on recent returns without having to explicitly specify ad hoc schemes for weighing individual returns to favor more recent data. By observing the behavior of the cumulative recursive residuals, we hope to identify market events that trigger a violation of error bounds. As these market events are exogenous to the regression equations, we have an unbiased way of identifying sample breakpoints that are consistent with a change in the regression regime.

[insert Figure 4 here]

Figure 4 plots the cumulative recursive residuals for the HFR FOF index, starting in December 2001 and working backwards to January 1994. The two dotted lines

represent 95% confidence bands. When the cumulative recursive residuals crossed the upper band in June 1999, it indicated a sample break from a statistical viewpoint. Similarly, the cumulative recursive residuals crossed back below the upper band, in October 1998, again indicating a sample break around that time. It is unlikely that the actual sample break happened exactly at those times, since the effect of the sample break shows up gradually in the regression. Instead, we looked for market events around the statistical sample breaks period to pinpoint the culprit and the timing for the actual break. Using an exogenous set of market events takes the pressure off over burdening the data set in identifying the regression equation structure. Another advantage of linking hedge fund returns to market events is the additional economic insight it offers.

This led us to identify March 2000, and September 1998 as triggering market events—they are, respectively the end of the Internet bubble, and the LTCM debacle. Accordingly, we divided the sample into two sub periods—January 1994 to September 1998, and April 2000 to Dec 2002.

Columns one and two of Table 1 reports the results for the respective periods. There are significant betas, with respect to the two equity ABS factors, in both sub periods. However, in the second sub period, the magnitude of the directional exposure to the S&P 500 was almost halved. This is consistent with bear market conditions that prevailed during the second sub period. Consistent with this bear-market effect is the increase in the beta with respect to the 10 Y Treasury indicating an increase in bond market bets (a more negative beta indicates a larger exposure to bonds because of the inverse price yield relation with bonds). In terms of exposure to credit spread, both

absolute value of the beta and the statistical significance level has declined. This too, is consistent with portfolio bets reflecting a bear market environment.

The same theme carries through to beta with respect to the trend-following ABS factor on Commodities—it increased in both magnitude and statistical significance. As pointed out in Fung and Hsieh (2001), this increase can be interpreted as a diversifying bet against potential stock market declines. Trend-followers tend to benefit during stressing equity market conditions. Note that by identifying the break points in the regression, the adjusted R^2 for both sub periods went up substantially (from 0.55 for the overall period to 0.69 in the first sub period and 0.80 for the second sub period).

The vanishing alpha:

Perhaps the most troublesome change is in the intercept, or alpha, term of the regressions. For the first sub period, both the magnitude and significance level dropped dramatically for the intercept term, indicating little to no added value from the average fund-of-hedge fund manager beyond systematic bets. Although the second sub period intercept term is marginally better both in magnitude and significance compared to the first sub period, it is still less than half of the intercept term when the entire sample period was used. Prima facial evidence suggests that there may have been an “alpha illusion” from the single period regression in that any apparent value added by the average fund-of-hedge fund manager beyond systematic bets took place during the bull market run of October 1998 to March 2000. This is not welcoming news to institutional investors in hedge funds as bull market alphas is at best a redundant feature of an alternative investment.

To conclude this section, it is clear that a properly structured risk factor model can reveal important insight to the risk profile of a hedge fund portfolio. In this case, it provided important clues as to where the average fund-of-hedge funds placed its bets, how these bets varied over time, and whether there was value added beyond systematic bets on the ABS factors—something that a simple index and its return statistics will not be able to convey. Next we apply the same analysis to standard hedge fund indices. This will help us gain insight as to whether the time-varying bets we observed among funds-of-hedge funds is simple a derivative of systemic shifts in the underlying hedge funds or a consequence of their portfolio management strategy.

5. Assessing Differences in Hedge Fund Indices Using the Risk Factors

In this section, we provide an empirical analysis the differences in existing hedge fund indices using the risk factors we have established.

Applying ABS factors to explore the characteristics of existing hedge fund indices:

Hedge fund indices are constructed from different databases with only a small overlap of funds. In fact, the HFR Composite Index (“HFRI”) and CSFB/Tremont Composite Index (“CTI”) are not highly correlated—the correlation coefficient is only 0.76. It will be reasonable to expect these two indices to have significantly different risk characteristics. As shown below, it turns out that the two indices in fact have very similar exposures to the risk factors.

[insert Table 2 here]

Table 2 reports the regression of the four hedge fund indices on the seven hedge fund risk factors—HFR, CTI, and MSCI (the MSCI Composite Equally-Weighted Index), for the period Jan 1994 until Dec 2002.⁷ The regressions show that both the HFRI and CTI have average exposures of the same sign and comparable magnitudes. They have very strong exposure to the two equity ABS factors. The CTI also has very strong exposure to the two fixed income ABS factors, but not the HFRI. This is the first significant difference in risk characteristics between the two indices. The second difference is the significant beta of the CTI trend-following ABS factor in bonds. While trend followers have positive exposure to this risk factor, as shown in Fung and Hsieh (2001), some other hedge funds in the CTI must have a negative exposure, leading to a net negative exposure at the index level. Both indices have significant alphas—66bp for the HFRI and 73bp for the CTI in their monthly returns. We defer the analysis of the different alpha characteristics to the next section.

The question arises as to how much of these risk differences is a result of different index construction methods. HFRI is an equally weighted index for all hedge funds in the HFR database. CTI is a value-weighted index for large hedge funds in the TASS database. To eliminate some of these differences, we created an equally weighted index (“TASSAVG”) using the TASS database ending in Mar 2003, after excluding funds-of-hedge funds. The average exposure of this benchmark is reported in the third column of Table 2.

