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The Risk in Hedge Fund Strategies: Theory and Evidence from Fixed Income Traders

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October 2001

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We acknowledge the LBS Centre for Hedge Fund Research and Education for providing the hedge fund data used in this paper.

Abstract

Hedge fund strategies have come under intense scrutiny since the fall of 1998. This paper provides a general classification of hedge fund strategies. First, we classify funds by the exposure to major market risk factors, such as stocks, bonds, currencies, and commodities. Directional funds have non-zero net exposure to these major risk factors, while non-directional funds do not. Second, we distinguish between static versus dynamic strategies. Static strategies keep a relatively constant exposure to underlying risk factors, while dynamic strategies change exposures with the underlying risk factors. The paper applies this classification structure to fixed income traders. The majority of funds use non-directional strategies, which include static exposures to spread factors (long convertible bond/short treasuries, long high yield bond/short treasuries, etc), as well as dynamic exposures to spread factors. Most of these funds, however, are exposed to extreme moves in credit spreads.

1. Introduction

Convergence trading strategies have come under intense scrutiny since the extreme stress in the financial markets during the fall of 1998, following the Russian default and the near bankruptcy of Long-Term Capital Management (LTCM). See, for example, the President's Working Group on Financial Markets (1999), and Bank for International Settlements (1999a, b, and c). Convergence trading strategies are employed by hedge funds as well as proprietary trading desks of banks. Since activities of proprietary trading desks are not generally available, we can only study the risk factors in the convergence trading strategies in hedge funds.

Hedge funds are generally regarded as private investment vehicles for institutional investors and high net worth individuals. They are typically organized as limited partnerships, in which the manager is the general partner and the investors are limited partners. The general partners typically charge a fixed fee (usually 1-2% of the capital under management) as well as a performance fee (usually 15-20% of the profits exceeding a high water mark). As private investment vehicles, hedge funds are exempt from the disclosure requirements on mutual funds, making information on hedge funds hard to come by. In addition, hedge funds are exempt from most of the regulatory restrictions on mutual funds regarding leverage, short sales, illiquid securities, position concentration, etc.

Hedge funds do not disclose their trades or their positions. The risk of hedge funds can only be inferred from their returns. In this paper, we follow the approach in Fung and Hsieh (2001). In that earlier paper, we showed theoretically that trend-following strategies can be presented as an option strategy, in particular, a long position on lookback straddles in the major asset markets. We verified empirically that returns of trend-following funds are strongly correlated to returns of lookback straddles.

For convergence trading strategies, unfortunately, the case is not as clear cut. In the first place, there is no widely accepted definition of what convergence trading means. Convergence trading is generally regarded as bets on the relative price between two assets to narrow (or "converge"). See, for example, the discussion in BIS (1999c, p. 11). The risk, therefore, is that the relative price will diverge. In section two, we provide a theoretical description. In the second place, there is no widely accepted group of hedge funds that claim to follow convergence trading. In section 3, we identify a group of fixed income hedge funds whose returns are consistent with the definition we provide.

The identification process uses the following classification scheme. Broadly speaking, BIS (1999a, p. 9) classifies hedge funds into two types based on their net exposure to market risks: directional (or macro) funds and nondirectional (also called market-neutral or relative- value) funds. Directional funds take positions in expected movements in stock prices, interest rates, and exchange rates. Nondirectional funds take offsetting (i.e. spread) positions in similar assets[1], betting on favorable changes in their relative values. These latter types of funds are close to the original A. W. Jones concept of a hedge fund, in the sense that they have low exposure to market risks.

We can further distinguish between static and dynamic trading strategies, applied by either directional or nondirecctional funds. In a static strategy, the net exposure to the underlying assets remaining fairly constant over time. Buy-and-hold (typically employed by mutual funds) is a static strategy for directional funds. A constant credit spread position – long corporate bonds/short treasury bonds – is a static strategy for nondirectional funds.   In a dynamic strategy, the net exposure to the underlying assets change dynamically over time with their prices. Trend following is a dynamic strategy for directional funds. Fung and Hsieh (2001) show that the simplest trend following strategy is a long position on a lookback straddle. The “delta” of the lookback straddle is the strategy’s net exposure to the underlying asset’s price. This is a dynamic strategy because the delta changes with the asset price.

In terms of this classification scheme, convergence trading is a nondirectional strategy, since it takes spread positions between two assets. In addition, convergence trading can be implemented as a static or a dynamic strategy. A static spread position is a static strategy, while an option on a spread position would be a dynamic strategy.

2. Theoretical Explanation of Convergence Trading

The term "convergence trading" refers to trading strategies that bet on the price difference between two assets will narrow (or "converge") in the future. A convergence trade generally involve buying (going long) the cheaper asset and selling (going short) the more expensive asset. The trades are reversed when the prices of the two assets become more similar.

The genesis of convergence trading is "riskless arbitrage". Riskless arbitrage is the activity that enforces the law of one price, which states that two assets with the same payoffs in every state of the world must have identical prices. If the law of one price is violated, riskless arbitrage profits can be obtained by buying (going long) the cheaper asset and selling (going short) the more expensive asset. This locks in the difference between the two asset prices. There is no risk in this trade, since the payoffs of the two assets are identical in every state, so the payoffs from the long position can be used to offset the payoffs of the short position. Well known examples are the "triangular arbitrage" and "covered interest arbitrage" in the foreign exchange markets, cash-futures arbitrage in the futures market, and coupon-STRIPS arbitrage in the US treasury securities market.

Convergence trading results from a modification of the law of one price. Here, the "theory" states that two assets with *similar* payoffs in most states of the world should have *similar* prices.[2] If the two similar assets have very different prices, then convergence traders would buy (go long) the cheaper asset and sell (go short) the more expensive one. Even though many convergence strategies contain the word "arbitrage", they all involve some risk, since the payoff from the long position is not always sufficient to cover the payoff for the short position. The convergence trade is a bet that the expected payoff is more than sufficient to compensate for the risk of any loss.

To be more exact, let i be the index for states of the world, i=1,...,I. Let p_i be the state prices, i.e., the cost of a payoff of $1 in state i. Thus, the risk neutral probability of state j is $\pi_j = p_j / \Sigma_i p_i$.

There are two assets, A and B. Asset A has payoffs a_i in state i. Its price is $p(A) = \Sigma_i p_i a_i$. Asset B has payoffs b_i in state i, so its price is $p(B) = \Sigma_i p_i b_i$. Without loss of generality, assume that $p(A) < p(B)$. Now, order the states so that there exists a state i' such that $a_i > b_i$ for $i<i'$ and $a_i \leq b_i$ for $i \geq i'$.

