Risk in Fixed-Income Hedge Fund Styles

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Hedge fund strategies came under intense scrutiny with the stressful market events surrounding the near collapse of Long-Term Capital Management (LTCM). Several studies were sponsored by regulatory agencies in the financial markets, including the President's Working Group on Financial Markets [1999], and the Bank for International Settlements [1999a, b, and c]. Besides asking whether hedge funds have a destabilizing influence on markets, the groups directed much of their attention to a particular type of strategy used by fixed-income hedge funds: convergence trading.

What are the risk characteristics of this strategy that caught the attention of financial regulators, and how do they differ from other hedge fund strategies?

Understanding hedge fund risk is complicated. Information on hedge funds is hard to come by. Although the hedge fund industry is gradually shifting towards greater disclosure and historical performance data is now readily available, we have yet to successfully model the link between hedge fund returns and observable asset returns.[1]

A model that would allow hedge fund investors and counterparties to identify and explicitly measure the different types of hedge fund risk. By linking these strategy risks to asset prices with long histories, one may be able to predict hedge fund returns even during market extremes.

A number of steps must be taken to achieve this. First, we need to extract common risk factors in groups of fixed-income hedge funds. Typically, hedge funds are grouped by location and strategy. *Location* refers to where (or what) a manager trades, such as stocks, bonds, commodities, or currencies. *Strategy* refers to how a manager trades, such as buy-and-hold, long-short, or trend-following. *Style* describes a combination of location and strategy, such as buy-and-hold on stocks or trend-following on currencies.

We use the peer groupings of Hedge Fund Research (HFR), a vendor of hedge fund data. Since funds that use similar styles have correlated returns, their common styles can be extracted by principal components analysis. These common styles are called *style factors*.

Second, we link the extracted style factors to observable market prices. In this case, we use asset-based style (ABS) factors to provide explicit links between hedge fund returns and observable asset prices; see Fung and Hsieh [2002] for a detailed discussion of asset-based hedge fund style factors.

Mitchell and Pulvino [2001] have simulated the returns of a merger arbitrage strategy applied to announced takeover transactions between 1968 and 1998. This strategy generates returns that are similar to those of merger arbitrage funds.

In Fung and Hsieh [2001], we show theoretically that trend-following strategies can be represented as an option strategy, in particular, a long position on look-back straddles in the major asset markets. We verify empirically that returns of trend-following funds are strongly correlated with returns of look-back straddles. Here, we directly model convergence trading with options, to explain the returns of fixed-income funds.[2]

The benefits of ABS factors are threefold. First, ABS factors can be applied to create performance benchmarks that depend solely on observable prices. This allows investors to directly assess a hedge fund's performance according to its strategy characteristics rather than indirectly through peer group averages that may include funds using different strategies.[3]

Second, ABS factors based on observable prices typically provide longer histories than hedge funds themselves. This is particularly helpful in modeling the risk of hedge fund investing under alternative scenarios that may otherwise be obscured by the short history of hedge fund returns.[4]

Third, from these explicit links, expected returns of hedge fund strategies can be directly linked to expected returns of the underlying assets. Therefore, in a unified framework, ABS factors can be used to answer questions on ex post performance evaluation, risk management, and return prospects of a hedge fund strategy.

We discuss in particular the distinctive risk characteristics of *convergence trading*. Convergence trading bets on the relative price between two assets to narrow (or *converge*), so "approximately offsetting positions are taken in two securities that have similar, but not identical, characteristics and trade at different prices" ("A Review of Financial Market Events" [1999b, p. 11]).[5]

Unlike riskless arbitrage, convergence trading is risky, because the relative price of these assets can just as easily diverge. This is particularly so in the case of fixed-income applications of convergence trading. While for stocks the dominant risk factor is the systematic market component, fixed-income securities are subject to several important risk factors, not just the level of interest rates. This is especially important in stressful market conditions when risk factors can move in opposite directions.

For example, a convergence trade involving a long position in mortgage-backed securities (MBS) and a short position in Treasuries will incur large losses if the interest rate spread between MBS and Treasuries widens dramatically. This can occur during extreme market conditions when there is a flight to quality, pushing up prices of Treasuries while depressing prices of credit-sensitive securities. We believe this characteristic together with the liberal use of leverage on illiquid securities by fixed-income convergence funds is the primary cause of concern for financial regulators. Fixed-income hedge funds ran into substantial financial difficulties in the fall of 1998.[6]

I. DATA FOR FIXED-INCOME HEDGE FUNDS

As of December 2000, the HFR database included 1,400 individual hedge funds with \$117 billion of assets under management. HFR groups hedge funds into roughly 30 style indexes. Nearly 8% of the funds with 17% of the assets are included in the five indexes for fixed-income hedge funds listed in Exhibit 1.

Fixed-income convertible bond funds invest primarily in convertible bonds.[7] Fixed-income high-yield bond funds invest in non-investment-grade debt. Fixed-income mortgage-backed funds invest in mortgage-backed securities (including collateralized mortgage obligations, real estate mortgage investment conduits, and stripped mortgage-backed securities), typically hedging the interest rate risk and prepayment risk. Fixed-income arbitrage is a strategy that exploits pricing inefficiencies between related fixed-income securities while hedging exposure to interest rate risk. Fixed-income diversified funds use

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EXHIBIT 1
HFR Fixed-Income Indexes—as of December 2000

Index	Number	Assets	Correlation with Bonds
HFR Fixed-Income Convertible Bond	12	\$1.5b	0.03
HFR Fixed-Income High-Yield Bond	20	\$8.9b	0.09
HFR Fixed-Income Mortgage-Backed	17	\$3.0b	0.11
HFR Fixed-Income Arbitrage	19	\$4.4b	– 0.20
HFR Fixed-Income Diversified	39	\$1.9b	0.51

Source: Hedge Fund Research.

EXHIBIT 2
Percent of Cross-Sectional Variation Explained by Principal Components

	% of Cross-Sectional Variation Explained		
Index	**PC 1**	**PC 2**	**PC 3**
HFR Fixed-Income Convertible Bond	59%	13%	
HFR Fixed-Income High-Yield Bond	63%	16%	
HFR Fixed-Income Mortgage-Backed	55%	17%	
HFR Fixed-Income Arbitrage	33%	24%	16%
HFR Fixed-Income Diversified	36%	21%	11%

either multistrategies or niche strategies. Their returns have low correlations with bond returns, as measured by the Lehman Aggregate Bond index.

As in Fung and Hsieh [1997, 2001], common styles among hedge funds in each grouping are extracted using principal components analysis.[8] The idea is that funds that have the same style (i.e., location and strategy) will have correlated returns. For this analysis, we use all funds that have returns between 1998 and 2000. The choice of the time period is motivated by practical considerations. We keep the data in 2001 as a holdout sample to validate our empirical findings, so the data analysis ends in 2000. Starting the analysis earlier than 1998 would greatly reduce the number of funds that have return data for the entire period.

The amount of cross-sectional variance explained by the first three principal components in each of the five groups is given in Exhibit 2. Three groups of fixed-income hedge funds (convertible, high-yield, and mortgage-backed) have only one common style. The first principal component explains more than 50% of the cross-sectional variation in returns.

Two other groups of fixed-income hedge funds (arbitrage and diversified) appear to have two or more common styles. The first principal component explains roughly 35% of the cross-sectional variation in returns, while the second component explains over 20% of return variation cross-sectionally.

We call these components *return-based style factors* to emphasize the dominant source of input in their construction.

II. ABS FACTORS FOR FIXED-INCOME HEDGE FUNDS

To extend the analysis, we link the return-based style factors to observable market risk factors that are exogenous to the hedge fund returns data. Using the qualitative descriptions of the fixed-income hedge fund styles, we postulate a variety of benchmark returns using observed asset prices. We call these ABS factors.

Each ABS factor involves a pair of key variables—location and strategy. Location refers to the market where a hedge fund manager trades. Locations for fixed-income hedge funds are typically defaultable bonds (such as high-yield bonds, convertible bonds, or corporate bonds), mortgages, asset-backed securities, and agencies and Treasuries.

We consider four main types of strategy: long-only, passive spread trading, trend-following, and convergence trading. For long-only strategies, we use standard fixed-income benchmarks such as the CSFB Convertible Bond index return, the CSFB High-Yield Bond index return, the Lehman Mortgage-Backed index return, or the J.P. Morgan Emerging Market Bond index return. Here, the ABS factor is simply the index return itself, which completely characterizes a passive buy-and-hold strategy in that location.

For passive spread trading, the ABS factor is the difference between two bond index returns. Examples are the convertible bonds-minus-Treasury return, the mortgage bond-minus-Treasury return, the high-yield bond-minus-Treasury return, and the emerging market bond-minus-Treasury return.

For trend-following strategies on spreads, the ABS factor is a look-back straddle on the difference between two interest rates.[9] In Fung and Hsieh [2001], we provide a general model for trend-following strategies on individual assets (such as stock indexes, government bonds, short-term interest rates, foreign currencies, and commodities) using look-back straddles. Here, we extend the application to spreads between two interest rates (or, more generally, two assets).

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The innovation in this study is the creation of an ABS factor for convergence trading. A convergence trade generally involves 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 basis 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, a riskless arbitrage profit may 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 *triangular arbitrage* and *covered interest arbitrage* in the foreign exchange markets, cash-futures arbitrage in the futures market, and coupon-STRIPS arbitrage in the U.S. Treasury securities market.

As a general class of strategy, convergence trading relies on a variation of the law of one price. The theory is that two assets with *similar* payoffs in most states of the world should have *similar* prices.[10] 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 trading strategies include 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 model convergence trading, we need a description of the entry and exit points. Let S be the price of an asset or a group of assets. A convergence trader believes that S will not move very far away from some price level, say, S_{mid}. If S is sufficiently below S_{mid}, a long position in the asset is initiated. If S is sufficiently above S_{mid}, a short position in the asset is initiated. For ease of notation, we denote the trigger price $S_{low}(S_{high})$ to be the price below (above) which the convergence trader will go long (short) the asset.

