Hedge Fund Risk Factors and the Value at Risk of Fixed Income Trading Strategies

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The fact that many hedge fund returns exhibit significant levels of serial correlation is now well-known and generally accepted as fact. The effect of this serial correlation on hedge fund returns is to diminish the apparent risk of this asset class as the true day-to-day, week-to-week and month-to-month variability of returns may easily be distorted by illiquidity, stale prices, averaged price quotes.[1] Nevertheless, in spite of this lack of clarity, ever larger segments of the investment community have continually shifted funds into the hedge fund asset class.[2] With their increasing prominence, potential investors need to be aware of the true risk underlying reported (or reputed) hedge fund returns.

Many researchers have attempted to map reported hedge fund returns onto a set of external factors in order to gain a better understanding of the true underlying risk level (see, Agarwal & Naik [2001, 2004] and Fung & Hsieh [2002a, 2002b]). Ideally, we would want to work directly with the adjusted hedge fund returns that have already removed the effects of serial correlation when conducting this type of analysis. Moreover, any attempt to subject hedge fund returns to a value-at-risk analysis would also wish to examine adjusted rather than reported hedge fund returns.[3]

We have several purposes for this article. First, neither Agarwal and Naik [2001, 2004] nor Fung and Hsieh [2002a, 2002b] properly adjust the returns of their hedge funds to take into account return smoothing. To the extent that smoothing does occur in reported individual hedge fund returns, the true realized volatility will exceed disclosed volatility and the underlying relation between the hedge fund returns and factor exposures will be obscured. We take high-order autocorrelations in hedge fund returns as evidence of this smoothing and present a new approach to completely eliminate any order of autocorrelation from reported returns to determine the "true" underlying returns for the hedge fund. In general, our process will show that the true risk for many fixed income hedge fund strategies ranges from 37% to 64% greater than that observed through reported returns.[4]

Second, we make use of the Agarwal and Naik [2001] stepwise regression framework to identify the underlying risk factors for the fixed income hedge funds. We choose to focus on the fixed income style because the hedge funds in this sector appear to have the most extreme levels of serial correlation in reported returns. In a closely related article, Fung and Hsieh [2002b] also examine the risk characteristics for five styles of fixed income hedge funds followed by HFR. While our ultimate results are roughly consistent with that found in Fung and Hsieh [2002b], we take a significantly different approach.[5] In our stepwise regressions, we include well over 100 candidate risk factors and allow the statistical process to identify the relevant factors rather than *a priori* guesswork.

Using the adjusted hedge fund returns, we attempt to identify the underlying risk factors for six fixed income styles: *Fixed Income Arbitrage, Fixed Income Convertible Bonds, Fixed Income Diversified, Fixed Income High Yield* and *Fixed Income Mortgage-Backed* and *Total*.[6] In addition to mapping hedge fund returns onto the underlying risk factors, we also examine the incremental benefit to using nonlinear payoffs as candidate exposures. In general, we find limited evidence of nonlinearities for the fixed income hedge fund styles.

Finally, the ultimate aim for mapping hedge fund returns onto factors is to use the underlying risk exposures to simulate future possible returns using historical datasets. Specifically, we conduct a value-at-risk analysis using the mappings and compare the estimations when nonlinear exposures are either included or excluded. We find that estimated downside risk exposures marginally increases when we take into account nonlinearities.

The structure for the article is as follows. In Section I, we discuss the data and methodology used for this study for both the hedge fund and the factor returns. In Section II, we present the mapping results. In Section III, we examine the value-at-risk for the various hedge fund styles. Finally, in Section IV, we conclude with the overall findings of the article.

I. DATA AND METHODOLOGY

To examine the fixed income hedge funds, we use returns from the HFR indices taken over the period January, 1995 through December, 2005. For clarity, we choose to work with the indices themselves rather than individual hedge fund returns.[7] The specific styles and indices we have chosen to use are given in Exhibit 1. We have chosen to confine our analysis to fixed income styles in general as our methodology for unsmoothing returns is most relevant in this sector. In addition, we show that these hedge fund styles are quite correlated and have many common underlying risk exposures.

Exhibit 1 presents statistics on excess returns (to the U.S. T-bill) for the six hedge fund indices we will consider. Considering first the unadjusted excess returns, we can clearly see that the *Total* index has the greatest return and reward to risk ratio. In addition, we can see that *High Yield* and *Mortgage-Backed* have significant levels of first and second order autocorrelations while *Arbitrage* and *Total* have significant levels of first order autocorrelations.

In relation to the adjusted hedge fund returns, we successfully eliminated the first two autocorrelations. Exhibit 1 reveals that the adjusted hedge fund returns for *Arbitrage, High Yield* and *Mortgage-Backed* have a higher standard deviation, in general, than does the original return series with a correspondingly lower information ratio. In these cases we find an increase in risk between 37% and 64%.

Exhibit 2 gives the correlations among the different hedge fund indices. We can quickly see for the unadjusted series that the correlations between *High Yield, Arbitrage, Convertible Bonds, Mortgage-Backed* and *Total* are of the order 0.5 suggesting there may be little diversification benefits in combining these strategies into a portfolio of strategies. However these correlations drop substantially when examining the correlations using the adjusted return series. Combining *High Yield* and *Mortgage-Backed* with *Arbitrage, Convertible Bonds and Diversified* may lead to considerable diversification as the correlations are approximately zero.

Exhibit 3 and Exhibit 4 present summary statistics for the candidate factors we use to identify the relevant risk exposures of the hedge fund indices. For this study, we have included 36 candidate factors that we label *Index Factors*. In Exhibit 3 we have included 11 equity factors, 14 bond indices, 4 commodity indices, 2 real estate indices, 2 currencies, as well as 3 miscellaneous factors (NYBOT Orange Juice, % Change in the VIX index, % Change in the VXN index). Most of these factors were taken directly from Datastream. The VIX and VXN indices were taken from the CBOE website. In addition to the variables reported in Exhibit 3, we also included various interest rates downloaded directly from Datastream. These are the U.S. Corporate Bond Moody's Baa rate, the FHLMC 30 year mortgage rate and the U.S. 10 year Treasury rate.

Exhibit 4 gives details for the data taken directly from Ken French's website. These include the standard small minus big factor, high minus low, and momentum. Definitions for each of these factors may be found at his website. Note that the difference between the *High* factor and the *Low* factor is not the same as the value for the *HML* factor due to slightly different definitions in the construction of the series. In addition, industry factors were taken directly from Ken French's site and included in Exhibit 4. We label all factors taken from Ken French's site, including industry factors as *Ken French* factors.