Consider a long position in A and a short position in B. This generates the positive cash flow:

$$p(B) - p(A),$$

and the payoffs:

$a_i - b_i$,

which is positive for i<i' and negative for i $\geq$ i'. In the risk neutral measure, the probability of a positive payout is $\rho = \Sigma_{i<i'} \pi_i$, and the probability of a negative payout is 1-ρ.

In essence, a convergence trader disagrees with the set of state prices, $\{p_i\}$. In particular, the convergence trader believes that the state prices of the negative states (i i') are too high.

Typically, in a convergence trade, the positive states (i<i') are more likely to occur than the negative states (i$\geq$i'). Thus, we call the positive states "normal", and the negative states "extreme" or "disaster". In addition, the losses in the "disaster" states are much greater than the gains in the "normal" states. Thus, the convergence trade tends to produce frequent positive returns and rare large losses.

It is useful to put convergence trades into an option framework. Consider, for example, a spread position between corporate bonds and treasuries. The credit spread is the difference in the interest rates; it represents the default probability of corporate bonds. A convergence trader who believes that the default probability is lower than that implied in the credit spread will buy the corporate bond and short the treasury. If the bonds have long maturity, the trade will appear to be static. Alternatively, the convergence trader may sell options on the credit spread. In this case, the trade will be dynamic.

3. Application to Fixed Income Hedge Funds

To search for convergence funds, we apply the classification scheme (directional/nondirectional, and static/dynamic) to hedge funds in the Tass database that focus on fixed income securities. We pick this group of hedge funds for two reasons. The first reason is that a number of fixed income funds (e.g., Ellington, LTCM) got into trouble in the fall of 1998. This prompted regulators to analyze hedge funds. See, for example, BIS (1999a, 1999b, 1999c), and the President's Working Group for Financial Markets (1999). These studies are primarily interested to understand the risks of these hedge funds, and how these risks can impact the financial markets. The second reason is that it is difficult to apply the very general classification structure to all hedge funds. It would require us to create replicating portfolios for strategies applied to a large number of markets. That is not feasible at this time. Instead, we limit this study to the fixed income market.

3.1 Sample of Tass Fixed Income Hedge Funds

The Tass database contains 285 hedge funds that focus on fixed income securities and have at least 12 monthly returns from Jan 1998 until Dec 2000. To determine whether a fund is directional or non-directional, we run the following 6-factor models: the return on Lehman aggregate bond index and five spread portfolios – non-US government bonds minus US treasury bonds, emerging market bonds minus US treasury bonds, convertible bonds minus US treasury bonds, high yield bonds minus US treasury bonds, and mortgage bonds minus US treasury bonds. This model is similar to the Fama-French-Carhart 4-factor model for stocks, that use the excess return of the market, small cap minus large cap stocks, high book-to-market minus low book-to-market stocks, and high momentum minus low momentum stocks.

Operationally, we define directional funds to have statistically significant (positive or negative) exposure to the Lehman aggregate bond index. There are 25 such funds. The remaining 260 are non-directional funds that have no statistically significant exposure to the Lehman aggregate bond index.

Next, we separate the 260 non-directional funds according to whether they use static or dynamic trading strategies. Operationally, if a fund has statistically significant (positive or negative) exposure to at least one of the five spread portfolios, we will consider it to use a static strategy. Otherwise, we will consider it to use a dynamic strategy. Using this operational definition, we determine that 120 funds use static strategies, and 140 funds use dynamic strategies.

3.2. Directional Funds with Exposure to the Aggregate Bond Market

To determine if there is a common trading strategy, we run a principal component model through the 15 funds with positive exposure to the aggregate bond market. The first principal component explains 47% of the total cross-sectional variation. The second component explains 24%. This says that there is one main trading style. We represent this main trading style as the equally-weighted average of the monthly returns of these 15 funds.

To determine what this common trading strategy is, we examine the group average against the various bond market factors. It turns out that the group average behaves as a straddle on high yield bonds, as shown in Figure 1. This return pattern is consistent with a trend-following strategy on high yield bonds.

We follow the same procedure for the 11 funds with negative exposure to the aggregate bond market. Principal component analysis reveals that there is only one major component – the first component explains 77% of the cross-sectional variation. The group average behaves as a long position on convertible bonds, as shown in Figure 2. This return pattern is consistent with a static strategy on convertible bonds.

3.3. Non-directional Funds with Static Spread Exposures

Next, we analyze the 120 funds that have either positive or negative net exposure to any of the five spread portfolios. We do this in three groups.

Static Group A has 45 funds that have (statistically significant) positive exposure to the spread between convertible bonds and treasuries. Principal component analysis shows that there is one dominant strategy; the first component explains 53% of the cross-sectional variation while the second component explains only 14%. Using the group average to proxy for this dominant strategy, Figure 3 shows that its return pattern is consistent with a static strategy on the spread factor between convertible bonds and treasuries. This

Static Group B has 35 funds that have (statistically significant) positive exposure to the spread between high yield bonds and treasuries. Principal component analysis shows that there is one dominant strategy; the first component explains 65% of the cross-sectional variation while the second component explains only 10%. Using the group average to proxy for this dominant strategy, Figure 4 shows that its return pattern is consistent with a static strategy on the spread factor between high yield bonds and treasuries.

Static Group C has 18 funds that have (statistically significant) positive exposure to the spread between emerging market brady bonds and treasuries. Principal component analysis shows that there is one dominant strategy; the first component explains 86% of the cross-sectional variation while the second component explains only 13%. Using the group average to proxy for this dominant strategy, Figure 5 shows that its return pattern is consistent with a static strategy on the spread factor between brady bonds and treasuries.

We ignore the remaining 22 funds that have static exposures to various spread portfolios.

3.4. Non-directional Funds with Dynamic Strategies

Next, we analyze the 140 funds that have no (statistically significant) exposure to either the aggregate bond market or the five spread factors. As discussed earlier, these funds are likely to be using dynamic trading strategies on spread factors. In principle, they can use either trend-following or contrarian strategies. However, in the fixed income market, traders tend to use contrarian strategies on spreads. The reason is quite simple. If one were to bet on the credit spread to widen, one would have to go short a higher yielding asset and go long a lower yielding asset. This leads to a negative carry position, something that money managers in general, and hedge fund managers in particular, loath to do. Thus, we expect the vast majority of the funds in this group to bet with contrarian strategies on spreads with positive carry.