A fully specified theoretical model of convergence trading strategies would require explicit knowledge of the key prices S_{mid}, S_{low}, and S_{high}. This is difficult to find, as hedge fund managers, protective of their skills, generally do not disclose their trading rules. To circumvent this problem, we use an option strategy to eliminate the need to specify these prices.

The option strategy relies on intuition as follows. The convergence trading strategy is basically the opposite of the trend-following strategy. A trend-following strategy tries to capture a large price move, up or down. Typically, the trend-follower *observes a trend* by waiting for the price of an asset to exceed certain thresholds. When the asset price goes above (below) the given threshold, a long (short) position in the asset is initiated. Assuming that the same set of key prices are used, the trend-following trader and the convergence trader will have similar entry and exit decisions, but in exact opposite positions.

Instead of modeling the myriad of possible entry and exit decisions of trend-following strategies, in Fung and Hsieh [2001] we model its payoff as a long position in a look-back straddle. Briefly, a look-back straddle is a pair of structured options. The look-back call option gives the owner the right (but not the obligation) to purchase an asset at the lowest price during the life of the option. The look-back put option gives the owner the right (but not the obligation) to sell an asset at the highest price during the life of the option.

Goldman, Sosin, and Gatto [1979] describe the theoretical pricing of a European-style look-back option. The look-back straddle consists of both the look-back call and look-back put. Given a sample period and a reference asset, the payout of the look-back straddle on that asset is the maximum any trend-following strategy can achieve. The question is the attendant cost (the look-back option's premium) to achieve this maximum payout.

Alternative trend-following strategies can be represented by variations on the entry/exit prices of those used in the look-back straddle. These variations will result in a lower payout than the look-back straddle, but should also involve less cost to implement than the look-back option's premium. These are the key considerations in choosing a particular form of trend-following strategy.

Since the convergence trading strategy is the opposite of the trend-following strategy, the convergence trading strategy can be modeled as a short position in a look-back straddle. In other words, the spread position of the convergence trade is identical to the negative of the "delta" of the look-back straddle.[11]

This primitive convergence trading strategy can differ from a convergence trader's actual strategy. If the trader has a better trading rule, it should generate better performance than the primitive convergence trading strategy (i.e., positive alpha).

The last theoretical issue is the horizon of the convergence trade. Since we have no good information on this, we use two extremes: a one-month and a ten-year horizon.[12] As data on structured options are not readily available, we simulate their returns, illustrated for the one-month look-back straddle, as follows.

For a given interest rate spread (e.g., the yield on Moody's Baa corporate bonds minus the yield on ten year Treasury bonds), we start with the daily spread. At the beginning of each month, we purchase a look-back straddle on the spread. The price of the straddle is based on the theoretical pricing formula in Goldman, Sosin, and Gatto [1979], using the historical volatility of the spread for the previous 21 trading days. At the end of the month, the payoff of the look-back straddle is the difference between the maximum and minimum spreads during the month. The return of the straddle equals the payoff, divided by the cost of the straddle, minus one.

Using this procedure, we simulate the returns of look-back straddles for four spreads: Moody's Baa bond yield minus the ten-year Treasury rate (Baa/Treasury spread), Merrill Lynch's High-Yield bond rate minus the ten-year Treasury rate (high-yield/Treasury spread), Lehman's mortgage yield minus the ten-year Treasury rate (mortgage/Treasury spread), and Intercapital ten-year swap rate minus the ten-year Treasury rate (swap/Treasury spread). In each case, the ten-year treasury rate is the ten-year constant-maturity interest rate in the Federal Reserve's H15 Statistical Release.

For the ten-year look-back straddles, we start these options in January 1994, and reprice the options at the end of each subsequent month. The straddle returns are the percentage price changes during each month. The returns on these look-back straddles are the asset-based benchmarks we use for convergence fixed-income funds.

Note that it is possible for the returns of look-back straddles (which are dynamic spread positions) to be highly correlated with the returns on static spread positions in a given sample period. This happens when the look-back straddle has a long horizon, and the underlying spread has widened or narrowed persistently during the sample period.

For example, high-yield/Treasury spreads and mortgage/Treasury spreads have generally risen since mid-1998. In this case, it is difficult to distinguish, statistically, between a static position and a convergence position in these two spreads.

III. LINKING RETURN-BASED STYLE FACTORS TO ASSET-BASED STYLE FACTORS

We identify the appropriate ABS factors as follows. First, we sort funds into groups according to HFR's qualitative style designations, and establish return-based style factors for each group using principal components analyses of the funds' returns. Second, we use Sharpe's [1992] asset class model to determine the location of these return-based style factors, regressing the factors' monthly returns on various commonly used asset benchmarks.

Third, an additional analysis is carried out to detect the presence of non-linear, dynamic trading strategies such as trend-following and convergence trading. From these analyses, ABS factors for each group of funds are identified. Finally, we test the out-of-sample explanatory power of these ABS factors.

Fixed-Income Convertible Bond Hedge Funds

As of July 2001, the HFR database included 12 operating and 4 defunct funds in the fixed-income convertible bond peer group. These funds have one style in common as shown in Exhibit 2. For this group of funds, we use the HFR Fixed-Income Convertible Bond peer group average as the return-based style factor, which has a correlation of 0.932 with the first principal component.

Next, this return-based style factor is linked to ABS factors via the Sharpe [1992] asset class model by regressing its monthly returns on various benchmarks. HFR describes this group of funds as "primarily long only convertible bonds," so we use the CSFB Convertible Bond index return and the difference between the CSFB Convertible Bond index return and the Lehman Treasury Bond index return (convertible bond-minus-Treasury return) as benchmarks.[13]

While the return-based style factor has a correlation of 0.824 with the CSFB Convertible Bond index returns, the convertible bond-minus-Treasury returns have stronger explanatory power in a joint regression of the two variables. The linear relationship is shown in Exhibit 3 (R^2 of 0.70). A summary of the regression is in Exhibit 4.

To detect the presence of non-linear, dynamic trading strategies, returns from look-back straddles on the convertible/Treasury spread are added to the set of regressors with the returns from look-back straddles on the Baa/Treasury spread, high-yield/Treasury spread, and swap/Treasury spread. Short-horizon and long-horizon look-back straddles on these variables are introduced to the regression separately in order to avoid multicollinearity. In both cases, the static convertible bond-minus-Treasury return remains the dominant regressor.

The only statistically significant regressor is the short-

EXHIBIT 3

HFR Convertible Peer Group Average versus Convertible Bond-Minus-Treasury Return

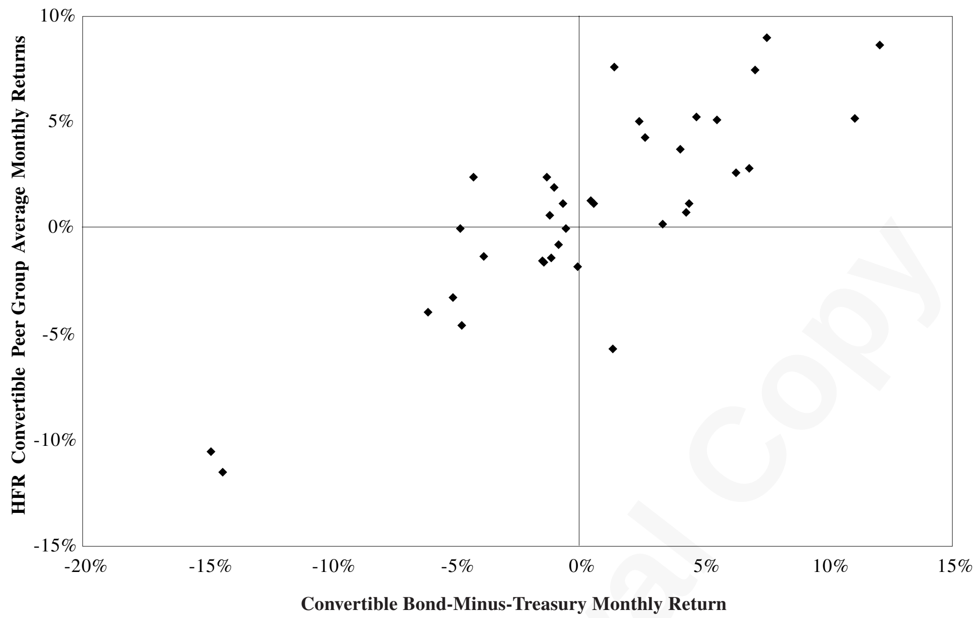

EXHIBIT 4

Summary of Regression Results for Hedge Fund Style Factors

Dependent Variable	Independent Variables	Coeff	T-stat	F-test	R^2
HFR Convertible	Convertible-Treasury	0.673	9.0	81.2	0.70
HFR High-Yield	High Yield-Treasury	0.631	7.1	123.6	0.78
HFR Mortgage-Backed	Change Mortgage Rate	-20.88	3.2	15.3	0.59
	Change Swap Rate	7.06	2.4		
	Change 10y Rate	7.65	2.1		
HFR Arbitrage PC 1	High Yield-Treasury	52.86	9.0	34.6	0.50
HFR Arbitrage PC 2	Convertible-Treasury	15.68	3.7	18.1	0.35
HFR Diversified PC 1	Corporate Bond	158.1	4.6	21.2	0.38
HFR Diversified PC 2	Emerging Mkt-Treasury	-29.61	-9.2	85.1	0.71

horizon look-back straddle on the swap/Treasury spread, which has a negative coefficient and is consistent with the presence of convergence trading. The increment in R^2 is rather modest, from 0.70 to 0.75, which indicates that convertible bond funds have primarily non-directional static exposure to long positions in convertible bonds hedged with short positions in U.S. Treasuries, with a small amount of short-horizon convergence trading.

To corroborate this analysis, we examine the out-of-sample correlation between the return-based style factor's returns and the convertible bond-minus-Treasury returns. As shown in Exhibit 5, the linear relationship continues to hold in 2001. This behavior is consistent with the view that convertible bond funds do not use dynamic trading strategies.