A direct comparison of Exhibit 1 with Exhibit 3 reveals that the adjusted returns of the hedge funds have, in general (except for *Mortgage-Backed*), a risk level comparable to many of the bond indices. This is not surprising

EXHIBIT 1
Hedge Fund Indices Excess and Adjusted Monthly Returns January 1995–December 2005

Index	Excess Returns			Autocorrelations		Adjusted Returns[1]		
	Mean	Std Dev	Info Ratio	First	Second	Mean	Std Dev	Info Ratio
Total	0.367	0.915	0.401	0.313*	0.158	0.354	1.400	0.253
Arbitrage	0.136	1.159	0.117	0.363*	0.045	0.138	1.588	0.087
Convertible Bonds	0.460	3.676	0.125	0.147	-0.112	0.466	3.786	0.123
Diversified	0.366	1.049	0.349	0.049	0.022	0.347	1.117	0.311
High-Yield	0.341	1.332	0.256	0.353*	0.232*	0.307	2.116	0.145
Mortgage-Backed	0.461	1.360	0.339	0.396*	0.273*	0.448	2.228	0.201

* Significant at 5% level

[1] Autocorrelations for Adjusted Returns are all zero to two decimal places

given that we are considering hedge funds that tend to operate in fixed income markets in the first place. The fact that the risk level for adjusted hedge fund returns is relatively close to the risk levels of the indices gives us some comfort in the adjustment process that we use. We should also note that none of the bond factors possess significantly positive first or second order autocorrelation. This fact makes us question the validity of the original autocorrelation process we find in unadjusted hedge fund returns. Exhibit 4 presents similar measures as Exhibit 3 for the *Ken French* factors.

As is clearly evident, we consider a very wide range of candidate risk factors and will make no prior assumptions regarding which should be the most important for assessing the risk factors underlying our hedge fund indices. If our initial assumptions regarding the most relevant risk factors are correct, then we should find these risk factors when we include a far greater array of candidate exposures. If we do not find the risk factors we would expect, then either our initial assumptions are incorrect or we must question our methodological approach.

Directional Factors

We now wish to map (regress) the individual adjusted hedge fund index returns onto the potential risk factors detailed in section above. For this part, we closely follow the methodology of Agarwal and Naik [2001]. Initially, for each *Index Factor* we create two directional factor exposures. For example, in addition to using the S&P 500 index returns as one potential risk factor, we will subdivide the S&P 500 returns into a positive and a negative component and use those as two additional risk factors. That is, we create the following two return series:

$$\begin{aligned} \text{S\&P 500}+ &= \text{S\&P 500 return if S\&P 500 return} > 0 \\ &= 0 \text{ otherwise} \\ \text{S\&P 500}- &= \text{S\&P 500 return if S\&P 500 return} < 0 \\ &= 0 \text{ otherwise} \end{aligned}$$

The motivation for doing this is that because hedge funds are quite free to change their exposures, they may face differing sensitivities to the risk factors in "up" or "down" markets. We posit that for some types of hedge funds modeling the risk exposures in this manner will provide greater explanatory power for realized returns. We define the directional factor return series as *Directional* factors.

EXHIBIT 2
Hedge Fund Indices Correlations January 1995–December 2005

	Excess Returns				
	Arbitrage	Convertible Bonds	Diversified	High-Yield	Mortgage-Backed
Total	0.624	0.622	0.486	0.788	0.663
Arbitrage		0.075	0.153	0.449	0.535
Convertible Bonds			0.029	0.537	0.102
Diversified				0.294	0.195
High-Yield					0.421
	Adjusted Returns				
	Arbitrage	Convertible Bonds	Diversified	High-Yield	Mortgage-Backed
Total	-0.033	0.065	-0.055	0.732	0.590
Arbitrage		0.127	-0.015	0.008	-0.026
Convertible Bonds			-0.113	-0.012	0.235
Diversified				-0.041	-0.065
High-Yield					0.306

EXHIBIT 3
***Index* Factors Excess Monthly Returns January 1995–December 2005**

	Mean Return	Std Dev Return	Info Ratio	Standard Deviation 95 – 97	98 – 01	02 – 05	Autocorrelation First	Second
SP500	0.686	4.350	0.158	3.260	5.283	3.919	-0.011	-0.020
DJIA	0.735	4.445	0.165	3.602	5.304	3.998	-0.068	-0.019
NASDAQ	0.981	7.970	0.123	4.642	11.282	5.745	0.042	0.005
Russell 2000	0.598	5.619	0.106	3.893	6.999	5.213	0.077	-0.071
Wilshire 5000	0.557	4.421	0.126	3.122	5.551	3.896	0.036	-0.044
SP Barra Growth	0.653	4.800	0.136	3.603	6.208	3.746	-0.011	0.027
SP Barra Value	0.710	4.373	0.162	3.088	5.144	4.295	0.009	-0.039
MSCI World	0.465	4.068	0.114	3.024	4.865	3.902	0.034	-0.040
Nikkei	-0.045	5.027	-0.009	5.042	5.398	4.476	0.171*	0.114
FTSE	0.503	3.851	0.131	2.677	4.286	4.119	0.038	-0.004
EAFE	0.315	4.250	0.074	3.541	4.805	4.149	0.063	-0.062
MSCI AAA	0.268	1.175	0.228	0.902	0.943	1.527	0.067	-0.169
MSCI 10 Yr +	0.376	2.414	0.156	1.802	2.074	3.053	0.044	-0.248*
MSCI WrldSovEx-US	0.175	2.496	0.070	2.519	2.428	2.502	0.182*	0.035
UBS AAA / AA	0.476	3.153	0.151	2.582	4.595	1.019	0.032	-0.209*
UBS sub BBB / NR	0.851	5.500	0.155	2.748	7.995	3.818	0.066	0.069
UBS Conv. Global	0.409	3.089	0.132	2.466	4.200	2.101	0.074	-0.031
Lehman US Aggregate	0.276	1.078	0.256	1.162	0.907	1.178	0.087	-0.151
Lehman US CredBond	0.325	1.382	0.235	1.487	1.134	1.526	0.051	-0.158
Lehman Mortg-Backed	0.263	0.794	0.332	0.922	0.702	0.781	0.127	-0.080
Lehman US Hi Yield	0.323	2.073	0.156	0.972	2.344	2.271	0.150	-0.028
Lehman US Govt	0.261	1.257	0.208	1.216	1.099	1.441	0.075	-0.156
Lehman US Corp IG	0.322	1.401	0.230	1.487	1.140	1.568	0.051	-0.167
JPM Global Eurobond	0.637	3.102	0.205	2.059	4.356	2.128	-0.112	-0.019
JPM Global Brady	1.060	4.260	0.249	4.373	5.181	2.991	-0.052	-0.093
GS Commodity Index	0.521	5.938	0.088	3.987	6.289	6.571	0.014	-0.195*
DJ Spot Commodity	0.419	3.901	0.107	2.611	4.374	3.945	0.014	-0.141
DJ Gold	-0.297	3.833	-0.078	2.717	3.914	4.119	-0.091	-0.113
DJ Silver	0.064	6.808	0.009	6.336	6.607	7.271	-0.209*	-0.073
Wrld Ex-US Real Est.	0.510	5.388	0.095	5.281	6.673	3.659	0.114	0.003
U.S. Real Estate	1.036	4.544	0.228	3.657	5.118	4.343	-0.054	0.036
CME Yen Futures	-0.376	3.648	-0.103	3.844	4.438	2.391	0.007	0.091
NYBOT Dollar Index	-0.270	2.178	-0.124	2.158	2.198	2.168	0.073	-0.040
NYBOT Orange Juice	0.160	8.570	0.019	8.455	9.316	7.958	-0.245*	0.152
% change VXN	0.431	14.007	0.031	9.722	17.978	12.048	-0.112	-0.050
% change VIX	0.906	16.798	0.054	17.180	18.773	14.496	-0.170	-0.042

