Preliminary – Comments Welcome

Hedge Fund Risk Factors and Value at Risk of Credit Trading Strategies

By

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Summary

This paper analyzes the risk characteristics for various hedge fund strategies specializing in fixed income instruments. Because fixed income hedge fund strategies have exceptionally high autocorrelations in reported returns and this is taken as evidence of return smoothing, we first develop a method to completely eliminate any order of serial correlation across a wide array of time series processes. Once this is complete, we determine the underlying risk factors to the "true" hedge fund returns and examine the incremental benefit attained from using nonlinear payoffs relative to the more traditional linear factors. For a great many of the hedge fund indices we find the strongest risk factor to be equivalent to a short put position on high-yield debt. In general, we find a moderate benefit to using the nonlinear risk factors in terms of the ability to explain reported returns. However, in some cases this fit is not stable even over the in-sample period. Finally, we examine the benefit to using various factor structures for estimating the value-at-risk of the hedge funds. We find, in general, that using nonlinear factors slightly increases the estimated downside risk levels of the hedge funds due to their option-like payoff structures.

I. Introduction

The fact that many hedge fund returns exhibit extraordinary 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 is easily camouflaged within a haze of illiquidity, stale prices, averaged price quotes and managed performance reporting.[1] Nevertheless, in spite of these difficulties large 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 hedge fund returns.

Several papers have examined the issue of serial correlation in reported hedge fund returns. Basically, these papers can be divided into two camps. On one side, attempts have been made to directly alter the reported returns themselves to moderate the influence of serial correlation. Papers that have taken this approach include Brooks and Kat (2001) and Kat and Lu (2002) and can be traced back to Geltner (1991, 1993) in the real estate literature. Unfortunately, the method employed in these papers is rather ad-hoc and, in fact, sometimes fails to adequately remove the serial correlation that exists for hedge funds operating in the most illiquid markets.[3]

The alternative, more econometrically rigorous, approach is to take the original hedge fund return series as given and attempt to modify the reported performance statistics such as the Sharpe ratio to control for the spurious serial correlation in reported returns. Papers that use this alternative method include Lo (2002) and Getmansky, Lo, and Makarov (2003). While this second method is theoretically appealing and can be of great benefit, some may still desire to examine the individual, period-by-period

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[1] Getmansky, Lo, and Makarov (2003) 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] Many hedge funds returns exhibit significant higher-order serial correlation. The current technology only acts to *approximately* remove the first-order serial correlation.

hedge fund returns. Unfortunately, the approach advanced by these papers does not provide guidance on how to do this.

While the exact method that one should use in order to remove the serial correlation from reported hedge fund returns depends upon the ultimate application, we believe that the first approach, suitably modified to remove any magnitude and any order of serial correlation, may prove more generally beneficial to those who wish to carefully analyze hedge fund performance. For instance, many papers 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, for example, Agarwal and Naik (2001, 2002) and Fung and Hsieh (2001b, 2002,)). 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.[4]

We have several purposes for this paper. First, neither Agarwal and Naik (2001, 2002) nor Fung and Hsieh (2001b, 2002) 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 realised 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 methodology 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 is at least 60 to 100 percent greater than that observed through reported returns. *Any* methodology that does not properly adjust for smoothing will severely underestimate the true, underlying risk level. We also believe that this process may have many applications beyond hedge fund research.

[4] 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.

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 paper, Fung and Hsieh (2002) 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 (2002), 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: *Convertible Arbitrage*, *Fixed Income Arbitrage*, *Credit Trading*, *Distressed Securities*, *Merger Arbitrage*, and *MultiProcess – Event Driven*.[6] For these hedge fund styles, we find alternative and, arguably, more reasonable risk factors than that identified in prior research. For example, Mitchell and Pulvino (2001) make a convincing case that the strategies underlying merger arbitrage are akin to holding a short put position on the value-weighted CRSP index. In fact, this is close to our result. We find merger arbitrage to be more closely explained by a short put position on high yield debt. In fact, we repeatedly find the short-put position on high-yield debt to be one of the most important explanatory factors across many of the hedge fund styles.