The TASSAVG index has similar equity ABS factor exposures to the CTI but have smaller exposure to the fixed-income ABS factors. This brings the risk profile of

⁷ This excludes the Van Hedge Global Index (which starts in 1995), the EACM100 index (which starts in 1996), and the S&P Hedge Fund Index (which starts in 1998).

the TASSAVG index closer to that of the HFRI. This is not surprising as the number of operating equity hedge funds (795 for TASS and 550 for HFRI) greatly exceed the number of fixed-income arbitrage hedge funds (88 for TASS and 34 for HFRI). The exposures to trend-following factors are also higher, consistent with the presence of commodity futures advisors (CTAs), who run managed futures programs, in the TASSAVG. Note that HFR excludes CTAs from their indices. What this reveals is that the construction of the CTI index over weights fixed-income risks and under weights trend-following risk compared to the average of the universe of TASS funds from which it is based. Both the CTI and TASSAVG have similar levels of alpha.

In the last column of Table 2, we provide the average exposure of the MSCI hedge fund index (“MSCI”). It, too, has exposure similar to HFRI and TASSAVG. The equity ABS factor exposures of the MSCI are comparable to that of the TASSAVG—both are lower than the HFRI. Interestingly, the MSCI has no significant beta with respect to either of the fixed-income ABS factors. Finally, exposures to trend-following factors are similar between the MSCI and the TASSAVG.

These results show how the risk factor model can identify differences in the databases from standard providers of hedge fund data. It appears that the HFR database is dominated by hedge funds with equity-related bets. The TASS database has a better balance between equity-related hedge funds and others that have interest rate-related bets. Another point picked up by the risk factors is the presence of trend-following hedge funds in the TASS database that is absent in the HFR database. The MSCI database also has a large equity-related hedge funds presence relative to interest rate-related hedge funds. But there is clear presence of trend-following hedge funds in the MSCI dataset.

The risk factors can provide an alternative method for quantifying the hedge fund style categorization by data based vendors.

Analysis of parameter stability:

Following the format of the analysis in section three, we applied the same cumulative recursive residual technique on a reversed time scale to look for regime changes in the risk factor model. Figure 5 plots the behavior of the cumulative recursive residuals for the four indices. Generally, we conclude on similar sample break points to our earlier analysis on HFRFOF but for the exception of the CTI where no discernable break point can be identified.

[insert Figure 5 here]

[insert Table 3 here]

Table 3 reports the summary statistics of the seven-factor model for the three indices—HFRI, TASSAVG and MSCI. The general conclusions on ABS factor betas for the HFRIFOF regressions remain valid for the indices. All three indices have statistically significant betas to the two equity ABS factors. All three showed declining equity ABS betas in the second sub period, albeit must less dramatic than in the case of the HFRIFOF. Similar conclusions hold for the beta with respect to the 10 Y Treasury factor but for the fact that none of the three indices exhibit significant interest rate beta in the first sub period. For these three indices, their bond bet appears to be a second sub period, bear market phenomenon. For the credit spread factor beta, the same behavior of declining magnitude and statistical significance occurred going from the first sub period to the second reflecting the bear market sentiment.

The beta behavior of the trend-following factor betas is less clear. For the HFRI, which has no CTAs, it was displaying a significant beta with respect to the trend-following factor on commodities. As the HFRI does not contain CTAs, one can only infer that trend-following strategies on commodities was adopted by some of the hedge fund managers that are classified as having other styles. More work is needed to fully explain this observation. As for the TASSAVG index, there is an increase in trend-following beta in the foreign exchange area as is the case with the MSCI index. It is possible that colinearity between the trend-following factors is making it hard to provide a simple interpretation of the results.

[Insert Table 4 here]

Table 4 provides the exposures of the indices across the two subperiods. The adjusted R^2 s of the risk factor equations are unusually high—well over 70% for the first sub period for all three broad-based indices with a high of 85.3% for the HFRI. For the second sub period the adjusted R^2 s rose to 91.2% for the HFRI, 0.903 for the TASSAVG and 0.852 for the MSCI. These high adjusted R^2 s are consistent with our assertion that only a limited number of risk factors are needed to capture the risk characteristics of large hedge fund portfolios. Look ahead from here, while unidentified factors remain a possibility, but whatever they are, it is hard to imagine any dramatic improvement on the explanatory power of the model.

The rediscovery of alpha:

Perhaps the most interesting result is the behavior of the intercept terms—alphas. All three indices show significant alphas for both sub periods. All three showed a small

decline in the alpha value in the second sub period. Nonetheless, the magnitudes of these alphas offer stark contrasts to the results from the HFRFOF regressions. They are at a level of difference that cannot be easily explained away by the additional fees charged by funds-of-hedge funds. At this point, one can only summarize that there is an alpha (statistically reliable) loss going from the industry's average (as proxied by these broad-based indices) to the average fund-of-hedge funds, after adjusted for systematic risk factors among hedge funds.

There are three possible interpretations. One, poor performing funds-of-hedge funds in the index constituent drag the average alpha towards zero. Two, there are structural costs in managing a very large hedge fund portfolio like these indices that is not accounted for by the index returns. Three, unrealistic index construction rules are creating pseudo alphas for these indices.

We analyze these three possibilities in reverse order. Index rebalancing rules can be misleading as we noted in section two. But, it is unclear whether this necessarily biases the index returns upwards relative to an actual portfolio of hedge funds. Still, it is important to acknowledge that artificial rebalancing rules assumed by hedge fund indices give indices an unrealistic cost advantage in portfolio rebalancing. Undoubtedly managing large portfolios carries costs. It is unclear whether this matters, as the cost should be part of the fund-of-hedge fund's fees, which cannot reasonably rise to such a magnitude to absorb the alpha differences. The most likely explanation is that there are simply too many inefficient funds-of-hedge funds—there are over five hundred in the HFR database. Undoubtedly, consolidation and the emergence of investable hedge fund

indices will correct this overtime. In the meantime, we will continue to monitor these developments in the hedge fund industry.