* Significant at 5% level

In addition to the *Index* factors, *Ken French* factors, and *Directional* factors, we use various interest rates, the difference in returns of various fixed income indices with respect to each other and to the U.S. T-bill rate, and the *changes* in these differences. For interest rates we use the U.S. Corporate Baa rate, the FHLMC 30 year mortgage rate and the U.S. 10 year Treasury rate. In addition, for the differences we use the MSCI world sovereign ex U.S. return less the U.S. T-bill rate and the Lehman high-yield return less the U.S. T-bill rate. In addition, we also create factors based on the changes that occur in these differentials. We should note that the interpretation of the factor correlations depends critically as to whether we use a difference in an index *return* or a difference in *yield*. The sign

EXHIBIT 4

***Ken French* Factors Excess Monthly Returns January 1995–December 2005**

	Mean Return	Std Dev Return	Info Ratio	Standard Deviation 95 – 97	98 – 01	02 – 05	Autocorrelation First	Second
SMB	-0.088	4.214	-0.021	3.046	5.917	2.637	-0.062	0.006
HML	0.110	3.798	0.029	2.393	5.587	2.115	0.038	0.036
Low	0.615	5.861	0.105	4.180	7.597	4.938	0.072	-0.079
High	1.039	4.110	0.253	2.654	4.482	4.605	0.184*	-0.054
Big	0.778	4.089	0.190	2.989	4.764	4.017	0.031	-0.049
Small	1.003	5.701	0.176	3.915	7.124	5.299	0.120	-0.077
Momentum	0.588	5.503	0.107	2.211	7.632	4.724	-0.076	-0.095
Europe High BM	1.128	5.829	0.194	3.761	6.600	6.340	0.088	-0.031
Europe Low BM	0.581	4.688	0.124	3.325	5.725	4.376	0.051	0.016
UK High BM	0.719	5.013	0.143	2.797	5.611	5.642	0.089	-0.140
UK Low BM	0.566	3.763	0.150	2.642	4.256	3.846	0.107	0.056
Pacific Rim High BM	0.764	7.032	0.109	5.440	9.136	5.098	0.117	-0.049
Pacific Rim Low BM	-0.277	5.450	-0.051	5.365	6.426	4.190	0.135	-0.007
Japan High BM	0.829	8.125	0.102	6.161	10.358	6.374	0.080	-0.066
Japan Low BM	-0.430	6.097	-0.071	5.935	7.007	5.077	0.136	-0.013
Non Durable	0.605	3.970	0.152	3.266	4.726	3.453	0.092	-0.046
Durable	0.425	6.261	0.068	3.676	7.871	6.073	0.055	-0.191*
Manufacturing	0.636	4.502	0.141	3.250	5.673	3.935	0.017	-0.033
Energy	1.109	5.304	0.209	3.390	6.256	5.478	-0.082	-0.045
HiTech	0.973	9.059	0.107	6.183	12.062	7.290	-0.009	-0.015
Telcom	0.250	5.820	0.043	3.733	6.638	6.175	0.068	-0.003
Shops	0.714	4.847	0.147	3.769	5.943	4.389	0.053	-0.152
Health	0.856	4.368	0.196	4.048	5.132	3.477	-0.100	0.073
Utilities	0.711	4.400	0.161	3.126	5.097	4.506	0.031	-0.076
Other	0.975	4.838	0.202	3.616	6.166	3.925	0.001	-0.089

* Significant at 5% level

of a correlation or a regression coefficient will have opposite interpretations in these two cases.

Non Linear Factors

Finally, we create a set of risk factors that attempt to model the nonlinear exposures that many hedge funds may face. That is, many hedge funds may produce after-fee option-like payoffs through the direct use of derivative products, through dynamic trading strategies, and/or through the nonlinear fee structure that is standard within the industry. We define this third category of risk exposures as the *Trading Strategy* factors.

To model the *Trading Strategy* factors, we create pseudo option-like payoff profiles for a subset of the *Index* factors. That is, for some (but not all) of the *Index* factors, we create a return series for a hypothetical at-the-money call and put option, a call and put option with exercise price set one-half standard deviations out-of-the-money from the current price of the underlying asset (defined as "shallow" out-of-the-money), and a call and a put option with exercise price set one full standard deviation out-of-the-money from the current price of the underlying asset (defined as "deep" out-of-the-money). For each of the *Index* factors used for this part, we create the payoffs for three call options and three put options.[8] We assume that each option has one month to maturity, is held for one month and if it expires out of the money, the return is −100%. We use the trailing 24 month standard deviation as the estimate for volatility. The payoff to the short position is assumed to be the inverse of the long.

Because many of the *Index* factors are highly correlated, we choose only to use a subset of the original *Index* factors to construct the *Trading Strategy* factors. Specifically, we create pseudo option returns for the following 12 factors: S&P 500, NASDAQ, EAFE, Nikkei, JPM Global diversified Eurobonds, UBS Convertible Bond Global index, UBS sub BBB and NR Convertible Bond index, Goldman Sachs Commodity Index, DJ AIG-Gold Sub Index, U.S. Real Estate Index, FINEX U.S. dollar index and the VIX index. We feel confident that this subset adequately spans the payoffs to options on the remaining *Index* factors.

We use the *Index* factors, *Ken French* factors, *Interest Rate* factors, *Directional* factors, and *Trading Strategy* factors as potential candidates to explain the risk exposures of the fixed income hedge fund indices. Clearly, these risk factors are highly correlated with each other and since we have chosen this many we may find a spurious relation between one or more of the risk factors and the hedge fund returns. Because of the high contemporaneous correlation among the candidate risk factors, simultaneous inclusion of even a fairly small subset may lead to extreme circumstances of multicollinearity. Moreover, having a large number of potential risk factors from which to choose may allow us to construct a mapping with an unrealistically high r-square—due not to any true underlying relation but instead to sheer statistical chance.

In order to overcome this potential dilemma, we follow the procedure outlined in Agarwal and Naik [2001]. We use stepwise regressions to determine the underlying risk factors to the hedge fund returns.[9] For each of the hedge fund indices, we attempt two types of mappings. First, as a conservative benchmark we use only the *Index* factors, *Ken French* factors, and *Interest Rate* factors as potential underlying risk factors. In the second stage we also include *Directional* factors and *Trading Strategy* factors. This will allow us to determine the incremental benefit to including directional and non-linear payoff structures as potential underlying risk exposures.

Before we actually conduct the regressions to do the mappings we make one final adjustment to the factors. Because the factors exhibit strong characteristics of time-varying volatility (see Exhibit 3 and Exhibit 4), we scale (divide) each return by its trailing 24 month standard deviation before we include the factor in the regression.[10] This should eliminate most concerns about heteroscedasticity in the resulting error terms to provide a more accurate fitting.[11]

Value-at-Risk Analysis

After we have completed the mappings, we are ready to proceed with the value-at-risk analysis for the individual hedge fund indices. We will estimate the value-at-risk using five different methodologies in order to determine a range of possible risk profiles. First, and most basically, we will use the actual historical adjusted excess returns of each hedge fund to simulate possible distributions for six-month and one-year excess returns. That is, we will randomly select the adjusted historical monthly returns (with replacement) to produce a total six-month and one-year excess return. We do this 50,000 times for the individual hedge fund indices in order to construct a distribution of possible returns.