Empirical support for this assertion can be seen from the fact that convertible bonds generally outperformed Treasuries from October 1990 until January 2001, with the exception of August/September 1998. Since the beginning of 2001, convertible bonds have underperformed Treasuries. If convertible bond funds followed dynamic trading strategies, they would have switched from long convert-

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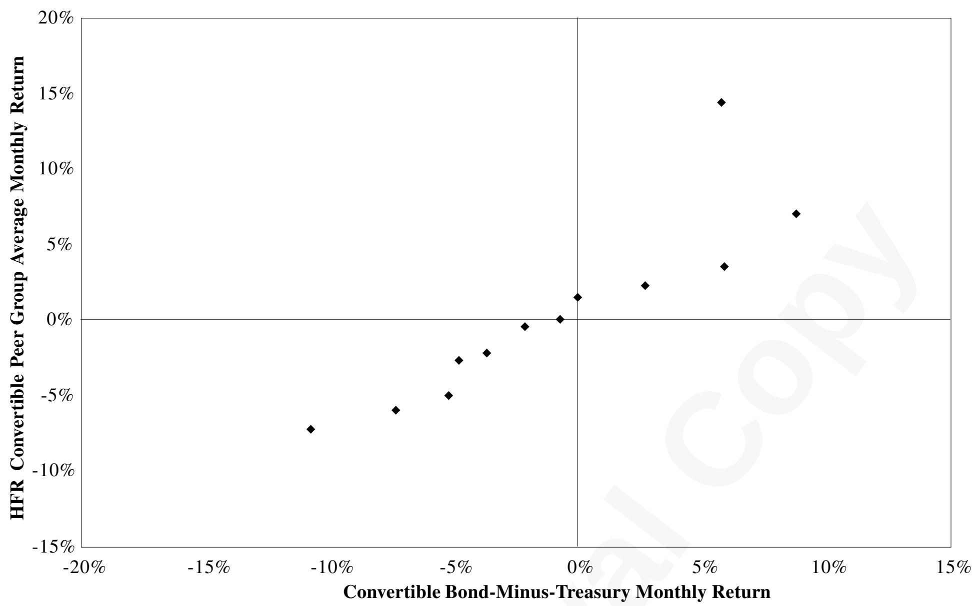
E X H I B I T 5
HFR Convertible Peer Group Average versus Convertible Bond-Minus-Treasury Return—2001



ible/short Treasury to long Treasury/short convertible, and their returns would not have a strong correlation with the convertible bond-minus-Treasury return in 2001.

Fixed-Income High-Yield Hedge Funds

As of July 2001, the HFR database included 12 operating and 4 defunct funds in the fixed-income high-yield peer group. These funds have one style in common, as shown in Exhibit 2. We use the HFR Fixed-Income High-Yield peer group average as a proxy for the return-based style factor. This proxy has a return correlation of 0.874 with the returns of the first principal component.

Next, we use Sharpe's [1992] style regression to determine the location of these funds. The HFR Fixed-Income High-Yield peer group average has a correlation of 0.853 with the CSFB High-Yield Bond index return, which is consistent with HFR's description of this group of funds as "invest[ing] in non-investment grade debt." However, in a joint regression of the peer-group average against both the high-yield bond return and the high-yield bond-minus-Treasury return, the latter has the dominant statistical explanatory power. The linear relationship is shown in Exhibit 6 (the R^2 is 0.78).

To detect the presence of non-linear, dynamic trading strategies, returns from short-horizon and long-horizon look-back straddles on the high-yield/Treasury spread are added to the set of regressors separately in order to avoid multicollinearity. Interestingly, both straddles have negative coefficients, which is consistent with the presence of convergence trading. The high-yield bond-minus-Treasury return statistically dominates the short-horizon straddle but is statistically dominated by the long-horizon straddle. If we use the long-horizon straddle as the sole regressor, the R^2 is 0.79.

Prima facie, this group of funds has mainly non-directional exposure to long positions in high-yield bonds hedged with short positions in U.S. Treasuries. However, the correlation of the long-horizon high-yield/Treasury spread look-back straddle return is 0.942 with the high-yield bond-minus-Treasury return. Thus, it is not clear whether the strategy is better described empirically by a dynamic, long-horizon convergence trading strategy or static exposure to the spread.

To answer this question, ~~observe~~ note that that high-yield bonds outperformed Treasuries from January 1991 until December 1999, but have generally underperformed Treasuries since January 2000. Similarly, high-yield funds performed well during the first period (averaging 1% per month), but poorly in the second period (averaging 0.09% per month). This would point to a passive exposure to a long high-yield/short Treasury position instead of a dynamic, con-

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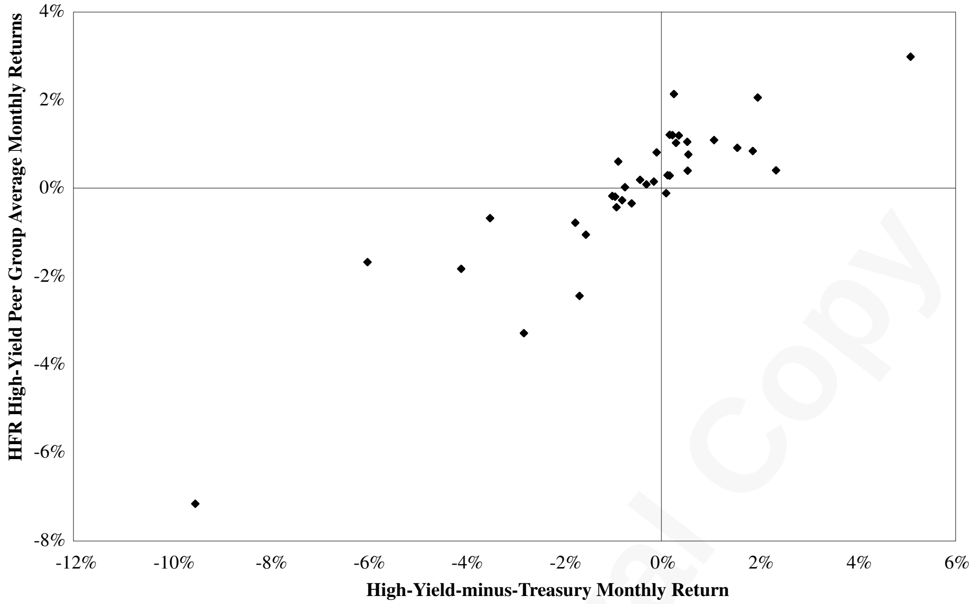
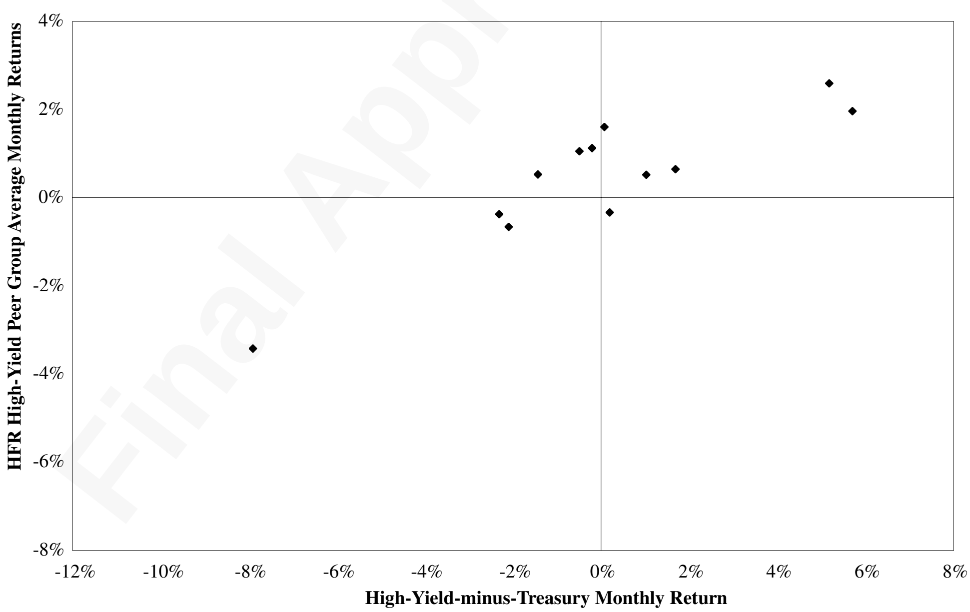
E X H I B I T 6
HFR High-Yield Peer Group Average versus High-Yield Bond-Minus-Treasury Return



E X H I B I T 7
HFR High-Yield Peer Group Average versus High-Yield Bond-Minus-Treasury Return—2001



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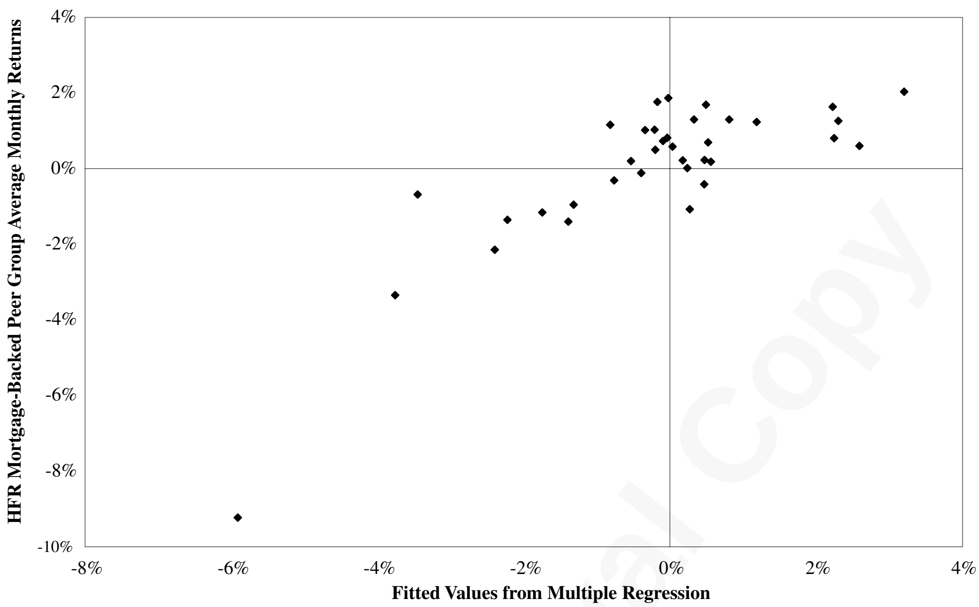
vergence trading strategy.