6. Accessing the Usefulness of the Risk-Factor Model with Out-of-sample Data

A standard way to gauge the usefulness of a model is to apply it to data not used in the model's construction. In this section, we apply the model to provide *conditional* forecasts of the returns of the various hedge fund indices in 2003. Specifically, we used the regression coefficients from the second sample period (April 2000 to December 2002), along with the realized values of the regressors in 2003, to estimate the returns of the indices in 2003. These estimates should be close to the actual returns, if the model correctly captures the risk exposures of hedge fund indices.

[insert Table 5 here]

Table 5 contains the actual 2003 annual returns of four hedge fund indices, along with the conditional forecasts. HFR, CTI, and MSCI are the three indices have analyzed in the previous section. To broaden the scope of our analysis, we included the S&P Hedge Fund Index (SPHF), which started in 1998 and therefore did not allow us to perform the analysis over the full sample.⁸

Although all these indices are targeted at conveying to investors the performance of the hedge fund industry, there are substantial variations in the performance of these indices in 2003--from a low of 10.58% to a high of 18.10%. Here is where a risk-based model can help to reconcile these performance differences from the same industry. A major difference among the indices is their equity exposures. According to our model, the

⁸ Note that the estimated exposure of the SPHF over the April 2000-December 2002 period is in the last column of Table 4.

HFR has the highest exposure to equity risk factors, and the SPHF the lowest. During 2003, the S&P 500 index rose by 26% and the Wilshire Small Cap 1750 index outperformed the Wilshire Large Cap 750 index by 19.25%. This contributed a great deal to the performance differences among the indices, favoring those with the highest exposure to equity risk factors.

Another interesting point to note is that the accuracy of the model depends on the how the index is constructed. The HFR, MSCI, and SPHF are equally-weighted broad-based indices. The error of the model is less than one percentage point in each case. The CTI index uses asset-weighting and depending on the relative sizes of the constituent funds it can be much less diversified than an equally-weighted index of an equivalent number of funds. It is not surprising that the error of our model is somewhat larger.⁹

7. Limitations of the Model and Possible Future Research Directions

The seven risk-factor model is designed to assess the exposure of a diversified portfolio of hedge funds, and as such it does have a number of limitations.

To begin with, the risk factors in our model are not necessarily unique. Other linear combinations of the seven risk factors can produce substantially similar results. In addition, another set of variable with high correlations to these seven risk factors can also generate similar results. There is, perhaps, a practical guiding principle one could adopt in future refinements of our models. Given the same level of explanatory power, statistically, the set of ABS factors that offers the most direct link to conventional asset-class indices is preferred.

⁹ Not to mention that the historical asset under-managed series are more susceptible to reporting errors and more open to interpretations.

The second limitation is that the model may not explain the performance of niche styles. Put differently, we expect to uncover additional specific factors when applying such a model to hedge fund portfolios that are more concentrated. Take, for example, Merger Arbitrage hedge funds. As Mitchell and Pulvino (2001) have shown, the risk characteristics of specific hedge fund strategies are better explained by risk factors that are constructed to fit that purpose. This echoes the findings of Fung and Hsieh (2001) on trend-following hedge funds. In general, as one moves away from a well-diversified portfolio of hedge funds to more specific hedge fund styles—and eventually to individual funds—there is no escape from the burden of having to construct additional risk factors that are specific to certain styles. This situation is similar to that in equity style models. For well-diversified large portfolios of stocks, we need only a market factor. However, funds that concentrate on specific sectors are better described by narrow benchmarks.

These limitations of the model provide useful guidance for future research. Additional risk factors would be needed for explaining narrower benchmarks and individual funds. However, what our model does say is that having narrower averages of hedge funds defined without reference to asset prices does not help. The same performance divergence among broad-based indices can re-emerge with a vengeance, when the narrower benchmarks have different exposures to risk factors.

8. Concluding Remarks

The seven hedge fund risk factors can explain a significant part of the systematic risk of a typical hedge fund portfolio measurable using conventional securities prices. This provides a vital link between hedge fund risks to familiar conventional asset-class

risks. Once a high level of explanatory power is reached, this type of risk factor model can also be used to measure differences between hedge fund databases. It provides a metric for comparing one source of hedge fund data from another. Our empirical findings suggest that these differences are not inconsequential.

In terms of portfolio management, the risk factor model helps us identify alternative betas in hedge fund investing. Analysis of the time-varying characteristics of alternative betas helps investors understand how bets are placed and changed over time by funds-of-hedge funds. Similarly, one can now define alternative alphas inherent in the total return of hedge fund investments. As far as we know this is a concept that has only been recently advanced by Fung and Hsieh (2003). Analysis of the time-varying characteristics of alternative alphas reveals interesting and uncomfortable conclusions on the value-added by the average fund-of-hedge funds. This provides an interesting framework for assessing hedge fund performance that accounts for both nonlinear and time-varying risk characteristics. Undoubtedly, more refinements can and should be executed. As an illustration we provided some example application of these tools by constructing customized hedge fund indices with no directional exposure to conventional asset classes. Results are promising.

What does this say about hedge fund risk disclosure and transparency?