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.

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[5] We use returns adjusted to remove serial correlation. Fung and Hsieh (2002) do not make use of the stepwise regression approach to determine their risk factors. Finally, in addition to the HFR indices, we also analyze the FRM, CSFB, Hennessee, and Zurich indices.

[6] Definitions for these hedge fund styles are given in Appendix A.

Specifically, we conduct a very simple value-at-risk analysis using the mappings and compare the estimations when nonlinear exposures are either included or excluded. First, we find that in some cases the underlying risk factors may change quite dramatically over time – even within sample – for some hedge fund styles. We also find, as we would expect, that estimated downside risk exposures increase when we take into account nonlinearities.

The structure for the paper is as follows. In Section II, we will discuss the data used for this study – both the hedge fund and the factor returns. In Section III, we will discuss the methodology to eliminate any order of autocorrelation from a given return series, to map the hedge fund returns to factor exposures and to conduct the value-at-risk analyses. In Section IV, we will present the mapping results. In Section V, we will examine the value-at-risk for the various hedge fund styles. Finally, in Section VI, we will conclude with the overall findings and remaining issues of the paper.

II. Data

To examine the fixed-income hedge funds, we use returns from various indices taken from FRM (the MSCI indices), HFR, CSFB, Hennessee, and Zurich over the period January, 1994 through December, 2001. 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 Table 1.[8] 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 will show that these hedge fund styles are quite correlated and have many common underlying risk exposures.

Table 1 presents statistics on excess returns (to the U.S. T-bill) for the 21 hedge fund indices we will consider. Each of the indices is grouped into its style category. Considering first the unadjusted excess returns, we can clearly see that the FRM index has the greatest return and reward to risk ratio in all cases. In addition, we can see

[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] A complete description of the construction for all indices except FRM is given in Brooks and Kat (2001). MSCI (2001) discusses construction of the FRM indices.

that for all styles with the possible exception of *Merger Arbitrage* that the reported returns are highly autocorrelated.

To this point, only one simple methodology exists to attempt to adjust these autocorrelated returns to find the true, underlying returns. This methodology can be traced back to Geltner (1991, 1993) in the real estate literature, and has been applied more recently by Brooks and Kat (2001) and Kat and Lu (2002) to hedge fund return series. To unsmooth a given hedge fund return series, Brooks and Kat (2001) assume that the observed (smoothed) return, r_t^*, of a hedge fund at time *t* may be expressed as a weighted average of the true underlying return at time t, r_t, and the observed (smoothed) return at time *t*-1, r_{t-1}^*:

$$r_t^* = (1 - \alpha)\, r_t + \alpha\, r_{t-1}^* . \tag{1}$$

Given equation (1), simple algebraic manipulation allows us to determine the actual return with zero first order autocorrelation:

$$r_t = \frac{r_t^* - \alpha\, r_{t-1}^*}{1-\alpha}. \tag{2}$$

It can be shown that the return series, r_t, will have the same mean as r_t^* and will have near zero first order autocorrelation. The standard deviation of r_t will be greater than that for r_t^* if the first order autocorrelation autocorrelation of r_t^* is positive. If the first order autocorrelation of r_t^* is negative then the standard deviation of r_t will be less than that for r_t^*.

Unfortunately, this adjustment process is intrinsically unsatisfying. The difficulty with this methodology is that it is only strictly correct for an AR(1) process and it only acts to remove first order autocorrelation. In fact, many of the hedge fund indices that we will consider have highly significant second order autocorrelation that will not be removed by using the process given in equation (2). We will show a more general approach in Section III to completely eliminate any order of autocorrelation from many general processes. For now, it will suffice to say that our methodology will have the same general effect as that found by Geltner (1991, 1993) and by Brooks and Kat (2001) in that our adjustment reveals true risk for many of these hedge fund styles to be much greater than that reported.[9] For adjusting the hedge fund returns, we successfully eliminated the first four autocorrelations. Table 1 reveals that the smoothed hedge fund returns have a much higher standard deviation, in general, than does the original return series with a correspondingly lower information ratio. In fact, in many cases we find an increase in risk of 60 to 100 percent.