To corroborate this analysis, we examine the out-of-sample correlation between this group's return-based style factor's returns and the high-yield bond-minus-Treasury returns. As shown in Exhibit 7, the linear relationship continues to hold in 2001.

One plausible explanation of these empirical observations may be consistent with time-varying betas from changes in leverage on a long high-yield/short Treasury position as distinct from trend-following, where betas with respect to the underlying variable can fluctuate from positive to negative.

E X H I B I T 8
HFR Mortgage-Backed Peer Group Average versus Fitted Values From Multiple Regression



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Fixed-Income Mortgage-Backed Hedge Funds

As of July 2001, the HFR database included 19 operating and 10 defunct funds in the fixed-income mortgage-backed peer group. These funds have one style in common, as shown in Exhibit 2. We use the HFR Fixed-Income Mortgage-Backed peer group average to proxy the return-based style factor. This proxy has a return correlation of 0.949 with the returns of the group's first principal component.

The key features in HFR's description of this group of funds are: "[invests] in mortgage-backed securities," and "hedging of prepayment risk and interest rate risk is common." The return-based style factor has a low correlation (–0.194) with the change in the mortgage yields (based on the Lehman Mortgage-Backed Index), while the correlation is higher (–0.411) with the change in the mortgage/Treasury spread.

In the Sharpe [1992] style regression, we find that three interest rate variables are needed to explain the returns of these funds: change in mortgage rate, change in the ten-year swap rate, and change in the ten-year Treasury rate. The R^2 is 0.59.

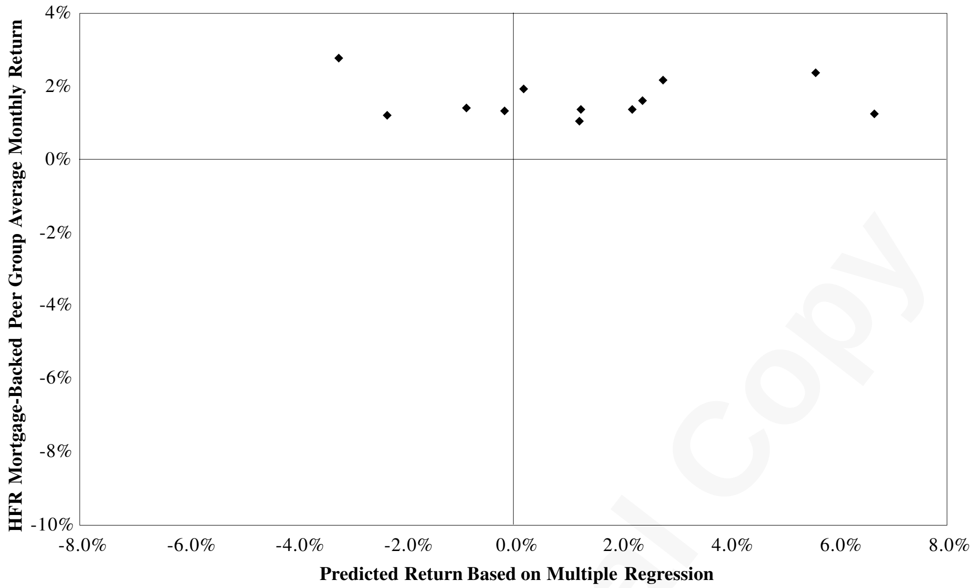
To detect the presence of non-linear, dynamic trading strategies, we add returns from look-back straddles on the mortgage/Treasury spread and swap/Treasury spread to the set of regressors. Short-horizon and long-horizon look-back straddles on these variables are introduced to the regression separately in order to avoid multicollinearity.

The short-horizon straddles do not improve the explanatory power of the regression, but the long-horizon straddles add explanatory power. In fact, the R^2 improves to 0.66 if we use the long-horizon straddles in swap/Treasury spread and mortgage/Treasury spread along with the change in mortgage rate. Interestingly, the swap/Treasury spread straddle has a positive sign (consistent with trend-following), and the mortgage/Treasury spread straddle has a negative sign (consistent with convergence trading). Exhibit 8 shows the relationship between the return-based style factor and the fitted value of the regression. The graph is roughly linear.

The out-of-sample predictive power of this regression model, however, is poor. Exhibit 9 shows that this relationship did not adequately describe the return-based style factor in 2001. More work is needed to explain this empirical phenomenon.

EXHIBIT 9

HFR Mortgage-Backed Peer Group Average versus Predicted Return in Multiple Regression—2001



Fixed-Income Arbitrage Hedge Funds

As of July 2001, the HFR database included 16 operating and 27 defunct funds in the fixed-income arbitrage peer group. As shown in Exhibit 2, these funds have at least two common styles. We use the first two principal components to directly proxy the return-based style factors of these styles.

HFR describes these funds as using "a market neutral hedging strategy that seeks to profit by exploiting pricing inefficiencies between related fixed-income securities while neutralizing exposure to interest rate risk." Indeed, the HFR fixed-income arbitrage peer group average has low correlation with the major bond indexes.[14]

The Sharpe [1992] style analysis shows that the first principal component is strongly correlated with high-yield bond-minus-Treasury returns, consistent with non-directional exposures to interest rates. Exhibit 10 shows that the relation is basically linear. (The R^2 is 0.50.) There are two outliers in the fall of 1998.

We noted earlier that the returns of long-horizon look-back straddles on the high-yield/Treasury spread are highly correlated with high-yield bond-minus-Treasury returns (0.942). A regression with both variables indicates that they have the same explanatory power. The straddle has a negative sign, consistent with convergence trading. Hence, the first principal component is primarily non-directional exposure to spreads, but the exposure can be both static and dynamic.

The Sharpe [1992] style analysis shows that the second principal component is most strongly correlated with convertible bond-minus-Treasury returns (with an R^2 of 0.35), again indicating non-directional exposures to interest rates. Exhibit 11 shows that the relation is largely linear. When we add the short- and long-horizon straddles as regressors, none of the straddles is statistically significant. This indicates that the second principal component has primarily non-directional static exposure to spreads.

Next, we construct the ABS factors for this group of hedge funds by regressing the HFR fixed-income arbitrage peer group average on the two principal components. This regression has an R^2 of 0.66. The slope coefficients of this regression are used to scale the exposure of each principal component to its risk factors, which are then added together to create a single ABS factor.

To check the quality of this procedure, we graph the HFR Fixed-Income Arbitrage peer group average against the fitted values of the risk exposures in Exhibit 12. It shows a reasonably linear relationship, with two large outliers in August and September of 1998. Additional statistical tests do not turn up any non-linear relationship with spread factors.

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EXHIBIT 10

Arbitrage Funds' First Principal Component versus High-Yield Bond-Minus-Treasury

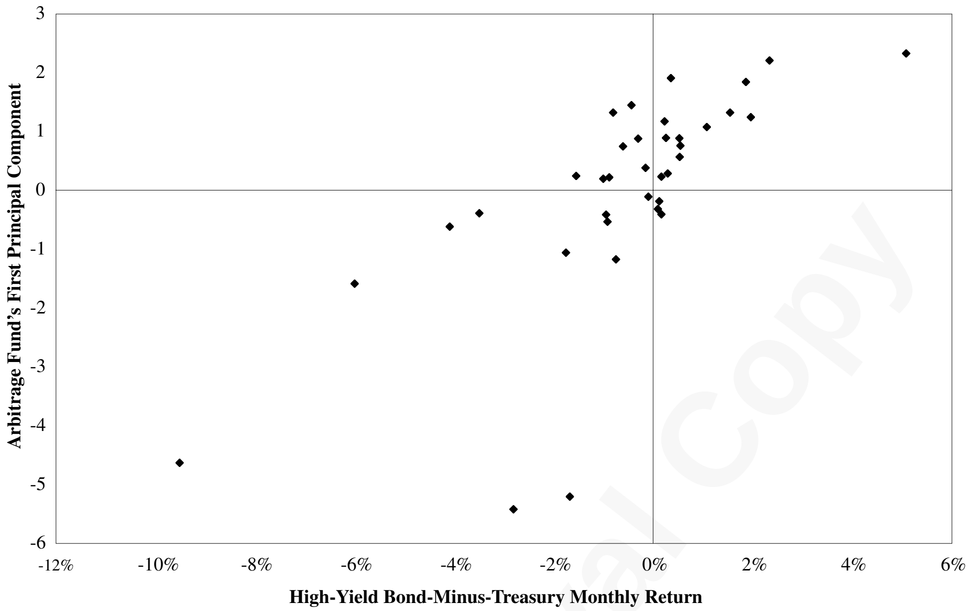

EXHIBIT 11

Arbitrage Funds' Second Principal Component versus Convertible Bond-Minus-Treasury

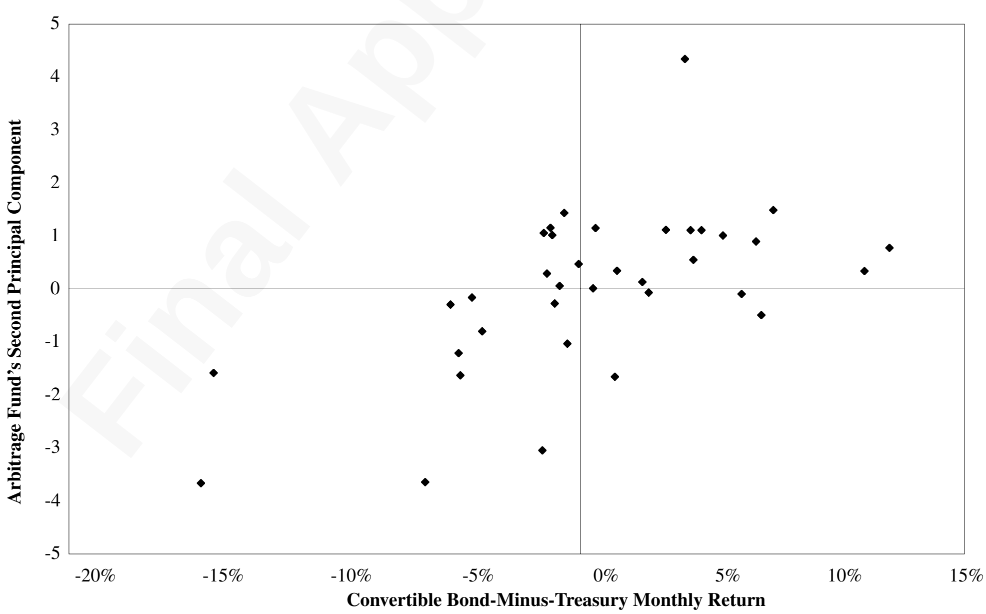

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EXHIBIT 12
HFR Arbitrage Peer Group Average versus Fitted Values