For investors, it would be useful to have individual fund exposures to a set of common market risk factors. That would help investors to better design hedge fund portfolios, manage their risk and set suitable performance benchmarks. On the one hand, it helps hedge fund managers communicate the systematic risk inherent in their strategy to investors, and on the other hand, it helps investors detect inconsistent bets from

managers. In other words, risk disclosure and transparency can be brought to a satisfactory, aggregated level without the burden of analyzing voluminous transactions of a hedge fund. As these risk factors are directly observable using market prices, investors can approximate the performance of their hedge fund investments on a daily basis in line with the changing conditions of global markets.

For regulators, it would also be useful to collect exposures of risk factors from various market participants. We illustrate the benefits of this using the bond market decline of 1994, one of the episodes of market stress in Fung and Hsieh (2000).

During 1993, the world bond markets rallied as interest rates declined. Then in February 1994, the Federal Reserve began to raise interest rates. This led to one of the worst bear markets in the history of the bond market. Fung and Hsieh (2000) used monthly returns of various subgroups of hedge funds to estimate their position sizes. We found that trend-following funds and “Global/Macro” hedge funds have large long positions on European bonds at the beginning of 1994. Trend followers were long European bonds because they saw a prolonged increase (“trend”) in their prices. Global/Macro funds were long European bonds because they were betting on a continued decline in European interest rates based on economic fundamentals. It turns out that “convergence traders” were also heavily involved in the European bond market. A study conducted by the International Monetary Fund (1998) found that convergence traders were betting on the convergence of European interest rates to each other, in anticipation of the launch of the single European currency in 1999. They were mainly long Spanish and Italian bonds, betting their yields would decline to the lower levels of German bonds.

When interest rates increased, there was a prolonged period of liquidation, first by trend followers and convergence traders, then by Global/Macro funds.

This episode indicates that different groups of hedge funds can “converge” on the same trade based on completely different motivations. Presumably, other “highly levered institutions” (a phrase coined by the Bank for International Settlements), such as proprietary trading desks of investment banks, also had large positions in European bonds. It is this type of situation that is the most dangerous from a systemic standpoint. Markets become stressed, as the bond market did in 1994, when everyone rushed for the exit. Prices declined, triggering margin calls, forced liquidations, and further price declines. From a regulatory standpoint, it would be useful to obtain risk exposures of all “highly levered institutions”, not only hedge funds. It would be useful for regulators to collect and to report aggregate exposures to various risk factors. This may forestall traders from adding on more positions, if they sense that it may be difficult to exit from them.

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Table 1
Regression of HFR Fund-of-Funds Index on Seven Hedge Fund Risk Factors

	Jan 94-Sep 98	Apr 00-Dec 02	Jan 94-Dec 02
Constant	0.00192 (0.00176)	0.00212 (0.00133)	0.00477 (0.00128)
S&P	0.32426 (0.04539)	0.17300 (0.02938)	0.21533 (0.02873)
SC-LC	0.17794 (0.06628)	0.14972 (0.03633)	0.22561 (0.03629)
10Y	-1.11718 (0.94950)	-2.70801 (0.63269)	-1.56445 (0.65403)
Cred Spr	-6.66498 (2.24776)	-2.13051 (0.98164)	-2.96390 (1.19194)
Bd Opt	-0.01057 (0.01064)	-0.00682 (0.00601)	-0.01529 (0.00731)
FX Opt	0.00655 (0.00741)	0.00313 (0.00692)	0.00703 (0.00670)
Com Opt	0.02719 (0.01382)	0.03563 (0.01280)	0.01903 (0.01042)
R ²	0.69	0.80	0.55

Standard errors in parentheses.

Coefficients in bold indicate statistical significance at the 99% one-tailed level.

S&P: Standard & Poors 500 stock return.

SC-LC: Wilshire 1750 Small Cap – Wilshire 750 Large Cap return.

10Y: month end-to-month end change in the Federal Reserve's ten year constant maturity yield.

Cred spr: month end-to-month end change in the difference between Moody's Baa yield and the Federal Reserve's ten year constant maturity yield.

Bd Opt: return of a portfolio of lookback straddles on bond futures.

FX Opt: return of a portfolio of lookback straddles on currency futures.

Com Opt: return of a portfolio of lookback straddles on commodity futures.

Table 2
Average Risk Exposure of HFRI, CTI, and TASS Average

Period	HFRI	CTI	TASSAVG	MSCI
	Jan 94-Dec 02	Jan 94-Dec 02	Jan 94-Dec 02	Jan 94-Dec 02
Constant	0.00660 (0.00102)	0.00730 (0.00191)	0.00780 (0.00100)	0.00942 (0.00092)
S&P	0.36852 (0.02292)	0.27075 (0.04280)	0.29167 (0.02236)	0.22991 (0.02074)
SC-LC	0.33075 (0.02895)	0.24496 (0.05406)	0.25882 (0.02824)	0.21806 (0.02620)
10Y	-0.50809 (0.52170)	-3.54883 (0.97428)	-1.06047 (0.50905)	-0.88658 (0.47222)
Cred spr	-1.09738 (0.95076)	-4.05286 (1.77556)	-1.60482 (0.92770)	-0.34130 (0.86058)
Bd Opt	-0.00855 (0.00583)	-0.03014 (0.01089)	-0.00417 (0.00569)	-0.00157 (0.00528)
FX Opt	0.00512 (0.00534)	0.01225 (0.00998)	0.01238 (0.00521)	0.01631 (0.00483)
Com Opt	0.00927 (0.00831)	0.03048 (0.01552)	0.02067 (0.00811)	0.01776 (0.00752)
R ²	0.84	0.48	0.73	0.67

Standard errors in parentheses.

Coefficients in bold indicate statistical significance at the 99% one-tailed level.

HFRI: HFR equally-weighted composite index.

CTI: CSFB/Tremont asset-weighted composite index.

TASSAVG: equally-weighted average return of all hedge funds in the TASS database.

MSCI: MSCI equally-weighted composite index.