One potential weakness to this approach is that this estimate of risk is only representative of future risk to the extent that the historical distribution of hedge fund returns is stable into the future. Given that the risk distributions of the actual underlying assets are not static, the assumption for the stability at the hedge fund level might be described as tenuous at best. Moreover, this situation is compounded by the fact that the trading style of the hedge fund manager is likewise fluid.

We have two motivations for mapping hedge fund returns onto physical, underlying assets. The first is that the mappings allow us to gain greater insight into the true risk profile underpinning hedge fund returns. While this level of analysis is indeed useful, our primary aim is to estimate the future risk distribution of the hedge fund. Given the weaknesses with simulating the hedge fund's actual historical returns, one possible approach is to randomly simulate the mapped factors with their given sensitivities to hedge fund returns. This potentially provides a greater historical perspective as the history of factor returns is substantially longer than the history of hedge fund returns.

For example, assume that we find the relation between the returns to the *Arbitrage* index and its factors is as follows:

$$\text{Return} = 0.005 + 0.25 * [\text{S\&P } 500] + (-0.50) * [\text{EAFE}]$$

with a standard error of 0.02.

Instead of randomly simulating the actual historical (adjusted, excess) returns of the *Arbitrage* index, we could randomly select the historical returns of the S&P 500 index and the EAFE index and multiply these returns by the factor sensitivities given in equation (32).[12] Since our regression equation does not perfectly fit the *Arbitrage* returns, we will need to add a residual component with a standard deviation of 0.02. If we assume that the errors have a normal distribution then we would simply use a random number generator to produce a standard normal random variate and then multiply that number by 0.02. So, to be perfectly clear if we randomly select an S&P 500 return of 4%, an EAFE return of 6%, and our random number generator gives us a value of 1.01 then the simulated return for month *t* from equation (3) would be:

$$\begin{aligned}\text{Return} &= 0.005 + 0.25 * [0.04] + (-0.50) * [0.06] \\ &\quad + 0.02 * 1.01 = 0.0052 \\ &= 0.52\%\end{aligned}$$

The value-at-risk literature quite commonly assumes assets and portfolios to possess fat tails—that returns at the extreme are more common than that estimated by a normal distribution. This is particularly the case for hedge funds that trade in markets with questionable liquidity. Unfortunately, the fund managers of *Long-Term Capital Management* found to their chagrin that markets that might appear as highly liquid in most circumstances may dry up at the most inopportune of times. If we assume the error distribution has this characteristic of fat-tails, we might more reasonably estimate the true value-at-risk during times of market turmoil.[13] In order to estimate risk with fat-tails we also conduct historical simulations using mapped factor returns and assuming the error distribution has a Student-t distribution with 4 degrees of freedom.[14] The Student-t distribution is symmetric like the normal but provides a greater probability for extreme events. In order to conduct this fat-tailed simulation, we need only use a random variate from the Student-t distribution instead of a normal distribution. The calculation for the simulated mapped return is otherwise identical.

In the end, we conduct five estimations of value-at-risk for each of the hedge fund indices. For each mapping (*Index* factors and *Ken French* factors, and *Index, Ken French, Directional,* and *Trading Strategy* factors) we conduct two types of simulations—one using a normally distributed error term and one using an error term with Student-t distribution. For each estimation, we will randomly generate six-month and one-year returns 50,000 times. In addition to the mapped simulations, as previously stated we estimate the value-at-risk using actual historical (adjusted, excess) returns.

II. MAPPING RESULTS

In this section, we describe the results from the mapping our full set of factors into the hedge fund returns.[15] We use the step-wise regression procedure as in Agarwal and Naik [2001] to determine the underlying risk factors for each of the hedge fund styles. All of the results for this section are presented in Exhibit 5. In this section, we also report a measure of the goodness of fit during two subperiods in-sample, 1995–2000 and 2001–2005. The measure we will use is straightforward:[16]

$$\text{sub-period r-square} = 1 - \frac{\text{residual sum of squares in sub-period}}{\text{total sum of squares in sub-period}}.$$

Note that, unlike with the total r-square, the sub-period r-square may take on values less than zero for various sub-periods if the regression is conducted over the entire time period.[17]

All the results that follow are detailed in Exhibit 5. In general, we found the most important risk factor to be the return on high-yield debt. However, we did find that using the non-linear factors resulted in marginal increases in explanatory power for some of the hedge fund styles.

Total

Exhibit 5 clearly shows that the most significant factors relating to the *Total* style are returns to Lehman U.S. High Yield and the UBS Convertible Global indices and negatively related to a short position in the Yen. A short position in the Yen may indicate a strategy of shorting Japanese bonds whilst simultaneously going long in U.S. High Yield. Given the differentials in yields between these two currencies, perhaps this result is not surprising. The results for the different sub periods are reasonably consistent with adjusted R squares over 42%. The inclusion of the short put position on the Nasdaq offers marginal increase in explanatory power with the R square being 60.1% for index factors and 63.7% with the inclusion of non linear factors.

Arbitrage

It is somewhat difficult to interpret the results of Exhibit 5 for the *Arbitrage* style. We find evidence of a negative exposure to directional SP Barra Growth

Exhibit 5

Mapping of Hedge Fund Indices Using All Factors January 1995–December 2005

Total		Arbitrage		Convertible Bonds	
Constant	0.067	Constant	0. 859	Constant	0.938
	[0.53]		[3.59]		[3.45]
Lehman US Hi Yield	0.625	SP Barra Growth Dir +	-1.026	UBS sub BBB / NR	1.578
	[7.01]		[-3.48]		[6.01]
UBS Conv. Global	0.536	SP Barra Growth	0.660	Healthcare	-1.081
	[4.98]		[2.34]		[-4.21]
CME Yen Futures	-0.322			NIKKEI Dir –	0.848
	[-3.67]				[4.06]
Healthcare	-0.302			SP500	1.121
	[-3.35]				[3.49]
NIKKEI Dir +	0.222			NYBOT Dollar Index	0.600
	[2.84]			Call Deep	[3.41]
NASDAQ Put Deep	-0.005			Lehman US Hi Yield	0.695
	[-2.49]				[3.32]
T-bill	-0.011			Momentum	-0.504
	[-2.48]				[-2.90]
UBS AAA / AA	0.213				
	[2.39]				
Adjusted R-sqd:		Adjusted R-sqd:		Adjusted R-sqd:	
1995-2005	0.637	1995-2005	0.089	1995-2005	0.721
1995-2000	0.702	1995-2000	0.099	1995-2000	0.697
2001-2005	0.419	2001-2005	-0.035	2001-2005	0.709