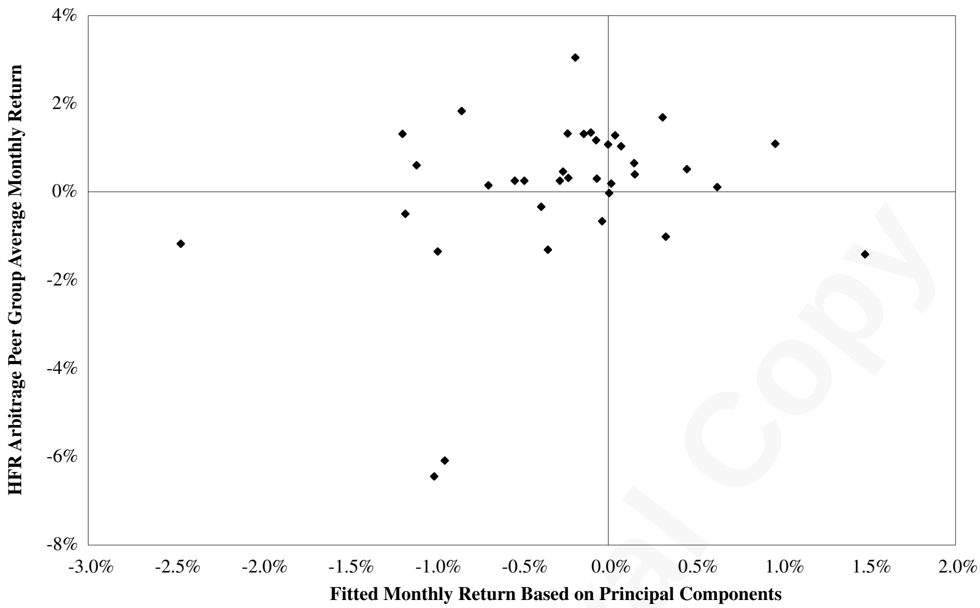
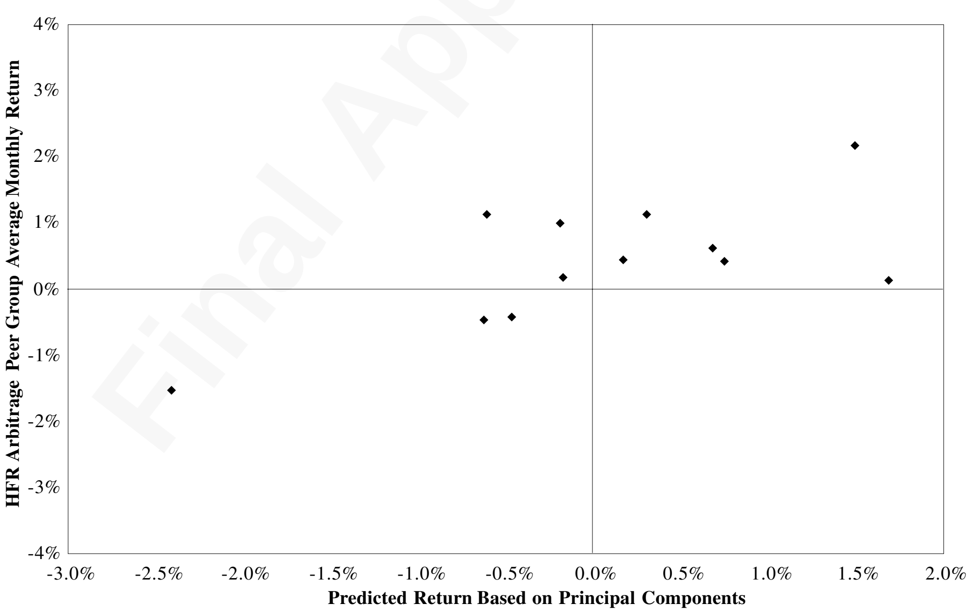


EXHIBIT 13
HFR Arbitrage Peer Group Average versus Predicted Return in Principal Components—2001



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To corroborate this analysis, we examine the out-of-sample correlation between the peer group average and the estimated risk exposures. As shown in Exhibit 13, the approximate linear relationship continues to hold in 2001.

Fixed-Income Diversified Hedge Funds

As of July 2001, the HFR database included 25 operating and 16 defunct funds in the fixed-income diversified peer group. As Exhibit 2 shows, these funds have at least two common styles. We use the first two principal components to directly proxy the return-based style factor for these styles.

The key feature of HFR's description of these funds is: "may invest in a variety of fixed-income strategies. While many invest in multiple strategies, others may focus on a single strategy less followed by most fixed-income hedge funds."

The Sharpe [1992] style analysis shows that the first principal component has a correlation of 0.62 with the Lehman Corporate Bond index return (with an R^2 of 0.38), indicating directional exposure to interest rates. Exhibit 14 shows that the relation is primarily linear, which is corroborated by further statistical tests. Regressions including the short- and long-horizon look-back straddles on corporate yields indicate that the short-horizon straddle does not improve the explanatory power. However, the long-horizon straddle has similar explanatory power as the corporate bonds and has a negative regression coefficient, which is consistent with convergence trading. By itself, the R^2 is 0.36. This indicates that the first principal component has primarily directional exposure to corporate bonds. This exposure can be either static or dynamic long-horizon convergence trading.

The second principal component has a correlation of –0.845 with the J.P. Morgan Emerging Market Bond-minus-Treasury return (with an R^2 of 0.71). Exhibit 15 shows that the relationship is primarily linear, indicating non-directional exposure to interest rates.

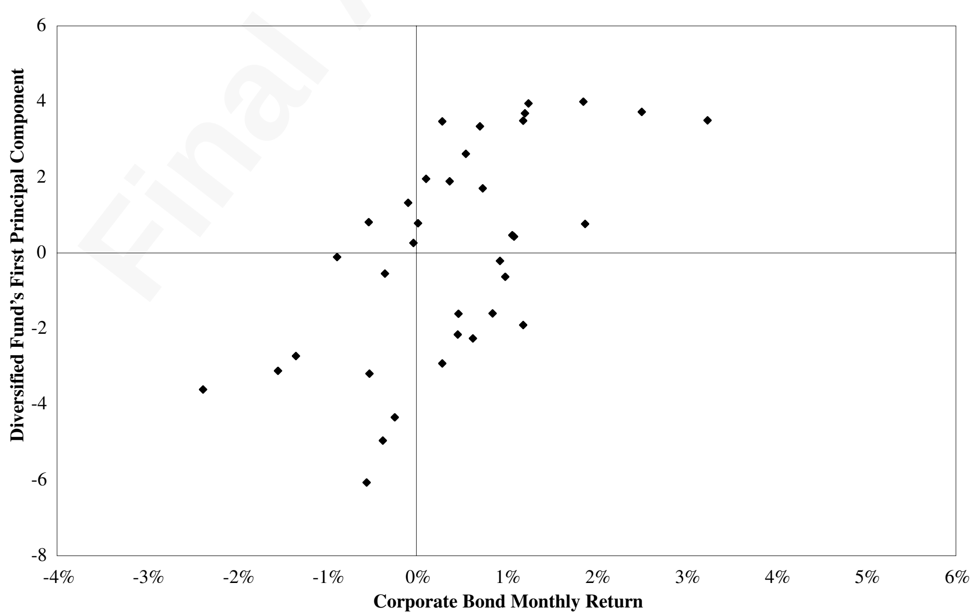
When we add the look-back straddles in Baa/Treasury spread, swap/Treasury spread, and high-yield/Treasury spread, the short-horizon straddles are not statistically significant, but in the long-horizon straddles, the high-yield/Treasury spread straddle is statistically significant. The coefficient has a positive sign, which is consistent with trend-following. The R^2 improves to 0.87.

This indicates that the second principal component has primarily non-directional exposure, part of it static (emerging market bond-minus-Treasury returns), and part of it dynamic (trend-following on high-yield/Treasury spreads).