S&P: Standard & Poors 500 stock return.

SC-LC: Wilshire 1750 Small Cap – Wilshire 750 Large Cap return.

10Y: month end-to-month end change in the Federal Reserve's ten year constant maturity yield.

Cred spr: month end-to-month end change in the difference between Moody's Baa yield and the Federal Reserve's ten year constant maturity yield.

Bd Opt: return of a portfolio of lookback straddles on bond futures.

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Com Opt: return of a portfolio of lookback straddles on commodity futures.

Table 3
Changing Exposures in Hedge Fund Indices in Two Subperiods

	HFRI	TASSAVG	MSCI
First Sub period: Jan 94-Sep 98			
Intercept	0.00550	0.00628	0.00847
	0.00132	0.00145	0.00138
S&P	0.41913	0.33080	0.28117
	0.03421	0.03741	0.03566
SC-LC	0.34719	0.23249	0.21695
	0.04995	0.05462	0.05207
10Y	-0.33904	-0.94795	-0.80738
	0.71558	0.78245	0.74595
Cred Spr	-3.94446	-4.02518	-3.13302
	1.69400	1.85229	1.76590
Bd Opt	-0.00289	-0.00052	0.00321
	0.00802	0.00877	0.00836
FX Opt	0.00382	0.01028	0.01438
	0.00558	0.00611	0.00582
Com Opt	0.00777	0.03257	0.02758
	0.01042	0.01139	0.01086
R ²	0.853	0.753	0.717
Second Sub period: Apr00-Dec 02			
Intercept	0.00403	0.00507	0.00576
	0.00144	0.00116	0.00105
S&P	0.34284	0.25759	0.18106
	0.03180	0.02575	0.02318
SC-LC	0.23729	0.20369	0.17990
	0.03932	0.03184	0.02866
10Y	-2.40964	-1.82051	-1.63979
	0.68477	0.55445	0.49915
Cred Spr	-1.77712	-1.20695	-0.05219
	1.06244	0.86024	0.77445
Bd Opt	-0.00537	-0.00139	0.00088
	0.00650	0.00527	0.00474
FX Opt	0.00618	0.01382	0.01840
	0.00749	0.00606	0.00546
Com Opt	0.03934	0.02735	0.01514

	0.01385	0.01121	0.01010
R ²	0.912	0.903	0.852

HFRI: HFR equally-weighted composite index.

TASSAVG: equally-weighted average return of all hedge funds in the TASS database.

MSCI: MSCI equally-weighted composite index.

S&P: Standard & Poors 500 stock return.

SC-LC: Wilshire 1750 Small Cap – Wilshire 750 Large Cap return.

10Y: month end-to-month end change in the Federal Reserve's ten year constant maturity yield.

Cred spr: month end-to-month end change in the difference between Moody's Baa yield and the Federal Reserve's ten year constant maturity yield.

Bd Opt: return of a portfolio of lookback straddles on bond futures.

FX Opt: return of a portfolio of lookback straddles on currency futures.

Com Opt: return of a portfolio of lookback straddles on commodity futures.

Table 4
Hedged Returns of Hedge Fund Portfolios in Two Subperiods

	HFROF	HFRI	TASSAVG	MSCI	SPHF
First Sub Period: Feb 95-Sep 98					
Intercept	0.00488	0.00594	0.00834	0.00967	
	0.00211	0.00173	0.00184	0.00175	
S&P	0.02228	0.03055	0.00516	-0.01507	
	0.05097	0.04178	0.04444	0.04231	
SC-LC	0.16584	0.35425	0.26437	0.28196	
	0.07555	0.06192	0.06586	0.06271	
10Y	-2.17529	-1.69288	-1.37452	-1.23181	
	1.29118	1.05832	1.12567	1.07186	
Cred Spr	-8.84449	-3.20838	-3.97172	-1.87101	
	2.63717	2.16156	2.29912	2.18921	
Bd Opt	0.00267	-0.00255	0.00429	-0.00719	
	0.01672	0.01370	0.01457	0.01388	
FX Opt	0.00560	0.00558	0.01246	0.02086	
	0.00836	0.00685	0.00729	0.00694	
Com Opt	0.00769	0.00150	0.02430	0.01595	
	0.01610	0.01320	0.01404	0.01336	
R ²	0.405	0.552	0.456	0.494	
Second Sub Period: Apr 00-Dec 02					
Intercept	0.00210	0.00400	0.00501	0.00576	0.0086
	0.00190	0.00179	0.00153	0.00156	0.0081
S&P	0.04245	0.06440	0.05858	0.05202	-0.1034
	0.04188	0.03964	0.03384	0.03437	0.1780
SC-LC	0.17205	0.27450	0.22972	0.19147	0.1272
	0.05179	0.04901	0.04184	0.04250	0.2201
10Y	-2.20149	-2.16200	-1.55506	-0.40285	-5.5372
	0.90190	0.85356	0.72865	0.74013	3.8338
Cred Spr	-1.82780	-1.27083	-0.74526	0.09160	5.2590
	1.39932	1.32431	1.13053	1.14832	5.9483
Bd Opt	-0.00177	-0.00296	0.00166	0.00715	0.0702
	0.00857	0.00811	0.00692	0.00703	0.0364
FX Opt	0.00167	0.00670	0.01551	0.02178	0.1115
	0.00986	0.00933	0.00797	0.00809	0.0419
Com Opt	0.02361	0.03580	0.02097	0.00813	0.0455
	0.01824	0.01726	0.01474	0.01497	0.0775

R ²	0.540	0.717	0.712	0.620	0.642
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HFRFOF: HFR funds-of-funds index.

HFRI: HFR equally-weighted composite index.