Principal component analysis shows that there is no dominant strategy for this group. The first component explains only 23% of the cross-sectional variation, while the next four components explain, respectively, 12%, 10%, 7%, and 5%. Unable to further divide these funds into smaller subgroups, we will present the results for the entire group. Figure 6 shows the return profile of the average monthly return of this group, against the spread factor between mortgage bonds and treasuries. This return patter is roughly consistent with a short straddle position on the spread, indicative of a contrarian strategy.

4. Risk of Non-directional Fixed Income Funds During Market Extremes

The non-directional fixed income funds have trading strategies that expose them to spreads widening. For example, the funds in Figure 3 have poor performance when the spread of convertible bonds over treasuries widen. The funds in Figure 4 are exposed to a widening of the spread of high yield bonds over treasuries. The funds in Figure 5 are exposed to a widening of the spread between brady bonds over treasuries. Lastly, the funds in Figure 6 are exposed to a widening of the spread between mortgage bonds over treasuries.[3]

While the non-directional fixed income funds have different spread exposures, they tend to have poor performance at the same time. The reason is that, empirically, interest rate spreads tend to widen together. To see this, we use the Moody's Corporate Baa interest rate minus the 10-year treasury yield as the underlying state variable. We use this variable because this spread has a very long history, going back to the 1920s. When this credit spread widens, we expect the other credit spreads (convertible-treasury, high yield-treasury, and brady-treasury) to widen as well. In addition, empirically, the mortgage-treasury spread also widens (since its correlation with Baa-treasury spread is 0.64). The exposure of the non-directional funds (Static A, Static B, Static C, and Dynamic) is evident in Figure 7.

It is important to note that the interest rate environment in the last decade has been quite benign to non-directional fixed income funds. This can be seen in Figure 8, which graphs the long history of the credit spread between Moody's Baa yields and 10-year treasury yields back to 1925. The decade of the 1990s has seen very little spread volatility, relative to the long history from 1925 until the mid 1980s, when large increases of this spread has occurred at various points in time. In these more hostile environments, non-directional fixed income funds would have performed quite poorly.

To show this using a different data set, we examine the HFR Fixed Income Arbitrage index. In the HFR database, there are 44 "fixed income arbitrage" funds. As of July 2001, 16 funds continue to report return information while 28 have stopped. HFR computes an equally-weighted monthly performance index from the returns of those funds that have return information each month.

To test the hypothesis that fixed income hedge funds are exposed to the credit spread, we graph the returns of the HFR Fixed Income Arbitrage index against the change in the credit spread, from Jan 1990 until Dec 2000, in Figure 9. The regression fits a straight line through these points:

$$\underset{}{\text{HFR FI Arb}} = \underset{(0.0012)}{0.0082} - \underset{(1.068)}{8.010}\,[\text{Change in Credit Spread}]$$

R-sq = 0.35
Period: Jan 90 - Dec 98

The regressions shows that a 100 basis point increase in the credit spread would cost fixed income arbitrage funds 8% of performance.

Using this regression, we can extrapolate the performance of Fixed Income Arbitrage funds back through time. We consider five years during which the credit spread widened dramatically. The performance of the Fixed Income Arbitrage funds are given in the following table:

Year	Estimated Return
1931	-24%
1970	-10%
1974	-14%
1979	-7%
1980	-9%

The annual mean and standard deviation of the HFR Fixed Income Arbitrage index is, respectively, 9.3% and 5.2%. These losses would be between 3 to 7 standard deviations events.

5. Conclusions

This paper analyzes the risk of fixed income hedge fund strategies by grouping them using a general classification scheme. Directional hedge funds have exposure to market risk factors, while non-directional hedge funds have low or no exposure to these risk factors. We further distinguish between static and dynamic strategies. Static strategies have constant exposure to an underlying risk factor, while dynamic strategies have varying exposure to an underlying risk factor. This produces four major types of hedge fund strategies: static directional, dynamic directional, static non-directional, and dynamic non-directional.

We applied this classification scheme to hedge funds in the Tass database that focus on fixed income securities. There were 25 directional funds that 260 non-directional funds. We further found that 120 non-directional funds used static strategies on various spread factors, while 140 non-directional funds used dynamic strategies. We showed that these funds have a common exposure to a spread factor, proxied by the credit spread between Moody's Baa corporate bonds and treasuries. As an out-of-sample exercise, we showed that the HFR Fixed Income Arbitrage index is exposed to this credit spread.

There are several implications. For an investor of non-directional fixed income hedge funds, it is important to make sure that the portfolio is not overly exposed to a widening of the credit spread, especially if the portfolio invests in fixed income securities.

In addition, an investment in trend-following funds can provide useful risk control with an investment in non-directional fixed income hedge funds. As shown in Fung and Hsieh (2001), trend followers tend to perform well during extreme market conditions, typically when credit spreads expand. As a case in point, trend-following funds had unusually large gains in the fall of 1998, while many fixed income hedge funds suffered large losses.

For counterparties of non-directional fixed income hedge funds, it is important to understand that these hedge funds face hidden risk. Given the benign interest rate environment of the 1990s, standard value-at-risk methods using historical data may not be useful in detecting these hidden risks. Counterparties must perform careful due diligence to understand the nature of these hidden risks. Stress testing, based on the experience of less benign interest rate environments, are needed to understand the potential counterparty risks.

For regulators of the financial industry, non-directional fixed income trades with leverage, whether practiced at proprietary trading desks or in hedge funds, can be destabilizing to markets when extreme events occur. Recognizing that some bankruptcies are unavoidable and even necessary, regulators should devise ways to measure the total exposure of all highly leveraged institutions. These can help to anticipate the next crisis.

Lastly, Long-Term Capital Management (LTCM) supposed was involved in many of the non-directional fixed income trades used by other hedge funds, as well as proprietary trading desks of investment banks. They all suffered losses in the fall of 1998, but few lost as much as LTCM. Based on LTCM's average returns and volatility, we can see that LTCM is 2 to 4 times move more levered than the typical fixed income arbitrage fund. From Mar 1994 until June 1998, LTCM's average return was 2.6 times higher than that of the HFR fixed income arbitrage funds, and its volatility was 4.1 times greater. It stands to reason that LTCM's losses would be greater as well. Thus, while the HFR fixed income arbitrage funds lost 6.5% in Sep 1998 and 6.1% in Oct 1998, LTCM lost nearly 100% of its capital during those two months. Thus, LTCM's troubles are not due to the soundness of these trades, but to the over extension of their risk bearing capacity.