We estimate the ABS factors of this group of hedge funds by regressing the HFR Fixed-Income Diversified peer group average on the two principal components. This regression has an R^2 of 0.64. The slope coefficients from this regression are used to scale each principal component's exposure to its corresponding risk factors—

EXHIBIT 14

Diversified Funds' First Principal Component versus Corporate Bond



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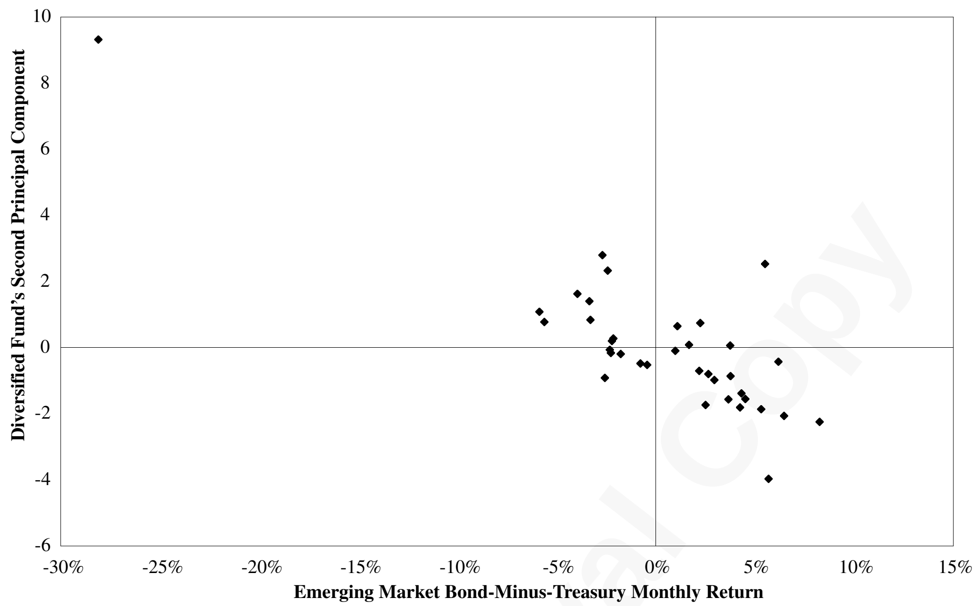
Diversified Funds' Second Principal Component versus Emerging Market Bonds-Minus-Treasury



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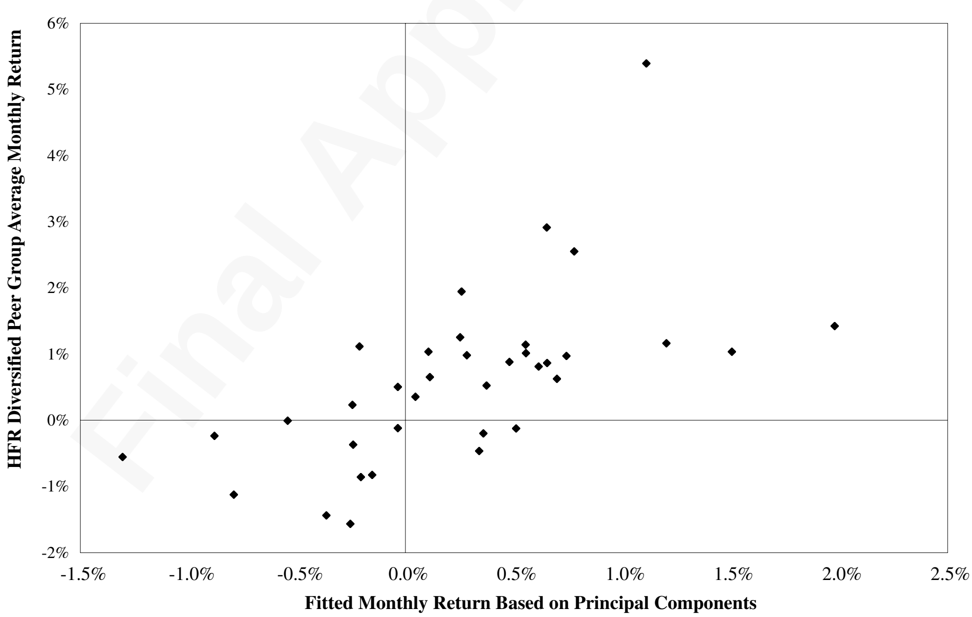
HFR Diversified Peer Group Average versus Fitted Values



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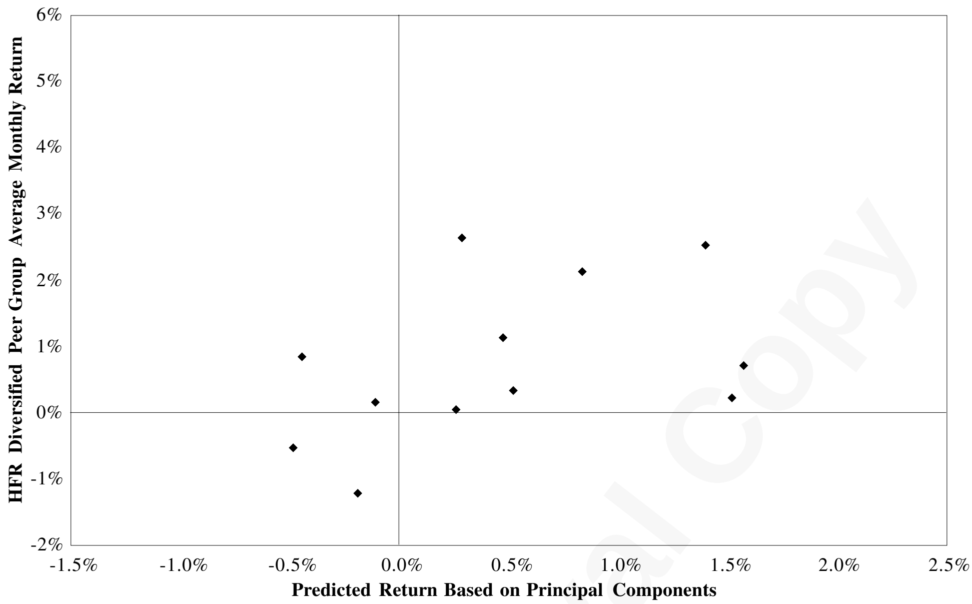
Lehman Corporate Bond Index, and the J.P. Morgan Emerging Market Bond-minus-Treasury returns. They are added together to form a single ABS factor.

To check the quality of this procedure, we graph the peer group average against the fitted values of the risk exposures in Exhibit 16. The result is a reasonably linear

EXHIBIT 17
HFR Diversified Peer Group Average versus Predicted Return in Principal Components—2001



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relationship. Additional statistical tests do not turn up any non-linear relationship with spread factors.

To corroborate this analysis, we examine the out-of-sample correlation between the peer group average and the estimated risk exposures. As shown in Exhibit 17, the approximate linear relationship continues to hold in 2001.

Fixed-Income Hedge Funds During Market Extremes

The explanatory power of our ABS factors for the seven fixed-income styles is comparable to that of the look-back straddles on trend-following funds (with R^2 of 0.45) in Fung and Hsieh [2001]. Yet, unlike trend-following funds that have directional exposures to market factors, fixed-income funds tend to have exposures to spread factors. Much of this exposure is static, but there are several instances of dynamic exposure, typically through the use of trend-following and convergence trading strategies.

Although the majority of the fixed-income hedge funds in our sample use non-directional strategies, they tend to perform poorly at the same time. The reason appears to be that, empirically, fixed-income related spreads tend to widen together at market extremes. To illustrate this, we construct a one-factor ABS model with the Baa/Treasury spread as the ABS factor. This particular credit spread variable has the desirable property of a very long history, dating back to the 1920s.

The conjecture here is that when this credit spread widens, other fixed-income yield spreads (convertible/Treasury, high-yield/Treasury, and mortgage/Treasury) will also widen. The sensitivity of fixed-income hedge funds to the change in credit spread is evident in Exhibit 18.[15]

The interest rate environment in the last decade has been benign for fixed-income spread-related strategies. Exhibit 19 graphs the long history of the Baa/Treasury spread back to 1925. Note that decade of the 1990s saw very little spread volatility, compared to the period of 1925 through the mid-1980s, when there were great increases at several times. In these more hostile environments, our one-factor ABS model would predict poor performance from fixed-income hedge funds.

To illustrate this point, we analyze the risk of fixed-income arbitrage funds using the HFR Fixed-Income Arbitrage peer group average as the return-based style factor for this group of funds. First, we relate the peer group average to changes in the credit spread from 1990 to 1997, deliberately excluding the effect of the extreme observations in the fall of 1998. The regression results are as follows (t-statistics in parentheses):