TASSAVG: equally-weighted average return of all hedge funds in the TASS database.

MSCI: MSCI equally-weighted composite index.

SPHF: S&P hedge fund composite index.

S&P: Standard & Poors 500 stock return.

SC-LC: Wilshire 1750 Small Cap – Wilshire 750 Large Cap return.

10Y: month end-to-month end change in the Federal Reserve's ten year constant maturity yield.

Cred spr: month end-to-month end change in the difference between Moody's Baa yield and the Federal Reserve's ten year constant maturity yield.

Bd Opt: return of a portfolio of lookback straddles on bond futures.

FX Opt: return of a portfolio of lookback straddles on currency futures.

Com Opt: return of a portfolio of lookback straddles on commodity futures.

Table 5
Conditional Forecasts of Various Hedge Fund Indices
Annual Return In 2003

	HFR	CTI	MSCI	SPHF
Actual	18.10%	14.48%	14.05%	10.58%
Predicted	18.17%	12.13%	14.84%	10.72%

HFRI: HFR equally-weighted composite index.

CTI: CSFB/Tremont asset-weighted composite index.

MSCI: MSCI equally-weighted composite index.

SPHF: S&P hedge fund composite index.

Figure 1: Trend Followers' Average Return (Actual Vs Predicted)

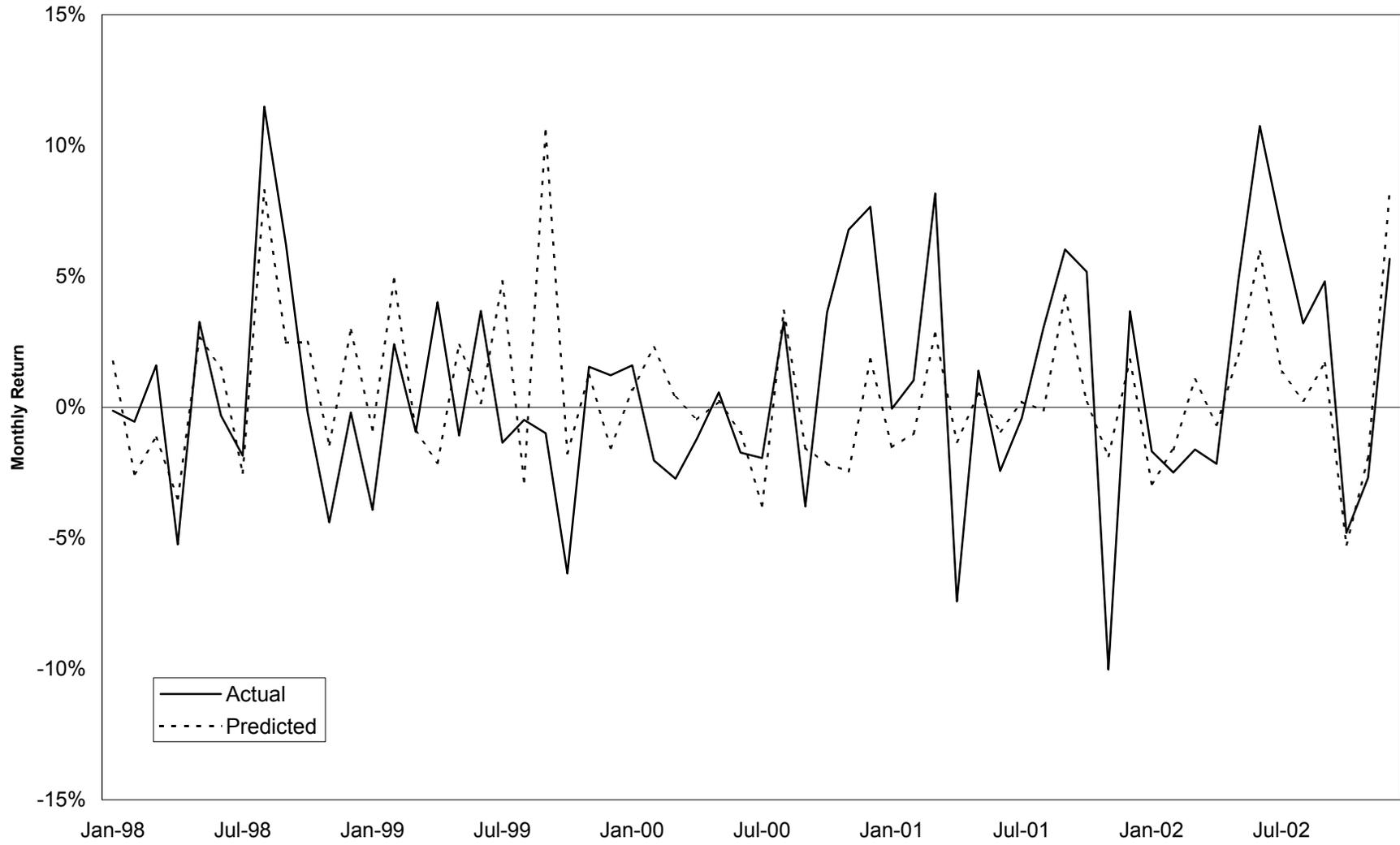


Figure 2: Merger Arbitrage Vs S&P (Jan 1990-Dec 2002)