Table 2 gives the correlations among the different hedge fund indices. We can quickly see that the correlations between hedge funds within the *Convertible Arbitrage*, *Fixed Income Arbitrage*, and *Credit Trading* strategies are much lower than within *Distressed Securities*, *Merger Arbitrage*, and *MultiProcess – Event Driven*. We also see relatively high correlations across different styles – particularly between *Credit Trading* and *Distressed Securities*, *Distressed Securities* and *MultiProcess – Event Driven*, and also between *Merger Arbitrage* and *MultiProcess – Event Driven.*

Table 3 and Table 4 present summary statistics for the candidate factors we will use to identify the relevant risk exposures of the hedge fund indices. For this study, we have included 40 candidate factors that we label *Index Factors*. In Table 3 we have included 11 equity factors, 19 bond indices, 3 commodity indices, 2 real estate indices, 2 currencies, as well as 4 miscellaneous factors (Lipper Mutual Funds, 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 CBOT website.[10] In addition to the variables reported in Table 3, we also included various interest rates downloaded directly from Datastream. These are the U.S. Corporate Bond Moody's Baa rate, the FHA Mortgage rate, the U.S. Swap 10 year rate, and the U.S. JPM Non-U.S. Govt bond rate.

Table 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.

[9] In fact, in many cases the risk levels we estimate using our process will be greater than that given by the Geltner (1991, 1993) and Brooks and Kat (2001) approach.
[10] The VXN data series does not begin until 1995. To fill in the 1994 values, we regressed the VXN on the VIX index and then used the fitted values to estimate what the VXN might have been during 1994.

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 Table 4. We will label all factors taken from Ken French's site, including industry factors as *Ken French* factors.

A direct comparison of Table 1 with Table 3 reveals that the adjusted returns of the hedge funds have, in general, a risk level comparable to many of the bond indices. This is not surprising 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 with the exception of 3 of the Lehman bond indices, 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. One final point can be made regarding the factors listed in Table 3. Many of the factors have experienced much greater standard deviations recently than they did during the mid 1990s. This is particularly the case for the equity indices which have experienced increases in risk up to 4 times. For example, the monthly standard deviation of excess NASDAQ returns has increased from 3.329 percent during 1994 – 1995 to 12.558 percent during 2000 – 2001. We also find similar increases in magnitude for the UBS Warburg bond indices. Later, when we map the hedge fund returns onto the potential underlying risk factors, we will need to control for this relative increase in risk.

Table 4 presents similar measures as Table 3 for the *Ken French* factors. As we found in Table 3, we find marked increases in risk for many of the candidate factors during the most recent two years. In addition, as others have documented the size effect and the value / growth effect have lain dormant during this time period. Finally, we should note that the risk underlying the momentum effect has increased by nearly 6 times over the period of this study.

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. We are now ready to discuss the methodology used in this paper.

III. Methodology

III.A. Adjusting Reported Returns to Remove Autocorrelation

We will assume the fund manager smooths returns in the following manner:

$$r_{0,t} = (1 - \alpha)\, r_{m,t} + \sum_i \beta_i\, r_{0,t-i}\,, \tag{3}$$

where $(1 - \alpha) = \sum_i \beta_i$,

$r_{0,t}$ is the observed (reported) return at time t (with 0 adjustments to reported returns),

$r_{m,t}$ is the true underlying (unreported) return at time t (determined by making m adjustments to reported returns).