EXHIBIT 18
HFR Fixed-Income Peer Group Averages versus Change in Credit Spread

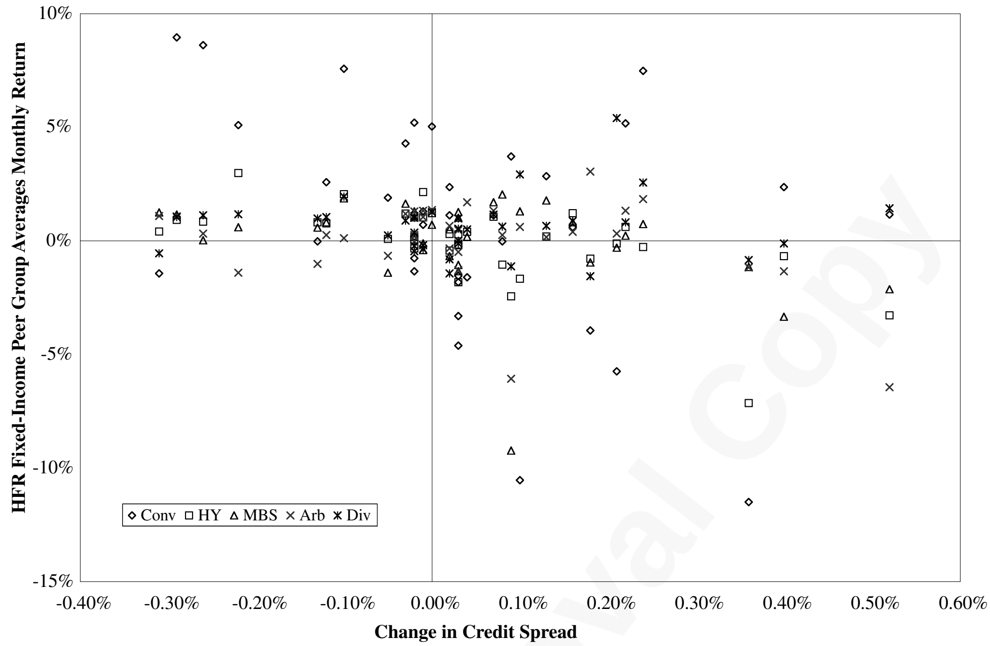
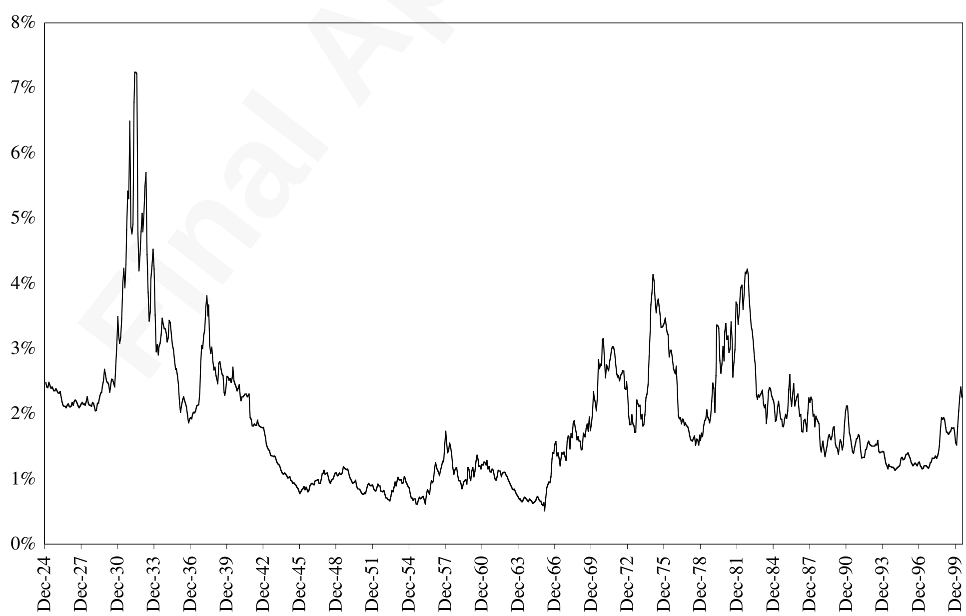
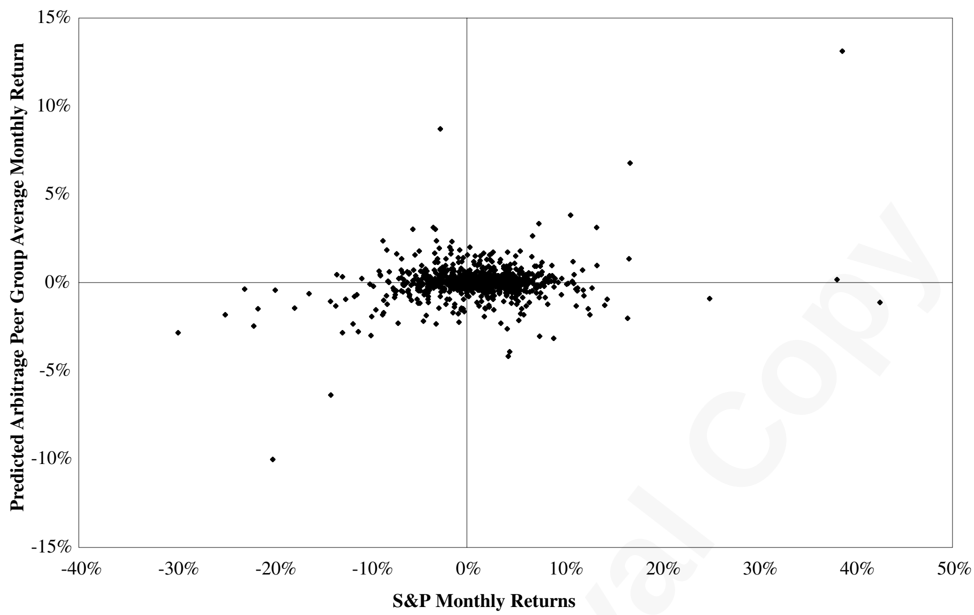


EXHIBIT 19
Long-Term History of the Credit Spread



E X H I B I T 2 0
Predicted Arbitrage Peer Group Average Monthly Returns versus S&P—1926-1997



$$\text{HFR FI Arb} = \underset{(10.0)}{0.0096} - \underset{(-6.6)}{5.37}\,[\text{Change in Credit Spread}]$$
$$R^2 = 0.32 \qquad (1)$$

During this period, the largest monthly loss in the peer group average is 2.58%, in September 1991. How good is this estimate of the tail risk for these funds?

To answer this question, we return to the one-factor ABS model. Applying the model to the period 1926 to 1990, we can estimate what the loss experience would have been for these funds over a longer history. According to the fitted values of the one-factor ABS model, the greatest monthly loss would have been 9.08%, during April 1932, when the spread widened 187 basis points (*see Exhibit 19*). This loss more than doubles the worst loss experienced during 1990-1997. Therefore, conditional on the outlook of this key credit spread, tail risk estimates of fixed-income arbitrage hedge funds can vary dramatically.

In this application, the one-factor ABS model provides an important link that extends the information content of the HFR Fixed-Income Arbitrage index's return history to provide important clues to conditional performance behavior in different market cycles.

This simple one-factor ABS model can also provide clues to how fixed-income arbitrage funds would have done if the S&P suffered large declines. If we graph the fitted values from the one-factor ABS model against the S&P returns during 1926-1997, we see a positive correlation with months when the S&P has a large loss, as illustrated in Exhibit 20.

Regressing the fitted values from the one-factor ABS model on the S&P using only months when it lost more than 5% (83 times), the slope coefficient is 0.15 (t-statistic of 4.97) with an R^2 of 0.23. This implies that fixed-income arbitrage funds would return –1.5% if the S&P were to drop 10% in one month.

If we look only at the HFR Fixed-Income Arbitrage peer group average and the S&P 500 index over the 1990-1997 period, as shown in Exhibit 21, we may conclude that there is no relationship between these funds and the S&P. What this tells us is that the cyclical exposure to risk factors inherent in most Fixed-Income Arbitrage funds may be masked by the short lives of the funds themselves. Using an ABS factor model helps to uncover the inherent risk of investing in funds with short histories.

We can apply this one-factor ABS model to one other recent market event. At the end of June 1998, the spread was 167 basis points. It widened steadily during the summer and fall of 1998, reaching 206 basis points at the end of August and 257 at the end of September, peaking at 277 on October 16. The cumulative increase of 110 basis points within four months was unprecedented

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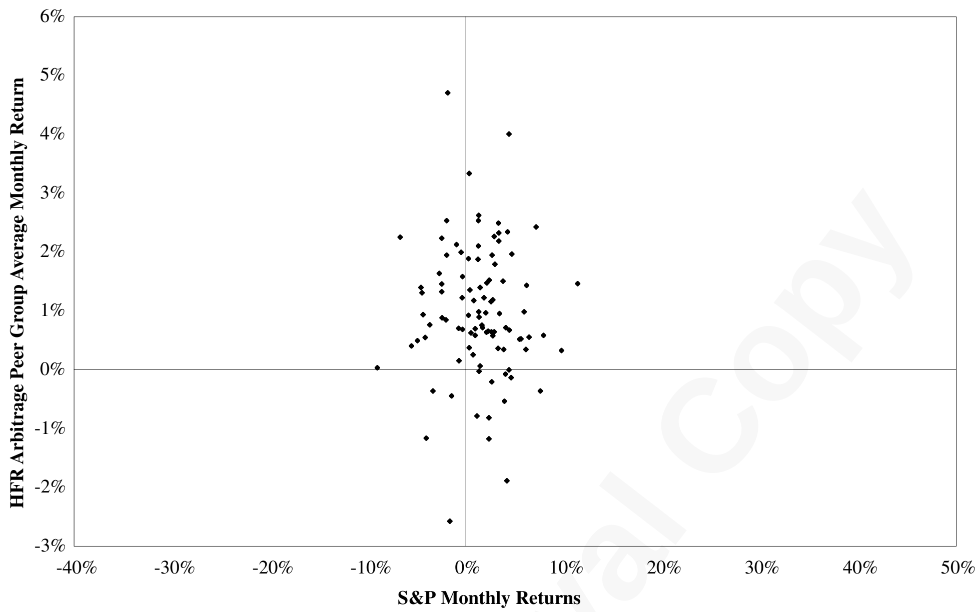
EXHIBIT 21
HFR Arbitrage Peer Group Average versus S&P—1990-1997



for the 1990s, creating unusually large losses for fixed-income funds.

Our one-factor ABS model applied to a spread widening of 90 basis points from June 30 to August 30 would imply a decline in value of 4.8% (–5.37 times 0.0090) for the typical fixed-income arbitrage fund. The HFR Fixed-Income Arbitrage peer group average actually lost 6.0%.

What about a more complex, highly leveraged fund like Long-Term Capital Management? LTCM's return standard deviation is approximately four times the HFR arbitrage peer group average (1994 through 1997). From this we can estimate LTCM's leverage to be at least four times the leverage of the typical fixed-income arbitrage fund. When the credit spread widened 39 basis points from June 30 through August 30, our simple one-factor ABS model would have predicted a loss of 15.3% for LTCM, compared to the actual loss of 44.8%. It is remarkable that a single ABS factor can help to explain one-third of the loss of a highly complex hedge fund such as LTCM.

While a one-factor ABS model is helpful to extend the limited return history of hedge funds, there are other day-to-day applications of ABS models. Investors can apply such a model to obtain estimates of how their fixed-income hedge fund investments are performing on a daily basis by observing the daily behavior of the key credit spread variable. In this instance, an ABS model helps to enhance the information content of peer group averages of hedge fund performance, which can be observed only at monthly intervals.

IV. CORROBORATION

There is some corroborating evidence that the ABS factors derived using the HFR fixed-income funds can also explain the returns of fixed-income funds in another sample, the TASS database (owned by Tremont Advisors). As of April 2001, the TASS database included 91 funds with a special focus on fixed-income securities. Of these, we eliminate the 41 funds already in our HFR fixed-income sample, leaving 50 fixed-income funds not in the original sample.

A principal components analysis of these 50 funds reveals that the first three components explain 22%, 17%, and 15% of their cross-sectional variation. They jointly account for more than 50% of the cross-sectional variation.

In terms of return-based style factors, the first component has a correlation of 0.88 with the first component of the HFR diversified funds. The second component has a correlation of 0.58 with the first component of the HFR arbitrage funds. The third component has a correlation of 0.70 with the HFR high-yield funds.