Diversified		High-Yield		Mortgage-Backed	
Constant	0.356	Constant	0. 481	Constant	0. 736
	[4.17]		[3.50]		[2.99]
Change in Mortgage	-0.913	Lehman US Hi Yield	1.631	Chg 10YrTreas	1.960
	[-6.12]		[13.73]		[5.16]
Chg 10YrTreas – T-bill	0.692	T-bill	-0. 040	Lehman Mortg-Backed	1.398
	[4.66]		[-4. 69]		[4.93]
Chg Leh.HiYld – T-bill	-0.321	MSCI 10YR	-0. 453	Change in Mortgage	-1.220
	[-3.93]		[-4.02]		[-3.46]
JPM Global Eurobond	0.264	EAFE	0.296	Lehman US Hi Yield	0.519
Call Shallow	[3.10]		[2.77]		[3.24]
Change in T-bill	0.326	JPM Global Eurobond	-0.066	Lehman US Aggregate	-0.868
	[2.96]	Put Deep	[-2.76]	Dir +	[-3.03]
DJ Gold	-0.188			EAFE Call Shallow	-0.394
	[-2.42]				[-2.29]
Adjusted R-sqd:		Adjusted R-sqd:		Adjusted R-sqd:	
1995-2005	0.343	1995-2005	0.733	1995-2005	0.355
1995-2000	0.373	1995-2000	0.762	1995-2000	0.397
2001-2005	0.254	2001-2005	0.641	2001-2005	0.135

t-statistics are in parenthesis

Dir+ and positive exposure to SP Barra Growth. Explanatory power for the sub periods and the whole period are weak and inconsistent. Fung and Hsieh [2002b] reported results for each of the first two principal components to this style for the HFR index and found the first principal component to be well explained by the difference between high yield and treasury returns. They found the second principal component to be somewhat explained by the difference between convertible bond less treasury returns. Though not reported here we did find the *Arbitrage* style is most highly positively correlated (0.19) with the spread between ten year government bonds and Tbills and the spread between mortgage yields and T-bills (0.15). This would suggest a strategy of investing in long bonds whilst simultaneously shorting T-bills. Ilmanen [1995] has shown that high spreads usually leads to out performance of long bonds relative to T-bills. However, the regression results do not seem to be picking up this relationship. Consistent with Fung and Hsieh [2002b], we do not believe that adding non-linear factors to this hedge fund style provides any improvements in explanatory power.

Convertible Bonds

We find the dominant factor for *Convertible Bonds* to be a long position on the UBS sub investment grade convertible bond index. This is consistent with the findings of Fung and Hsieh [2002b] who found that the convertible index was highly correlated with the HFR *Convertible Bonds index.* Other significant factors were: a short position on the health care index, a long position on the Nikkei Dir-, a long position on the SP500, a deep call on the NYBOT Dollar index and long position on Lehman U.S. High Yield. Explanatory power is consistent across sub periods and approximates to 70%.

Diversified

The *Diversified* style as described in the HFR website represents a variety of fixed income strategies and may represent multiple strategies. In this case we find the most significant factor to be negative changes in mortgage rates. Additional significant factors include positive changes in the spread between 10 year government bonds and T-bills and negative changes in High yield and T-bills. This may indicate taking long positions in Mortgage-Backed/High yield securities and shorting Treasuries. As mentioned previously high spreads typically leads to out performance of long bonds relative to T-bills. The inclusion of a long call position of Euro bonds marginally increases the R squares from 34.3% to 35.9%.

High Yield

A number of factors enter quite strongly in this style. The return on high-yield debt is by far the most dominant factor. This is followed by short positions in T-bills and MSCI 10 year bonds. This suggests a strategy of taking a long position in high yield debt and shorting T-bills and 10 year bonds. A deep put position in global Euro bonds though being significant adds little explanatory power. Explanatory power is very consistent across sub periods and ranges from 64% to 76%.

Mortgage-Backed

The most significant factors in relation to *Mortgage-Backed* style are, changes in 10 year Treasury Yields, Lehman Mortgage-Backed index, Changes in Mortgage rates and Lehman U.S. High yield index. These factors are consistent with those of Fung and Hsieh [2002b]. Similar to *High Yield,* this suggests taking a long position in Mortgage-Backed/High Yield securities. As with other investment styles the inclusion of short position in options adds marginal improvement in explanatory power. Explanatory power overall is 35.5%, but this has tapered off from 39.7% from 1995–2000 to 13.5% from 2001–2005.

III. VALUE-AT-RISK ANALYSIS

As previously stated, we conduct five different value-at-risk estimations with each built from 50,000 simulations. Four of the estimations are based upon the two mappings: *Index, Ken French,* and *Interest-rate; Index, Ken French, Interest-rate, Directional,* and *Trading Strategy.* For each mapping one estimation will assume normally distributed errors and a second estimation will assume errors with a Student-t (degrees of freedom = 4) distribution.

Before we present the results for the individual hedge fund styles, we would like to present as a benchmark the value-at-risk for various *Index* and *Ken French* factors. This estimation is based solely upon historical monthly returns from January, 1995 through December, 2005. We build our value-at-risk estimates for the *Index* factors by randomly selecting with replacement monthly returns to build up a total six-month and one-year return. This process is repeated 50,000 times for each *Index* factor.

Exhibit 6 presents the value-at-risk estimations for excess returns (relative to the yield on a U.S. T-bill) for 29 of the 40 *Index* factors. Exhibit 7 contains the value-at-risk estimates for the *Ken French* factors. In general, as we would expect we find the bonds to have the safest level of value-at-risk, followed by real estate, equities, and then commodities. The safest of all the *Index* factors is the Lehman Brothers U.S. Mortgage-Backed index with a one-year, one percent value-at-risk estimate of only 3.3 percent. On the opposite end of the risk spectrum lie the Nasdaq, DJ Silver NYBOT orange juice indices with one-year, one percent value-at-risk levels being approximately 45%.

We are now ready to proceed with the value-at-risk estimates for the individual hedge fund styles. The risk levels of the styles should be compared directly back to Exhibit 6 and Exhibit 7 which give downside risk estimates to the factors. Exhibit 8 gives the value-at-risk estimates for every hedge fund style. In the following discussion we will only focus on the 1% VAR for the one year horizon.

Total

In relation to the 1% VAR of the *Total* style it appears there is little difference in VAR no matter whether we use index factors or all factors. However, using Student-t errors does increase the downside risk estimates. The VAR measures based on normally distributed errors are very close to the historical VAR. Recall that this style is the aggregation of all fixed income strategies and that the correlations between *Total, Arbitrage, Convertible* and *Diversified* are approximately zero and it is not surprising that the VAR of *Total* is substantially lower than the VAR of U.S. high yield which was the dominant factor in the mappings. The Lehman U.S. High Yield index has a VAR of 13.6% whilst the VAR of the *Total* style was approximately 8.0%.

Arbitrage

For this style, the VAR varies quite substantially depending upon whether we assume the residuals are normally distributed or follow a Student-t distribution. Based on the normal distribution, the VAR estimate of 11% is much lower than the 16% obtained when the Student-t distribution is used. By way of comparison, the historical VAR is 13.1%. These VAR estimates are substantially higher than any of the VAR estimates of the Lehman bond indices, apart from the Lehman U.S. High Yield index. However in interpreting these factor VAR estimates, remember that the explanatory power of the factor regressions were of the order of only 9% over the whole period.