Our objective is to determine the true underlying return by removing the autocorrelation structure in the original return series without making any assumptions regarding the actual time series properties of the underlying process. We are implicitly assuming by this approach that the autocorrelations that arise in reported returns are entirely due to the smoothing behavior funds engage in when reporting results. In fact, we will show that our method may be adopted to produce any desired level of autocorrelation at any lag and is not limited to simply eliminating all autocorrelations.

III.A.1. To Remove First Order Autocorrelation

Geltner's method for removing or reducing first order autocorrelation is given in equation (2). To completely eliminate first order autocorrelation, a simple modification to the adjustment process in equation (2) is required:

$$r_{1,t} = \frac{r_{0,t} - c_1 r_{0,t-1}}{1 - c_1}, \tag{4}$$

where c_1 is a parameter that we will set to remove the first order autocorrelation in the return series given by $r_{0,t}$. Note that the subscript, 0, indicates returns that have been adjusted 0 times. The subscript, 1, for $r_{1,t}$ indicates one adjustment where the adjustment is given in equation (4). This is slightly different from the notation in equation (1) and equation (2), but we feel the notation used in each section is most clear for the discussion in that section.

Using the definition of true returns, $r_{1,t}$, given in equation (4) we may solve directly for the new first order autocorrelation:

$$a_{1,1} \equiv \text{Corr}\,[r_{1,t}\ ,\ r_{1,t-1}] = \frac{\left[a_{0,1} c_1^2 - (1 + a_{0,2}) c_1 + a_{0,1}\right]}{\left[1 + c_1^2 - 2 c_1 a_{0,1}\right]}, \tag{5}$$

where $a_{m,n}$ is the *n*th autocorrelation made after *m* adjustments to returns.

We may reset the autocorrelation given by equation (5) to any desired level, d_1. The general solution for c_1 may be found by directly solving the second order polynomial. The general solution for c_1 is:

$$c_1 = \frac{\left(1 + a_{0,2} - 2 d_1 a_{0,1}\right) \pm \sqrt{\left(1 + a_{0,2} - 2 d_1 a_{0,1}\right)^2 - 4\left(a_{0,1} - d_1\right)^2}}{2\left(a_{0,1} - d_1\right)}. \tag{6}$$

The solution given in equation (6) for c_1 will apply for any time series process that fulfills the following condition:

$$\left(a_{0,1} - d_1\right)^2 \le \frac{\left(1 + a_{0,2} - 2 d_1 a_{0,1}\right)^2}{4}. \tag{7}$$

While it must remain for future work to determine the generality of the result given by equation (6), we were able to successfully remove first order autocorrelation for all 100 different hedge fund indices we examined in work related to this project. We were also successful for the 21 indices we examine in this paper. Note that if we assume the underlying process is AR(1) and we wish to completely remove first order autocorrelation, we find c_1 to be:

$$c_1 = a_{0,1} \quad \text{or} \quad c_1 = \frac{1}{a_{0,1}}.$$

For more general processes, c_1 will be a complicated function of the parameters underlying the time series process.

We may derive the variance of the new process, $r_{1,t}$:

$$\text{Var}[r_{1,t}] = \frac{\left(1+c_1^2-2c_1 a_{0,1}\right)}{\left(1-c_1\right)^2}\text{Var}[r_{0,t}]. \tag{8}$$

Note that the variance of the adjusted (unsmoothed) returns will be greater than the variance of the original series if the parameter, c_1 is positive. Since all of the hedge fund indices we consider have positive first order autocorrelation, the effect of this unsmoothing will be to increase the riskiness of returns.

We may also determine the new correlation between any variable, *x*, and the new, adjusted return series, $r_{1,t}$:

$$\rho_{r_{1,t},x} \equiv \text{Corr}[r_{1,t}, x] = \frac{\rho_{r_{0,t},x} - c_1 \rho_{r_{0,t-1},x}}{\sqrt{1+c_1^2-2c_1 a_{0,1}}}, \tag{9}$$

where $\rho_{r_{0,t},x} \equiv \text{Corr}[r_{0,t}, x]$ and $\rho_{r_{0,t-1},x} \equiv \text{Corr}[r_{0,t-1}, x]$.