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EXHIBIT 22
Morningstar Fixed-Income Mutual Fund Styles—December 2001

Morningstar Style Category	Number	Assets
Convertible Securities	66	$ 7.7b
Emerging Market Bonds	41	$ 3.0b
High-Yield Bonds	371	$ 82.1b
International Bonds	137	$ 13.5b
Intermediate Bonds	656	$215.3b
Intermediate Governments	302	$ 86.6b
Long-Term Bonds	96	$ 16.2b
Long-Term Governments	62	$ 7.4b

Source: Morningstar January 2002 CD-ROM.

EXHIBIT 23
Percent of Cross-Sectional Variation Explained by Principal Components

Morningstar Style Category	PC 1	PC 2
Convertible Securities	87%	5%
Emerging Market Bonds	97%	1%
High-Yield Bonds	87%	3%
International Bonds	63%	13%
Intermediate Bonds	86%	6%
Intermediate Governments	89%	5%
Long-Term Bonds	77%	13%
Long-Term Governments	92%	4%

In terms of ABS factors, the first component is strongly negatively correlated with the ten-year look-back straddle on corporate bonds ($R^2 = 0.36$), which is indicative of the presence of convergence trading strategies. The second component is strongly negatively correlated with the ten-year look-back straddle on mortgage spreads ($R^2 = 0.41$), also indicating that convergence trading strategies are being used. The third component is strongly positively correlated with the high-yield bond-minus-Treasury return ($R^2 = 0.52$). This may also be evidence of convergence trading, since the high-yield bonds-minus-Treasury return is highly negatively correlated with the ten-year look-back straddle on the high- yield spread.

V. COMPARISON WITH FIXED-INCOME MUTUAL FUND STYLES

Another insight may be gained by comparing the styles of fixed-income hedge funds and fixed-income mutual funds. From the Morningstar January 2002 CD-ROM, we extract mutual funds in seven style categories that invest in similar fixed-income securities as the HFR fixed-income hedge funds. Exhibit 22 shows the details.

For each Morningstar category, we perform principal components analysis on all the funds using data for 1998-2000 to determine the number of common styles. Exhibit 23 shows the percentage of cross-sectional variation explained by the first two principal components in each category. Clearly, each category has only one main style. Furthermore, the first principal component of each category is highly correlated with the average return of the mutual funds in that category (the lowest correlation is 0.985).[16] This allows us to use the average return to proxy for the return of that particular style.

Results of Sharpe's [1992] style regressions on these mutual fund peer group averages are summarized in Exhibit 24. In four instances, only one benchmark is needed to achieve high explanatory power. In three other cases, two to three benchmarks are needed. The lowest R^2 is 0.92.

EXHIBIT 24
Summary of Regression Results on Mutual Fund Style Factors

Dependent Variable	Independent Variables	Coeff	T-stat	F-test	R^2
Convertible Securities	CSFB Convertible	0.82	22.6	509.3	0.94
Emerging Market Bonds	JPM Brady	1.16	27.6	71.6	0.96
High-Yield Bonds	CSFB High Yield	1.10	37.0	1368.6	0.98
International Bonds	JPM World ExUS	0.41	15.9	155.7	0.94
	JPM Brady	0.07	7.0		
	Lehman Credit	0.24	5.9		
Intermediate Bonds	Lehman IT Credit	0.96	24.7	612.2	0.95
Intermediate Governments	Lehman IT Gov	0.68	12.8	617.1	0.92
	Lehman IT Mortgage	0.49	8.6		
Long-Term Bonds	Lehman LT Credit	0.45	8.8	164.5	0.94
	Lehman LT Gov	0.09	2.2		
	Lehman Mortgage	0.38	3.8		
Long-Term Governments	Lehman LT Gov	0.65	34.2	1420.9	0.99
	Lehman Mortgage	0.35	7.1		

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Finally, we add static spread factors (e.g., mortgage-minus-Treasury returns) and dynamic strategies (e.g., short- and long-horizon look-back straddles) to the style regressions. None can replace or replicate the explanatory power of the standard benchmarks in Exhibit 24. This evidence confirms the idea that fixed-income mutual fund styles have predominantly passive exposure to standard benchmarks.

VI. CONCLUSIONS

In this article we analyze the common risk of fixed-income hedge funds by extracting seven return-based style factors, which are then linked to ABS factors. Fixed-income hedge funds have primarily static exposure to fixed-income related spreads—these are convertible/Treasury spread, high-yield/Treasury spread, mortgage/Treasury spread, and emerging market bond/Treasury spread. At the same time, there is weak evidence that these funds employ convergence trading and market-timing strategies. By identifying the ABS factors, we are able to show that most fixed-income hedge funds have considerable exposure to a large increase in credit spreads.

The findings have several implications. For an investor in fixed-income hedge funds, it is important to make sure that a portfolio is not overly exposed to a widening of credit spreads. Because of the contagion effect of a large increase in credit spread, diversifying among funds using apparently different fixed-income (and related) strategies may only have limited effect in mitigating the tail exposure to credit risk. This consideration is of particular importance if the investor's overall asset allocation includes other fixed-income securities.

The ABS factors we put forth help to make explicit the common risks in fixed-income hedge fund strategies. This is an important step toward an overall framework for management of risk in a portfolio of hedge fund strategies.

For counterparties of fixed-income hedge funds, it is important to identify the inherent risk that may be common to different hedge funds. Given the short operating history of most hedge funds, stress tests based on these limited experiences can be misleading. This is especially so given the benign interest rate environment of the 1990s. Standard value at risk methods need to be extended to include factors that motivate observed return changes. Identifying the relevant ABS factors helps to extend the assessment of risk through much longer market cycles thus providing better insight into potential tail risks.

For regulators of the financial industry, fixed-income spread trades with leverage, whether practiced at proprietary trading desks or in hedge funds, can destabilize markets when extreme events occur. The effects would be exacerbated by the convergence of strategies for market participants, leading to similar risk exposures.

The key question is how to detect the risk of such convergences early. This is not an easy question to answer. The path to a reasonable solution must begin with understanding the underlying risk characteristics of the particular strategies. ABS factors can help, by identifying seemingly different strategies that actually have common ABS factors. This in turn helps to devise early warning indicators that are risk factor-based rather than specific position-based.

ABS factors also help to explain where fixed-income hedge funds can add value to investors' portfolios. The absence of dynamic ABS factors in the returns of traditional investment vehicles like (mutual funds) is prima facie evidence that hedge fund strategies, through their exposure to ABS factors, are exposed to alternative sources of risk. It follows that the returns for bearing these added sources of risk offer investors an alternative source of income from standard asset categories. The caveat is that exposure to these alternative risks requires additional tools to manage the attendant tail risk.

The challenge here is to develop a complete model of ABS factors for hedge funds in general. We need an ABS factor model that can be integrated into an overall asset allocation framework, and that explicitly identifies the hedge fund alpha that managers bring over and above the common risks of different styles.

ENDNOTES

The authors thank the LBS Centre for Hedge Fund Research and Education for providing the hedge fund data used in this article. Earlier versions of this research were presented at Princeton University, Boston University, New York University, an NBER Risk of Financial Institutions Workshop, and Vanderbilt University. The authors thank Wayne Ferson for comments and suggestions.

[1]As private investment vehicles, hedge funds are exempt from the disclosure requirements imposed on publicly traded companies and mutual funds, and hedge fund managers rarely disclose their trading strategies. Hedge funds are typically organized as limited partnerships, with the manager as the general partner and the investors as limited partners. The general partners typically charge a fixed fee (usually 1%-2% of the assets under management) as well as a performance fee (usually 15%-20% of the profits exceeding a high-water mark). Hedge funds are exempt from ~~both~~ most of the disclosure requirements on mutual funds and the regulatory restrictions on mutual funds regarding leverage, short sales, illiquid securities, or position concentration. For further details, see Fung and Hsieh [1999].

[2]Aggrawal and Naik [2001] use returns of S&P 500 index options to capture option-like behavior in the returns of equity hedge funds. They do not, however, explicitly model the option structure implicit in these trading strategies.

[3]See Fung and Hsieh [2002] for a more detailed comparison of asset-based style factors and peer group-based style factors.

[4]There are different ways to use value at risk (VaR) models to study hedge fund risk. One method applies VaR directly to hedge fund returns. The drawback is the short history, which is especially severe if there are catastrophic risks that have not been observed. Another method applies VaR to positions of hedge funds. This approach is subject to two problems: a) hedge fund positions are not generally available, and b) these positions are not static.

The asset-based style factor provides a third method: to apply VaR to the asset-based style factor itself. This solves the problem of the short history of hedge funds. If the style factor itself is a dynamic trading strategy, as in the case of trend-following, an asset-based VaR will automatically adjust to the dynamics of the strategy.

[5]Examples are government bonds with slightly different maturity dates, or equities listed on different exchanges.

[6]Convergence trading is employed also by proprietary trading desks of banks, but information on their activities is not generally available.

[7]Note that fixed-income convertible bond funds are different from convertible arbitrage funds. The latter also hedge by shorting the underlying common stock.

[8]Principal components is a statistical procedure that extracts common correlations across a group of funds; see Fung and Hsieh [1997].

[9]We use the differences in bond yields, rather than bond index returns, to simulate returns on look-back straddles, because our procedure requires daily observations. While bond yields have daily observations, bond index returns typically have only monthly observations.

[10]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.

[11]The delta of the look-back straddle is calculated in Fung and Hsieh [2001].

[12]We also try a one-year look-back straddle. It does not materially alter the results.

[13]Bond return indexes include capital gains and coupon payments. HFR's style definitions are provided at the website: https://www.hfr.com/hfram/index.php?action=moreInfo_monthlyIndices.

[14]The correlation of the HFR fixed-income arbitrage peer group average with the Lehman Aggregate Bond index is –0.199.

[15]Another way to see this is to extract principal components from the seven style factors. The first principal component explains 47% of the cross-sectional variation, while the second component explains only 26%. The first component is

indeed credit risk, since it has a correlation of –0.86 with the change in the high-yield credit spread.

[16]There is survivorship bias in the Morningstar CD, since funds that ceased operation prior to December 2001 are eliminated from the January 2002 CD. This would affect the estimate of mean return, but not the correlation with market benchmarks, given the homogeneity of mutual fund returns within the same Morningstar category.

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