Footnotes:

[1] Here, we use the term "assets" to denote a single asset or a group of assets.
[2] To avoid dominance, one asset must have higher payoffs in some states of the world and lower payoffs in some other states of the world.
[3] These funds are also exposed to a narrowing of the mortgage-treasury spread.

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Figure 1: Directional Funds with Positive Exposure to Bonds

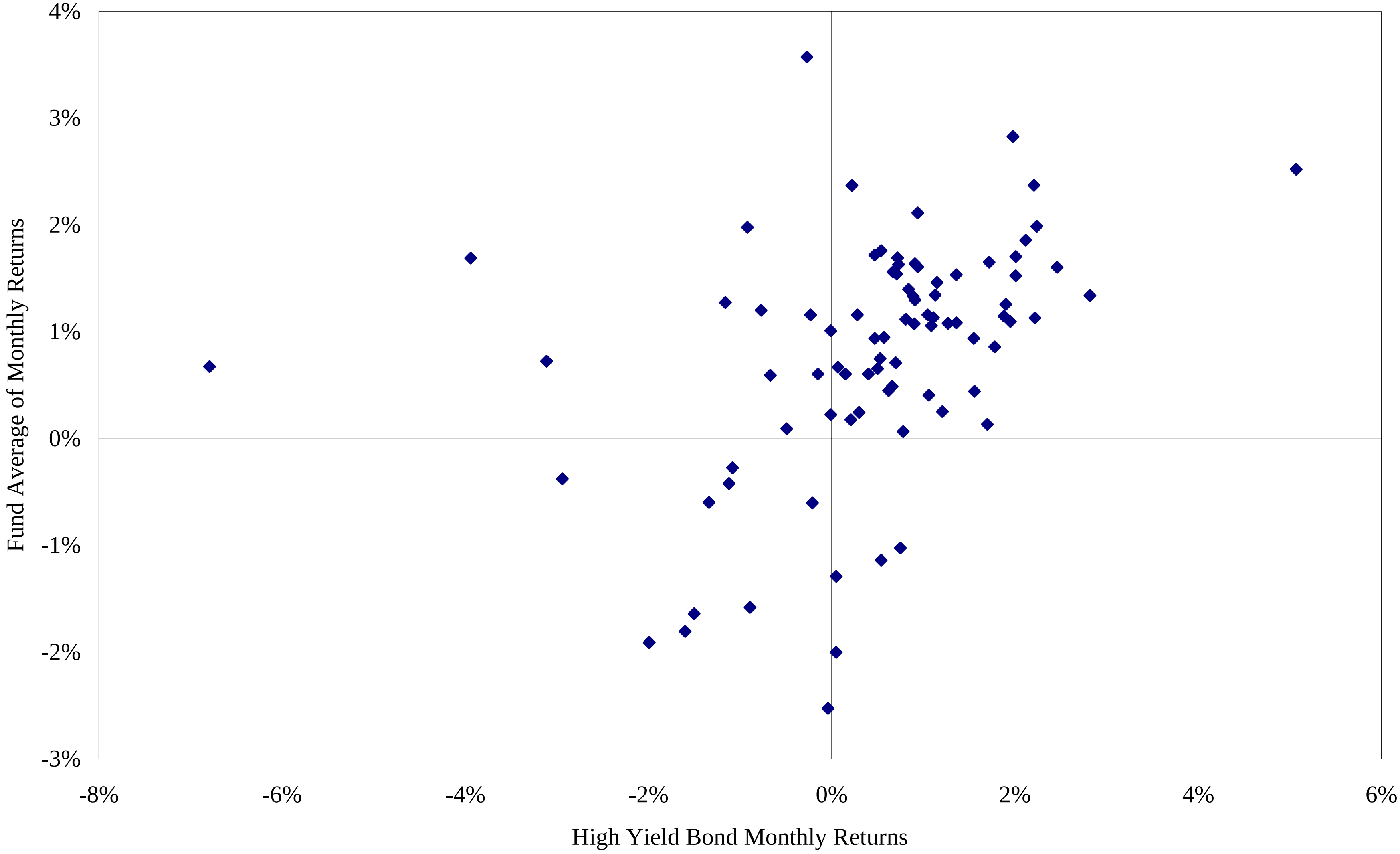

Figure 2: Directional Funds with Negative Exposure to Bonds