Note that, in general, the greater is the correlation between the original returns series and any other variable, *x*, the greater will be the correlation between $r_{1,t}$ and *x*.[11]

[11] In tests not reported, this result was confirmed for the 21 hedge fund indices of this paper and their associated factors. While not perfect, we found a near monotonic relation between correlations with unadjusted returns and correlations with our adjusted returns. In addition, we found that factors statistically significant with the original series remained statistically significant with adjusted returns.

For simplicity we will now assume the objective is to completely remove first order autocorrelation. That is, we will set d_1 to be equal to zero. It is quite straightforward to modify the results that follow for a non-zero d_1.

We may also derive the higher order autocorrelations with the adjusted process:

$$a_{1,n} \equiv \text{Corr}\,[\,r_{1,t}\ ,\ r_{1,t-n}\,] = \frac{\left[a_{0,n}\,(1+c_1^2)-c_1\,(a_{0,n-1}+a_{0,n+1})\right]}{\left[1+c_1^2-2c_1 a_{0,1}\right]}. \tag{10}$$

We will later make use of these new higher order autocorrelations on adjusted returns.

Finally, we should comment on the implicit assumption we are making regarding the behavior of the fund manager if we make the adjustment as given in equation (4). Implicitly, we are assuming the relation between reported return, $r_{0,t}$, and the true return, $r_{1,t}$, is:

$$r_{0,t} = (\,1- \ c_1)\,r_{1,t} \ + c_1 \ r_{0,t-1}. \tag{11}$$

This is easily achieved by a direct manipulation of equation (4).

III.A.2. To Remove the First and Second Order Autocorrelations

The process demonstrated in Section III.A.1. was a straightforward extension of that proposed by Geltner (1991, 1993). We wish now to illustrate the methodology to remove first and second order autocorrelation from a given return series. To completely eliminate second order autocorrelation, we may make a simple modification to the adjustment process in equation (4):

$$r_{2,t} = \frac{r_{1,t}-c_2\,r_{1,t-2}}{1-c_2}, \tag{12}$$

where c_2 is a parameter that we will set to remove the second order autocorrelation in the (once) adjusted return series given by $r_{1,t}$. Note that the subscript, 1, indicates

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The impact of adjustments primarily affected the value (but not significance) of the regression coefficients.

returns that have been adjusted 1 time. The subscript, 2, for $r_{2,t}$ indicates two adjustments with the first adjustment given in equation (4) and the second given in equation (12).

Using the definition of true returns, $r_{2,t}$, now given in equation (12) we may solve directly for the new second order autocorrelation:

$$a_{2,2} \equiv \text{Corr}\,[\,r_{1,t}\;,\;r_{1,t-2}\,] = \frac{\left[a_{1,2}c_2^2-(1+a_{1,4})c_2+a_{1,2}\right]}{\left[1+c_2^2-2c_2a_{1,2}\right]}, \tag{13}$$

where $a_{m,n}$ is the *n*th autocorrelation made after *m* adjustments to returns.

We may reset the autocorrelation given by equation (13) to any desired level, d_2. The general solution for c_2 may be found by directly solving the second order polynomial. The general solution for c_2 is:

$$c_2 = \frac{\left(1+a_{1,4}-2d_2a_{1,2}\right)\pm\sqrt{\left(1+a_{1,4}-2d_2a_{1,2}\right)^2-4\left(a_{1,2}-d_2\right)^2}}{2\left(a_{1,2}-d_2\right)}. \tag{14}$$

The solution given in equation (14) for c_2 will apply for any time series process that fulfills the following condition:

$$\left(a_{1,2}-d_2\right)^2 \le \frac{\left(1+a_{1,4}-2d_2a_{1,2}\right)^2}{4}. \tag{15}$$

As with the first order case, we were successful in finding a direct value for c_2 in all 100 hedge fund indices we examined.