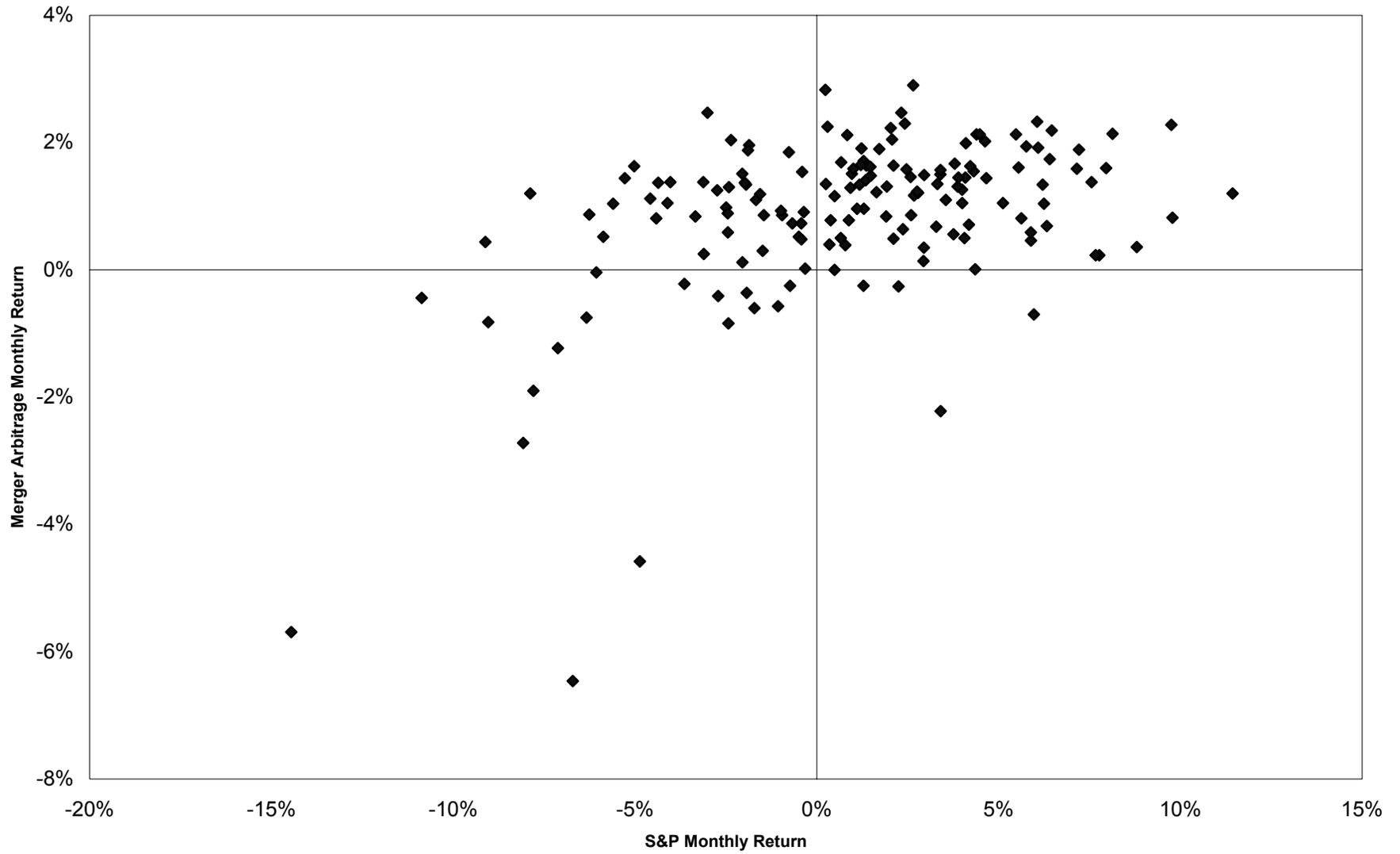


Figure 3: Long History of the Credit Spread

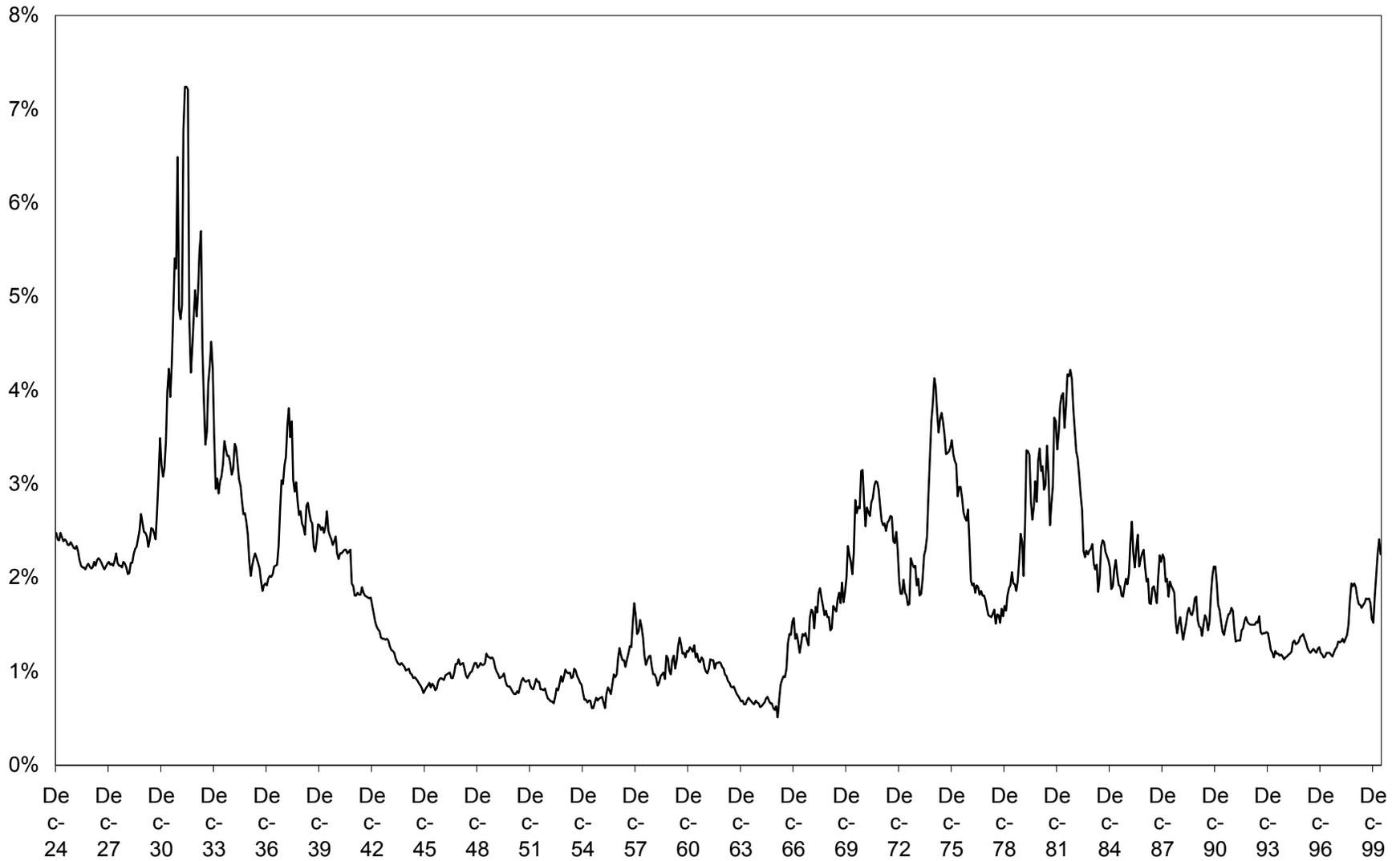