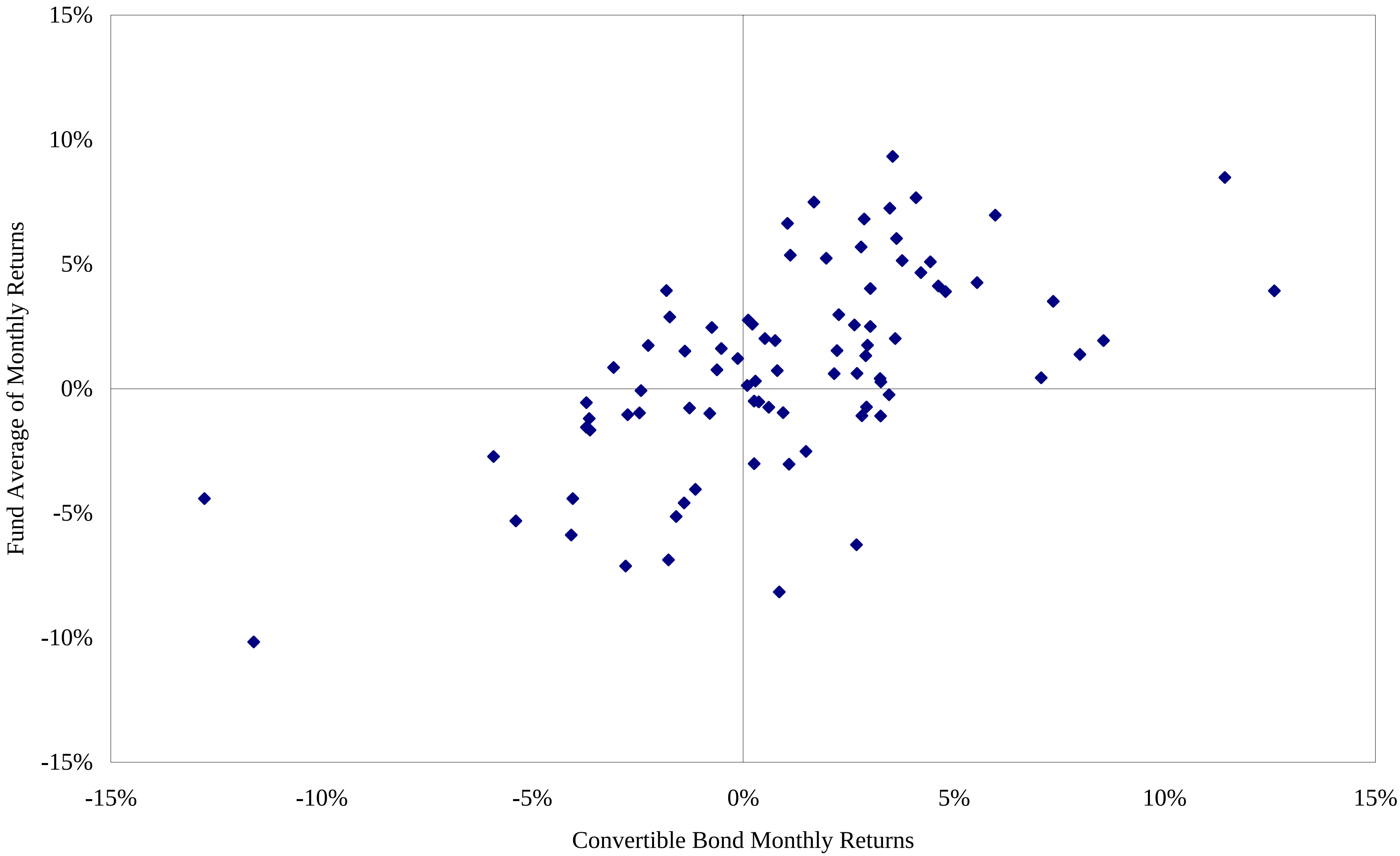

Figure 3: Non-Directional Funds with Exposure to Convertible-Treasury Spread

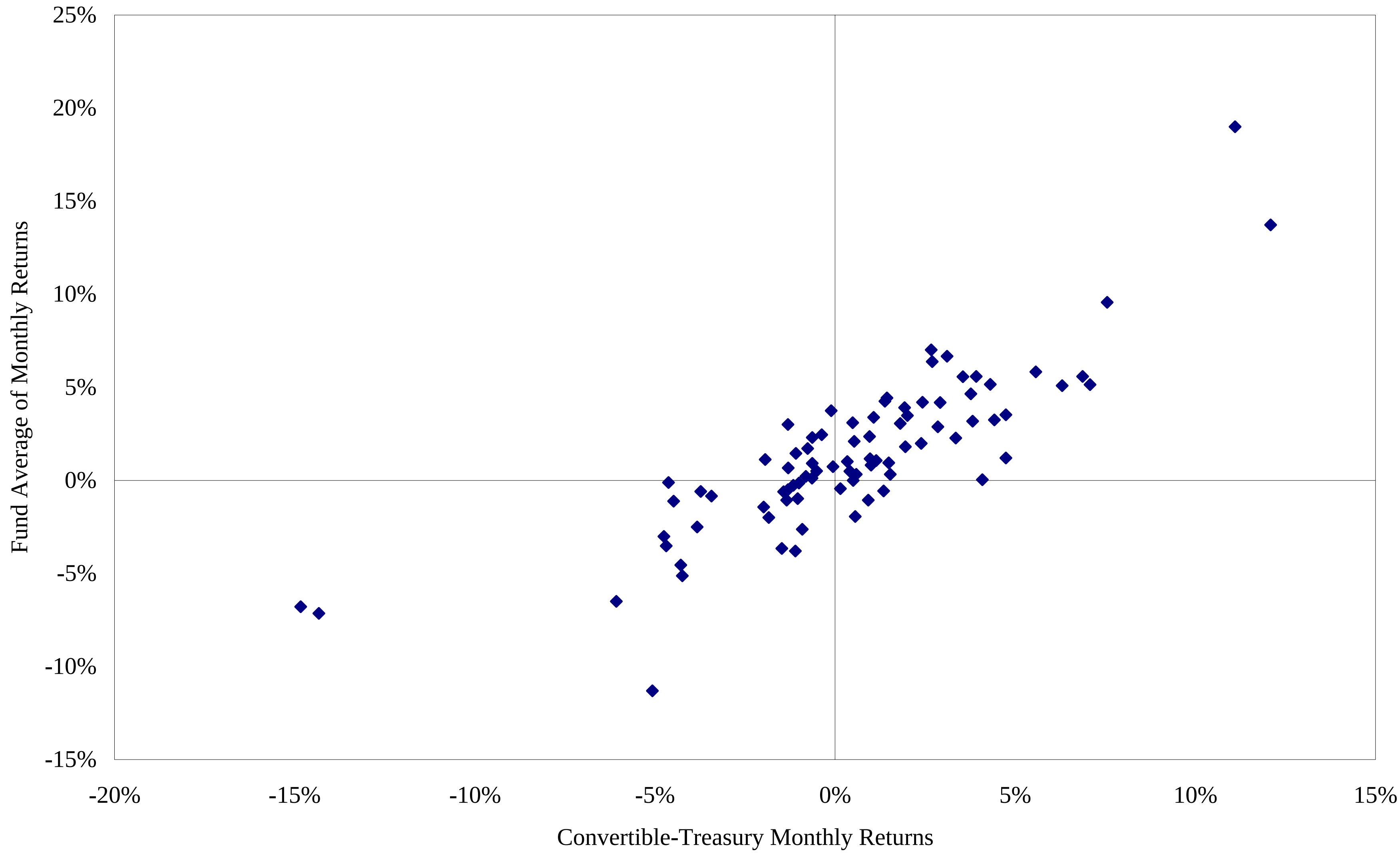

Figure 4: Non-Directional Funds with Exposure to High Yield-Treasury Spread