Note that if we make the adjustment as given by equation (12), the first order autocorrelation of $r_{2,t}$ will no longer be zero. We will get back to this issue shortly. Let us first find the effect of making this second adjustment on variance, correlations with additional variables, *x*, as well as autocorrelations that are not second order.

We may derive the variance of the new process, $r_{2,t}$:

$$\text{Var}\,[r_{2,t}] \;=\; \prod_{i=1}^{2} \frac{\left(1+c_i^2-2c_i\,a_{i-1,i}\right)}{\left(1-c_i\right)^2} \text{Var}\,[r_{0,t}]. \tag{16}$$

Note that the variance of the adjusted (unsmoothed) returns will be greater than the variance of the original series if the parameters, c_1 and c_2 are positive. Since many of the hedge fund indices we consider have positive first and second order autocorrelations, we find further increases in variance beyond that achieved by making the adjustment of equation (4).

We may also determine the new correlation between any variable, *x*, and the new, adjusted return series, $r_{2,t}$:

$$\rho_{r_{2,t},x} \;\equiv\; \text{Corr}\,[r_{2,t}, x] \;=\; \left(\prod_{i=1}^{2}\left(1+c_i^2-2c_i\,a_{i-1,i}\right)^{\frac{-1}{2}}\right)$$

$$* \,(\rho_{r_{0,t},x} - c_1\,\rho_{r_{0,t-1},x} - c_2\,\rho_{r_{0,t-2},x} + c_1\,c_2\,\rho_{r_{0,t-3},x}\,) \tag{17}$$

As was the case with the adjustment for first order autocorrelation, we find that highly correlated factors remain highly correlated after the second adjustment. The dominant component in equation (17) remains the correlation between $r_{0,t}$ and *x*, $\rho_{r_{0,t},x}$.

For simplicity we will now assume the objective is to completely remove second order autocorrelation. That is, we will set d_2 to be equal to zero. It is quite straightforward to modify the results that follow for a non-zero d_2.

All autocorrelations for $r_{2,t}$ are given by:

$$a_{2,n} \;=\; \frac{\left[a_{1,n}(1+c_2^2) - c_2(a_{1,n-2}+a_{1,n+2})\right]}{\left[1+c_2^2-2c_2\,a_{1,2}\right]}. \tag{18}$$

Note that

$$a_{2,1} \;=\; \frac{-c_2\,a_{1,3}}{\left[1+c_2^2-2c_2\,a_{1,2}\right]} \;\neq\; 0, \tag{19}$$

since $a_{1,1} \;=\; 0$ and $a_{1,-1} \;=\; a_{1,1}$. That is, once we adjust returns to remove second order autocorrelation, the first order autocorrelation of the new series will no longer be exactly zero. We did find in all cases we considered, however, that $a_{2,1}$ is very small in magnitude.

The process we use to remove both first and second order autocorrelation is straightforward. Working with the new adjusted return series, $r_{2,t}$, we remove first-order autocorrelation as described in Section III.A.1. That is, we will create a new adjusted return series:

$$r_{3,t} = \frac{r_{2,t} - c_3 r_{2,t-1}}{1 - c_3}. \tag{20}$$

The solution for c_3 to remove the first order autocorrelation is given by:

$$c_3 = \frac{\left(1+a_{2,2}\right) \pm \sqrt{\left(1+a_{2,2}\right)^2 - 4a_{2,1}^2}}{2a_{2,1}} = \frac{1 \pm \sqrt{1-4a_{2,1}^2}}{2a_{2,1}}. \tag{21}$$