Convertible Bonds

The VAR estimates for *Convertible Bonds* are quite substantial. The simulated VAR estimates range from 23% to 34% compared to the historic VAR of 23.4%. Recall from Exhibit 6 that the 1% VAR of the UBS sub investment grade convertible bond index was 31% which is within the range of the simulated VAR measures. Using errors generated from a Student-t distribution produced much larger VAR estimates compared to the normal distribution. Conversely, the addition of non linear factors only slightly changed these estimates. The VAR estimates of *Convertible Bonds* were the highest of the fixed income strategies reviewed.

Diversified

Across all styles, *Diversified* appears to be the safest and one of the stronger performing hedge fund styles. Downside risk estimates are safer than those for the *Total* style and far safer than those for the remaining styles. In fact, this should not be surprising given that this strategy was documented to be one of the safest in Exhibit 1 and required no adjustment due to autocorrelation in original returns. As with the other indices, we find no evidence that including the non-linear factors leads to substantially different estimates for value-at-risk. However, using Student-t errors increased the order of magnitude of VAR estimates by about one-half. Factor VAR estimates ranged between 4.9% to 7.7% compared with the historical VAR of 4.28%.

High Yield

Recall that the dominant factor for this style was the Lehman U.S. High Yield index. The mappings from this style produced the highest R squares of any style and it is not unexpected that the VAR should be similar to the VAR of the High Yield index. Generally the estima-

Exhibit 6

Index **Factors Value-at-Risk Estimation**

Index Factors	Six Month Analysis					One Year Analysis				
50,000 simulations	Mean	Std Dev	Min	1 Percentile	5 Percentile	Mean	Std Dev	Min	1 Percentile	5 Percentile
SP500	4.14	11.08	-41.62	-21.34	-14.16	8.61	16.28	-59.99	-26.48	-17.20
DJIA	4.49	11.30	-37.09	-21.52	-13.85	9.13	16.61	-45.04	-26.74	-17.01
NASDAQ	6.01	20.55	-63.31	-36.90	-25.87	12.59	31.05	-72.62	-45.67	-32.36
Russell 2000	3.66	14.12	-48.17	-28.10	-19.08	7.49	20.79	-58.51	-35.15	-24.47
Wilshire 5000	3.38	11.14	-41.97	-22.99	-15.09	6.78	16.30	-49.58	-28.91	-19.00
SP Barra Growth	3.98	12.20	-42.92	-23.34	-15.84	8.13	17.88	-49.04	-29.55	-19.78
SP Barra Value	4.26	11.09	-41.25	-21.58	-14.18	8.77	16.43	-53.19	-26.89	-17.33
MSCI World	2.86	10.13	-37.28	-20.48	-13.95	5.68	14.87	-47.04	-26.52	-17.88
Nikkei	-0.27	12.30	-39.46	-25.66	-19.20	-0.52	17.44	-55.03	-34.62	-26.53
FTSE	3.10	9.68	-36.62	-20.05	-13.21	6.08	14.15	-44.94	-25.25	-16.75
EAFE	1.96	10.55	-37.70	-21.70	-15.29	3.83	15.21	-47.79	-28.58	-20.03
MSCI AAA	1.61	2.89	-11.21	-5.52	-3.28	3.32	4.16	-15.68	-6.70	-3.58
MSCI 10 Yr +	2.25	6.01	-26.04	-11.48	-7.48	4.55	8.65	-27.97	-14.52	-9.21
MSCI WrldSovEx-US	1.09	6.17	-19.85	-12.09	-8.48	2.13	8.80	-29.11	-16.24	-11.43
UBS AAA / AA	2.91	7.91	-29.43	-14.38	-9.15	5.86	11.51	-33.11	-18.03	-11.54
UBS sub BBB / NR	5.14	13.99	-46.69	-24.88	-16.41	10.74	20.95	-53.15	-30.96	-20.43
UBS Conv. Global	2.52	7.69	-30.30	-14.98	-9.86	5.04	11.11	-33.66	-19.22	-12.48
Lehman US Aggregate	1.68	2.66	-10.64	-4.79	-2.75	3.36	3.85	-13.45	-5.67	-3.03
Lehman US CredBond	1.96	3.44	-13.02	-6.21	-3.75	3.98	4.94	-16.72	-7.39	-4.14
Lehman Mortg-Backed	1.58	1.96	-6.68	-3.03	-1.67	3.19	2.82	-8.38	-3.33	-1.43
Lehman US Hi Yield	1.95	5.16	-21.86	-10.92	-6.85	3.92	7.40	-26.43	-13.62	-8.28
Lehman US Govt	1.57	3.09	-12.37	-5.83	-3.61	3.22	4.48	-16.42	-7.25	-4.13
Lehman US Corp IG	1.96	3.47	-14.09	-6.29	-3.76	3.93	5.00	-16.16	-7.40	-4.18
JPM Global Eurobond	3.92	7.79	-55.04	-22.36	-9.49	7.95	11.50	-52.10	-24.22	-14.75
JPM Global Brady	6.50	11.01	-56.56	-26.23	-13.46	13.58	16.60	-57.95	-28.46	-15.67
GS Commodity Index	3.07	14.99	-46.01	-27.25	-19.50	6.42	21.87	-55.05	-35.54	-25.53
DJ Spot Commodity	2.51	9.68	-31.04	-17.62	-12.36	5.12	14.14	-39.37	-23.43	-16.18
DJ Gold	-1.78	9.17	-32.12	-19.89	-15.35	-3.41	12.98	-40.82	-28.67	-22.42
DJ Silver	0.32	16.74	-59.59	-35.01	-25.38	0.72	23.93	-66.21	-44.98	-34.00
Wrld Ex-US Real Est.	3.06	13.56	-48.54	-27.02	-18.25	6.33	19.89	-58.63	-34.24	-23.89
U.S. Real Estate	6.39	11.75	-40.68	-20.65	-12.96	13.18	17.70	-50.12	-25.02	-14.59
CME Yen Futures	-2.20	8.77	-29.90	-19.64	-15.05	-4.31	12.18	-44.91	-27.68	-21.94
NYBOT Dollar Index	-1.60	5.25	-22.60	-13.34	-10.05	-3.22	7.29	-34.18	-19.07	-14.77
NYBOT Orange Juice	1.00	21.29	-57.55	-38.29	-29.14	2.03	30.55	-70.69	-49.86	-38.97
% change VXN	2.76	36.15	-73.61	-54.07	-43.30	5.23	53.08	-85.50	-67.36	-55.56
% change VIX	5.65	44.07	-76.47	-58.28	-47.31	12.03	69.86	-86.79	-71.64	-60.50