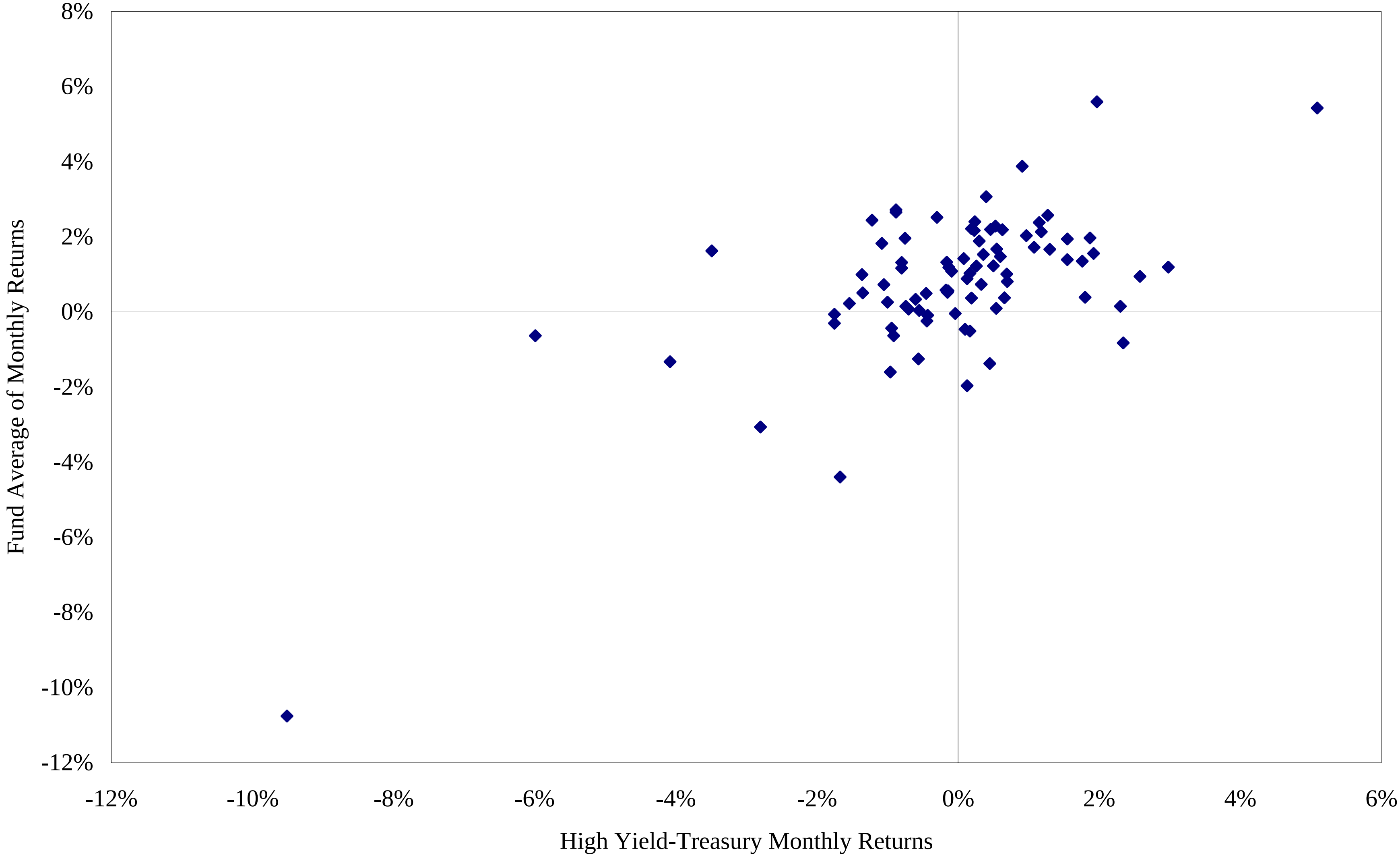

Figure 5: Non-Directional Funds with Exposure to Brady-Treasury Spread

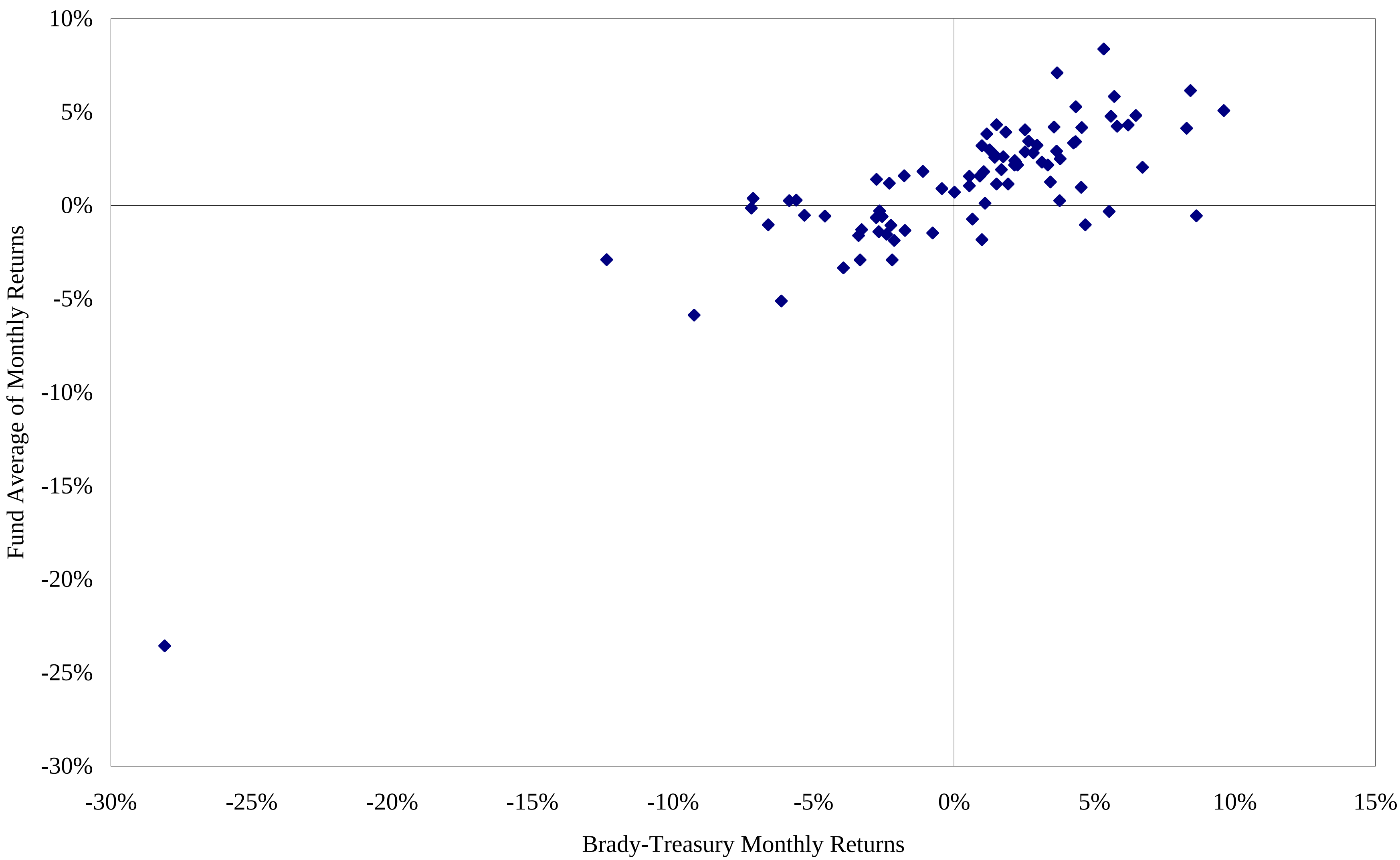

Figure 6: Non-Directional Funds with Dynamic Strategies

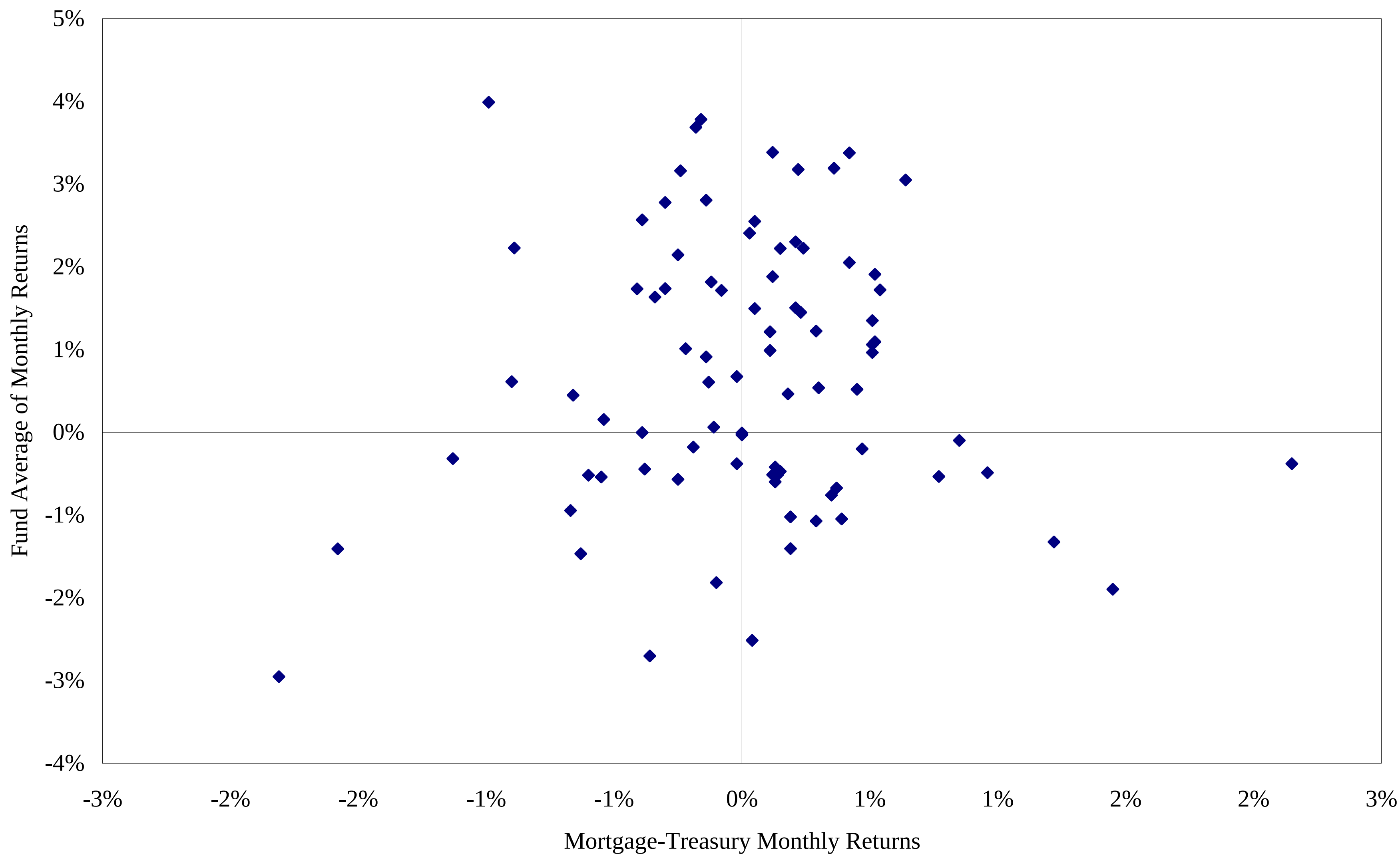