Figure 4: Cumulative Recursive Residuals for HFRFOF

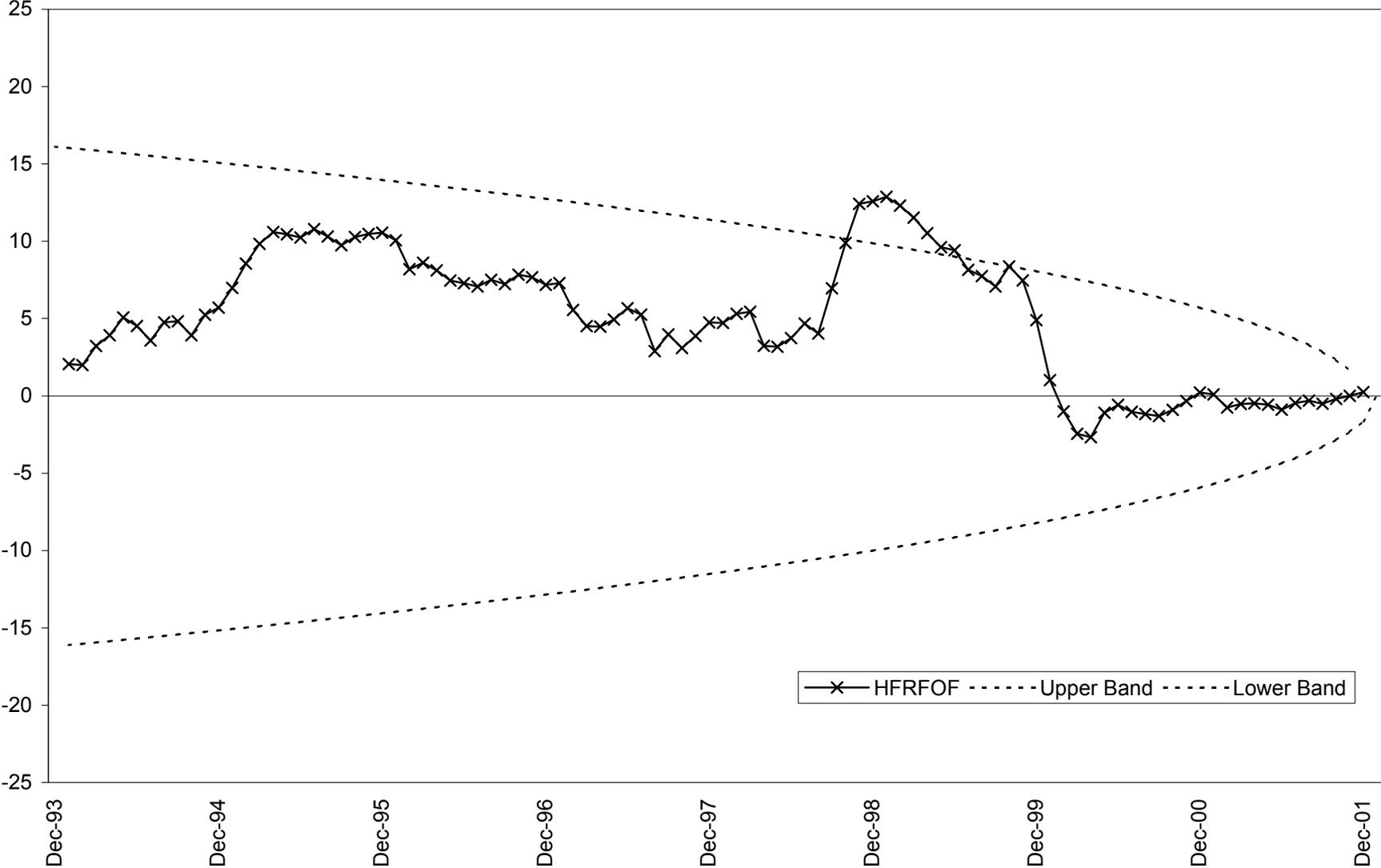


Figure 5: Cumulative Recursive Residuals for HFRI, CTI, TASSAVG, and MSCI