EXHIBIT 7
***Ken French* Factors Value-at-Risk Estimation**

Index Factors	Six Month Analysis					One Year Analysis				
50,000 simulations	Mean	Std Dev	Min	1 Percentile	5 Percentile	Mean	Std Dev	Min	1 Percentile	5 Percentile
SMB	-0.61	10.18	-42.61	-22.86	-15.87	-1.00	14.45	-51.12	-30.39	-22.33
HML	0.69	9.32	-39.74	-20.33	-14.24	1.37	13.34	-45.79	-27.08	-19.29
Low	3.75	14.78	-51.59	-28.96	-20.08	7.71	21.89	-60.66	-36.76	-25.56
High	6.40	10.58	-41.02	-19.46	-11.52	13.26	15.95	-44.14	-22.32	-12.60
Big	4.76	10.39	-40.17	-19.65	-12.42	9.84	15.57	-46.22	-24.25	-14.87
Small	6.17	14.74	-50.31	-27.05	-17.59	12.68	22.00	-63.89	-32.26	-20.92
Momentum	3.58	14.01	-55.56	-30.78	-19.82	7.26	20.49	-71.12	-37.11	-25.05
Europe High BM	7.00	15.04	-47.39	-26.97	-17.23	14.51	22.83	-61.02	-32.74	-20.45
Europe Low BM	3.54	11.86	-43.21	-23.20	-15.87	7.33	17.28	-49.18	-29.02	-19.33
UK High BM	4.38	12.76	-43.87	-23.72	-15.94	9.01	18.82	-52.34	-29.72	-19.70
UK Low BM	3.48	9.46	-29.40	-17.26	-11.61	7.02	13.92	-43.39	-22.06	-14.6
Pacific Rim High BM	4.72	17.84	-46.74	-28.52	-20.81	9.41	26.51	-56.21	-37.37	-27.18
Pacific Rim Low BM	-1.55	13.11	-43.28	-28.58	-21.78	-3.4	18.43	-57.82	-39.22	-30.85
Japan High BM	5.08	20.86	-48.08	-32.20	-23.91	10.64	31.51	-63.89	-42.09	-31.02
Japan Low BM	-2.40	14.64	-45.62	-31.32	-24.53	-5.08	20.27	-58.91	-43.02	-34.44
Non Durable	3.67	10.00	-36.73	-19.14	-12.66	7.45	14.74	-46	-24.43	-15.76
Durable	2.58	15.65	-60.95	-31.35	-22.12	5.21	22.89	-69.3	-40.26	-28.69
Manufacturing	3.87	11.35	-41.43	-22.14	-14.46	7.87	16.78	-47.37	-27.59	-18.31
Energy	6.76	13.71	-37.26	-20.68	-13.68	14.17	20.84	-44.97	-25.2	-16.16
HiTech	6.17	23.57	-62.84	-40.84	-29.68	12	35.59	-74.08	-51.55	-37.97
Telcom	1.53	14.47	-47.10	-29.13	-20.96	3.04	20.92	-58.81	-37.39	-27.9
Shops	4.28	12.25	-44.81	-22.89	-15.32	8.99	18.11	-47.9	-28.31	-18.9
Health	5.20	11.09	-36.05	-19.79	-12.72	10.81	16.73	-39.44	-24.16	-15.37
Utilities	4.35	11.14	-35.40	-20.76	-13.74	8.85	16.5	-43.98	-25.84	-16.83
Other	5.97	12.49	-43.75	-23.61	-14.74	12.4	18.69	-54.69	-27.79	-16.98

Exhibit 8
Value-at-Risk Estimation: Hedge Fund Returns

50,000 simulations			Six Month Analysis Mean	Std Dev	Min	1 Percentile	5 Percentile	One Year Analysis Mean	Std Dev	Min	1 Percentile	5 Percentile
Total	Index, French, Interest	Normal	2.12	3.53	-13.66	-6.26	-3.68	4.33	5.07	-16.14	-7.34	-3.95
		T-dist	2.18	4.14	-33.19	-7.47	-4.49	4.36	6.03	-36.25	-9.56	-5.31
	All	Normal	2.15	3.53	-12.91	-6.22	-3.66	4.35	5.09	-17.19	-7.36	-3.95
		T-dist	2.14	4.12	-24.79	-7.49	-4.58	4.32	5.92	-30.15	-9.27	-5.20
	Historical		2.12	3.48	-15.55	-6.85	-3.89	4.32	5.02	-18.36	-7.82	-4.03
Arbitrage	Index, French, Interest	Normal	0.84	3.95	-15.01	-8.05	-5.55	1.63	5.68	-20.55	-11.07	-7.43
		T-dist	0.80	5.49	-43.28	-12.17	-7.81	1.66	7.83	-87.14	-16.09	-10.56
	All	Normal	0.82	3.95	-16.87	-8.17	-5.58	1.68	5.65	-19.70	-11.01	-7.37
		T-dist	0.83	5.41	-51.92	-12.10	-7.68	1.67	7.74	-52.00	-15.87	-10.52
	Historical		0.83	3.88	-23.84	-10.37	-6.39	1.67	5.57	-28.20	-13.13	-8.11
ConvertibleBonds	Index, French, Interest	Normal	2.75	9.57	-30.65	-17.89	-12.27	5.74	13.96	-41.77	-23.14	-15.74
		T-dist	2.81	13.11	-100.00	-27.12	-17.35	5.79	19.13	-98.44	-34.25	-22.78
	All	Normal	2.88	9.67	-31.81	-18.55	-12.57	5.78	14.05	-44.68	-23.79	-16.05
		T-dist	2.86	12.57	-100.00	-25.59	-16.63	5.92	18.48	-78.03	-32.36	-21.79
	Historical		2.85	9.46	-33.71	-18.59	-12.33	5.64	13.73	-41.21	-23.37	-15.53
Diversified	Index, French, Interest	Normal	2.11	2.84	-9.48	-4.30	-2.52	4.22	4.07	-12.51	-5.00	-2.36
		T-dist	2.12	3.59	-27.30	-6.28	-3.60	4.24	5.19	-48.54	-7.66	-4.02
	All	Normal	2.09	2.83	-8.60	-4.40	-2.50	4.26	4.07	-10.97	-4.98	-2.35
		T-dist	2.10	3.60	-29.23	-6.43	-3.65	4.26	5.27	-50.60	-7.74	-4.10
	Historical		2.10	2.78	-9.14	-3.77	-2.20	4.23	4.00	-10.55	-4.28	-1.99
High-Yield	Index, French, Interest	Normal	1.85	5.29	-25.74	-11.31	-7.06	3.77	7.62	-29.43	-14.14	-8.78
		T-dist	1.84	5.91	-33.08	-12.50	-8.00	3.75	8.54	-35.93	-16.12	-10.08
	All	Normal	1.85	5.28	-21.80	-11.59	-7.26	3.80	7.60	-29.90	-14.47	-8.81
		T-dist	1.82	5.95	-33.49	-13.05	-8.20	3.74	8.55	-46.27	-16.14	-10.26
	Historical		1.88	5.25	-28.24	-13.81	-7.96	3.75	7.53	-33.26	-16.19	-9.77
Mortgage-Backed	Index, French, Interest	Normal	2.72	5.68	-20.06	-10.41	-6.51	5.50	8.25	-27.64	-12.76	-7.76
		T-dist	2.69	7.20	-68.53	-14.17	-8.77	5.51	10.43	-60.73	-18.10	-10.79
	All	Normal	2.70	5.65	-19.43	-10.07	-6.38	5.44	8.22	-25.31	-12.76	-7.69
		T-dist	2.69	7.21	-44.98	-13.80	-8.77	5.55	10.51	-72.24	-17.69	-10.85
	Historical		2.69	5.58	-39.27	-15.07	-9.43	5.49	8.10	-45.89	-18.01	-10.00

tion of the VAR from the mappings lies within the range of 14% to 16%. This closely matches the VAR of 13.6% of Lehman U.S. High Yield index.