Figure 7: Non-Directional Funds Vs Changes in Credit Spread

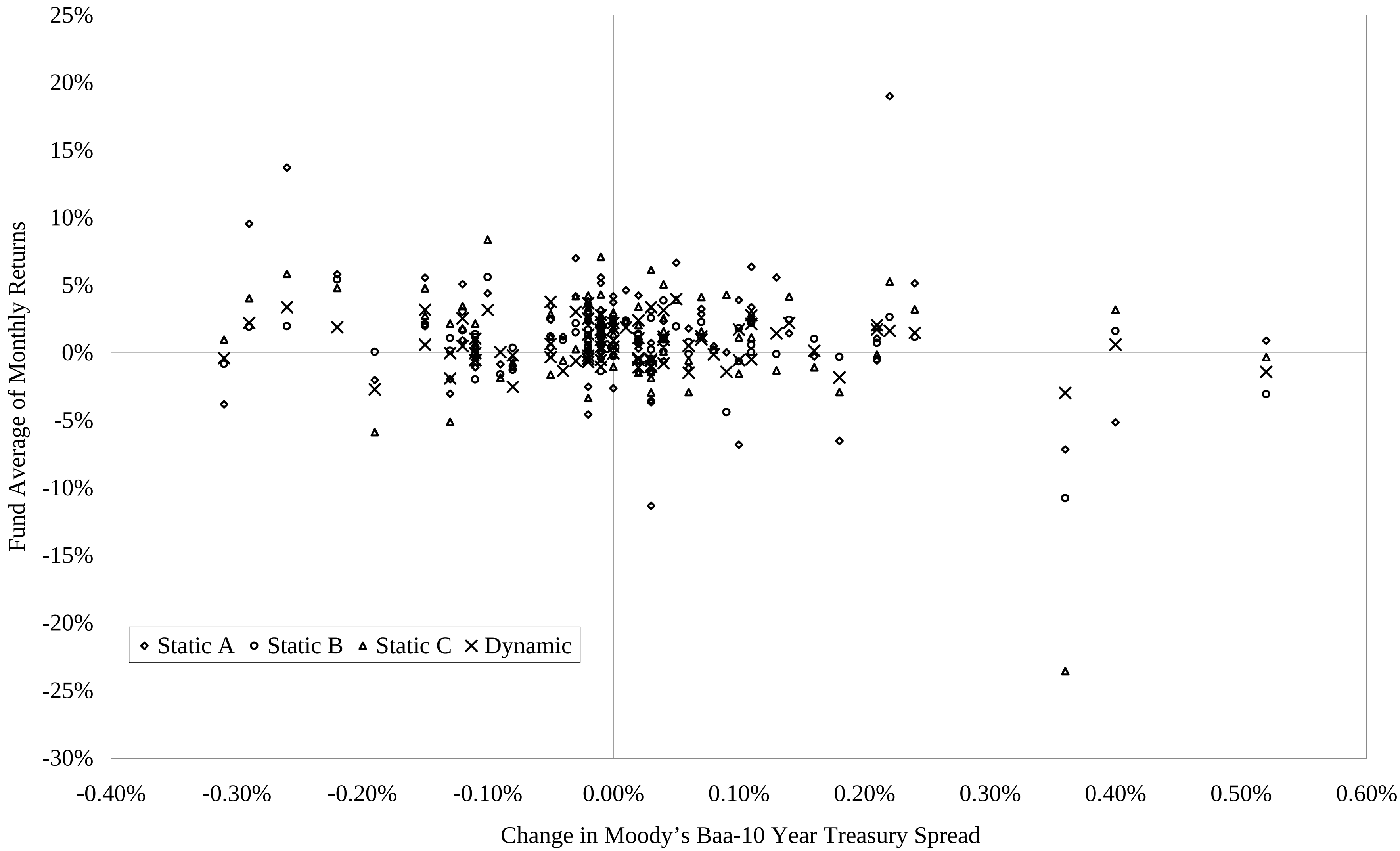

Figure 8: Long History of the Credit Spread (Moody's Baa Above 10-year Treasuries)

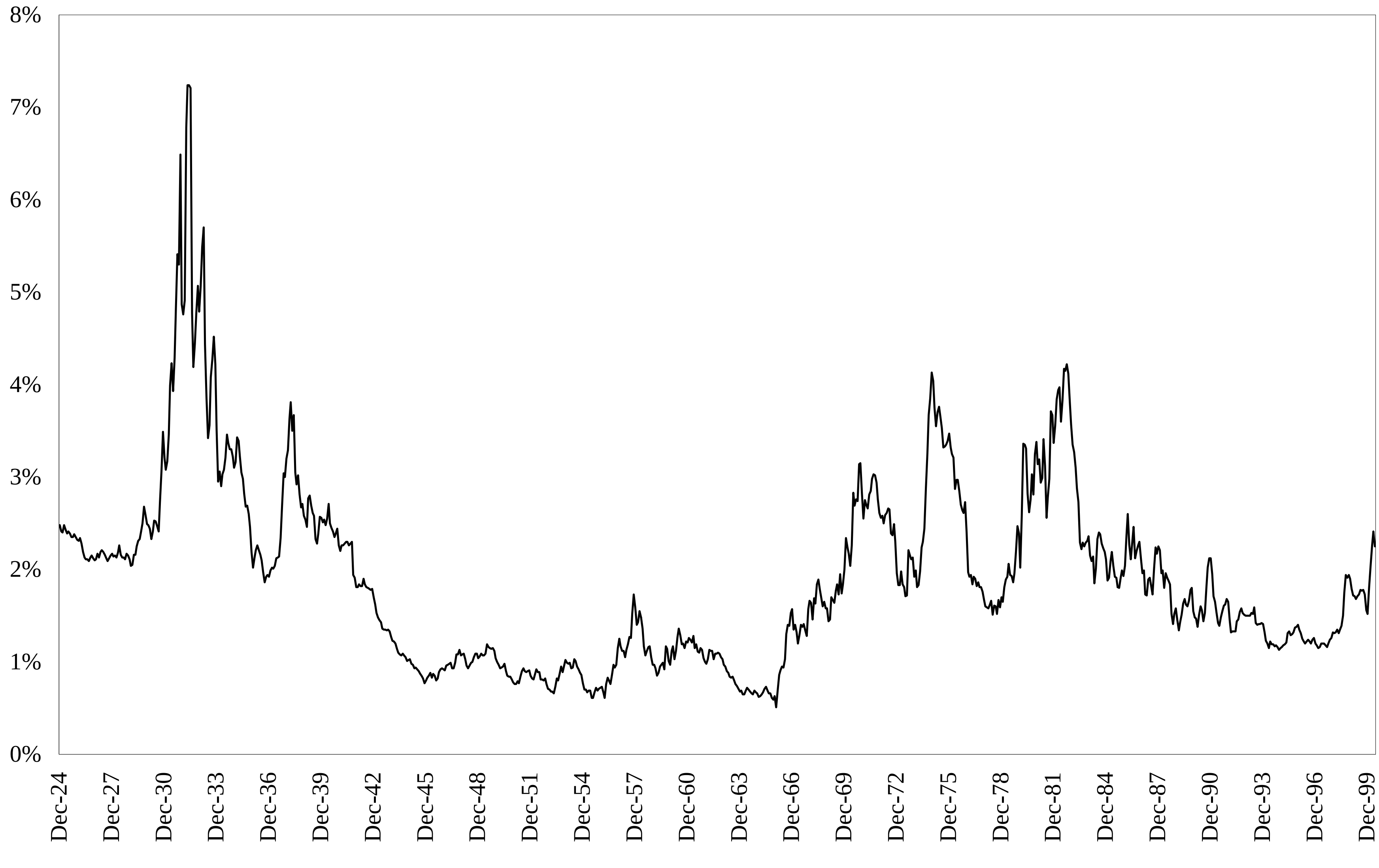

Figure 9: HFR Fixed Income Arbitrage Index