Mortgage-Backed

This hedge fund category has outperformed all other styles excepting *Convertible Bonds* during the sample period. Assuming that the residuals were Student-t distributed generated VAR estimates similar to the historic VAR of 18%. This estimate is substantially higher than the VAR of the Lehman Mortgage-Backed index of 3.3%. Once again we find evidence that including non-linear payoffs marginally increases downside risk. It appears from these results that this hedge fund style is significantly more risky than just investing in mortgage-backed securities.

IV. CONCLUSION

In this article, we removed the effects of autocorrelation from reported returns that may arise due to smoothing to find, in theory, the true underlying returns. We apply this method to six different hedge fund indices in six different style—*Total, Fixed Income Arbitrage, Convertible Bonds Arbitrage, Diversified, High Yield* and *Mortgage-Backed*. After removing the autocorrelations from returns, we find increases in risk of between 37% and 64% for four of the individual indices. In particular, the autocorrelations were most severe for *High Yield* and *Mortgage-Backed* styles.

Using the adjusted return series we identify the underlying risk factors for the individual indices to facilitate comparison within each style. In fact, we find remarkable similarities across as well as within the individual hedge fund styles. The hedge fund indices have a very strong exposure to high-yield credit. The inclusion of non linear factors produced a marginal improvement of explanatory power of the risk factors.

Finally, we conduct value-at-risk analyses using the individual mappings onto risk factors. For some hedge fund styles we find a wide range of downside risk estimates. In addition, we find that the inclusion of non-linear factors only marginally changes the magnitude of the downside risk estimate. In summary we find that the VAR estimates for all styles are well approximated by the historical VAR estimates except for *Convertible Bonds*. For all styles, VAR estimates generated from the Student-t distribution are consistently higher than those based on a normal distribution and for the *Fixed Income Arbitrage, Convertible Bonds* and *Mortgage-Backed* styles the increase is quite substantial.

ENDNOTES

[1]Getmansky, Lo, and Makarov [2004] give an excellent overview and analysis of the potential sources of serial correlation in reported hedge fund returns.

[2]The September 2003 staff report to the SEC, "Implications of the Growth of Hedge Funds", estimated that hedge fund assets have grown from $50 billion in 1993 to $592 billion in 2003.

[3]As we will later show, value-at-risk estimations that do not make this adjustment will underestimate the true risk underlying the hedge fund returns.

[4]In an earlier version of this article the methodology of removal of any order of serial correlation is described, however for the sake of brevity in the current article this description has been removed. This information is available from the authors on request.

[5]We use returns adjusted to remove serial correlation. Fung and Hsieh [2002b] do not make use of the stepwise regression approach to determine their risk factors.

[6]Definitions for these hedge fund styles can be obtained from the HFR website. Total represents the equally weighted average of the five styles.

[7]For many individual hedge funds our method would be even more applicable as their serial correlation is even greater than that found at the index level.

[8]To maintain simplicity, we use simple Black-Scholes prices to determine the payoffs to the options. Since our goal is not to correctly price the option, but simply to correctly model behavior we do not expect that the option-pricing model used will materially affect the results. Agarwal and Naik [2001] and Mitchell and Pulvino [2001] find that the exact form of the option-pricing model does not materially affect the results.

[9]In a stepwise regression each potential independent factor is entered one at a time into a regression on hedge fund returns. The factor that produces the highest R^2 is then chosen. An F-test is conducted to determine if the selected factor is truly related to the hedge fund return. If the null of no incremental explanatory power is rejected, we proceed to then, one at a time, place each remaining factor in the regression with the already chosen factor. The risk factor that provides the greatest increase in R^2 is then selected and the process continues until the F-test on the final factor fails to reject the null of no incremental explanatory power.

[10]If we do not have data prior to the sample period, we use a fixed two year window for standard deviation during the first two years.

[11]Due to this scaling, the resulting regression coefficients will give the effect on hedge fund returns for each unit of standard deviation that the factor value exceeds a zero return. For example, a regression coefficient of 0.02 would imply that for each unit of standard deviation that the factor value exceeds zero, the hedge fund returns will experience a positive return of 2%.

[12]In order to maintain the correlation structure across factors, we actually will randomly select a row from the factor dataset and then use the S&P 500 return and the EAFE return on the same row.

[13]One valid counterpoint is that if we include historical returns during times of market turmoil, we have no further need to make adjustments for liquidity and other forms of fat-tail risk. Unfortunately, many fund managers have failed to fully appreciate that future market conditions might exhibit more extreme deterioration than that captured in historical datasets. We do not feel that the Asian crisis, the tech stock meltdown, or the poor performance of Japanese equities over the previous decade will adequately encompass the worst possible scenarios for what could transpire during the next 100 years. Making use of fat-tailed distributions allows us to model the unthinkable.

[14]The smaller the degrees of freedom, the fatter the tails produced by the Student-t distribution. Jorion [2000] recommends using a Student-t with 4 degrees of freedom. As the degrees of freedom approaches 30, the Student-t distribution will converge to a normal distribution.

[15]In the interests of brevity, we have not tabulated the mapping results where only the Index, Ken French and interest rate factors are used. These are available from the authors on request.

[16]We actually report the adjusted r-square which adjusts for the number of explanatory variables.

[17]If this is not clear, imagine running a regression using 1,000 data points and then calculating a sub-period r-square using only 5 of those data points. Clearly, the residual variance during those 5 days could be greater than the total variance over those 5 days. (This could occur if the 5 data points were all outliers, but with low in sub-sample total variance.)

REFERENCES

Agarwal, Vikas, and Narayan Naik. "Performance Evaluation of Hedge Funds with Option-Based and Buy-and-Hold Strategies." Working paper, London Business School, 2001.

——."Risks and Portfolio Decisions Involving Hedge Funds." *Review of Financial Studies,* Vol. 17, No. 1 (2004), pp. 63–98.

Fung, William, and David A. Hsieh. "Asset-Based Hedge Fund Styles and Portfolio Diversification." *Financial Analyst Journal,* Vol. 58, No. 5 (2002a), pp. 16–27.

——."The Risk in Fixed Income Hedge Fund Styles." *Journal of Fixed Income,* Vol. 12, No. 2 (2002b), pp. 6–27.

Getmansky, Mila, Andrew W. Lo, and Igor Makarov. "An Econometric Model of Serial Correlation and Illiquidity in Hedge Fund Returns." *Journal of Financial Economics,* Vol. 74 (2004), pp. 529–609.

Ilmanen, Antti. "Time-Varying Expected Returns in International Bond Markets." *Journal of Finance,* Vol. 50, No. 2 (1995), pp. 481–506.

Jorion, Philippe. "Risk Management Lessons from Long-Term Capital Management." *European Financial Management,* Vol. 6, No. 3 (2000), pp. 277–300.

Mitchell, Mark, and Todd Pulvino. "Characteristics of Risk and Return in Risk Arbitrage." *Journal of Finance,* Vol. 56, No. 6 (2001), pp. 2135–2175.