Given that $a_{2,1}$ is likely to be very small, we will likely need to make only a minimal adjustment to remove the first order autocorrelation from $r_{2,t}$ when we create $r_{3,t}$. In fact, a direct application of L'Hopital's rule shows that c_3 will approach zero as $a_{2,1}$ approaches a zero limit. With the adjustment we make in equation (20), however, second order autocorrelation will not remain zero. We can determine the second order autocorrelation for the adjusted series, $r_{3,t}$ by using the result from equation (10):

$$a_{3,2} = \frac{\left[a_{2,2}(1+c_3^2) - c_3(a_{2,1}+a_{2,3})\right]}{\left[1+c_3^2 - 2c_3 a_{2,1}\right]} = \frac{-c_3(a_{2,1}+a_{2,3})}{\left[1+c_3^2 - 2c_3 a_{2,1}\right]}. \tag{22}$$

Given that c_3 is likely to be very small, $a_{3,2}$ will be very nearly zero.

To remove both the first and second autocorrelations, we repeat this process until both the first and second order autocorrelations fall below a given threshold level. That is, we will once again form a new series of the same form as given in equation (12) to create $r_{4,t}$ and so on. Once we have completed this iteration process, the final variance given by equation (16) will only approximately hold. The correlations with other variables given by equation (17) will also hold only approximately. In general, the adjustments the iteration process has very little impact once we have initially adjusted for the first and second autocorrelations.

Finally, we should comment on the implicit assumption we are making regarding the behavior of the fund manager if we make the adjustment as given in equation (12). Implicitly, we are assuming the relation between reported return, $r_{0,t}$, and the true return, $r_{2,t}$, is:

$$r_{0,t} \approx (1 - c_1)(1 - c_2) r_{2,t} + c_1 r_{0,t-1} + c_2 r_{0,t-2} - c_1 c_2 r_{0,t-3}, \quad (23)$$

where equation (23) holds exactly if it were not necessary to proceed with the iteration process.

III.A.3. To Remove Up to *m* Orders of Autocorrelation

To remove the first *m* orders of autocorrelation from a given return series we would proceed in a manner very similar to that detailed in Section III.A.2. We would initially remove the first order autocorrelation, then proceed to eliminate the second order autocorrelation through the iteration process. In general, to remove any order, *m*, autocorrelations from a given return series we would make the following transformation to returns:

$$r_{m,t} = \frac{r_{m-1,t} - c_m r_{m-1,t-m}}{1 - c_m}, \quad (24)$$

where $r_{m-1,t}$ is the return series with the first ($m - 1$) autocorrelations removed. The general form for all autocorrelations given by this process is:

$$a_{m,n} = \frac{\left[a_{m-1,n}(1+c_m^2) - c_m(a_{m-1,n-m} + a_{m-1,n+m})\right]}{\left[1 + c_m^2 - 2 c_m a_{m-1,n}\right]}. \quad (25)$$

If $m = n$ then equation (25) may be reduced to:

$$a_{m,m} = \frac{\left[a_{m-1,m}(1+c_m^2) - c_m(1 + a_{m-1,2m})\right]}{\left[1 + c_m^2 - 2 c_m a_{m-1,m}\right]}. \quad (26)$$

If our objective is to set $a_{m,m} = 0$, we find the value of c_m to be:

$$c_m = \frac{\left(1+a_{m-1,2m}\right) \pm \sqrt{\left(1+a_{m-1,2m}\right)^2 - 4a_{m-1,m}^2}}{2a_{m-1,m}}, \tag{27}$$

which requires that

$$a_{m-1,m}^2 \leq \frac{\left(1+a_{m-1,2m}\right)^2}{4} \tag{28}$$

for a real solution to obtain.

Once we have found this solution for c_m to create $r_{m,t}$, we will need to iterate back to remove the first ($m - 1$) autocorrelations again. We will then need to once again remove the *m*th autocorrelation using the adjustment in equation (24). We will continue this process until the first *m* autocorrelations are sufficiently close to zero.

Note that the approximate variance for $r_{m,t}$ is:[12]

$$\text{Var}\,[\,r_{m,t}\,] \approx \prod_{i=1}^{m} \frac{\left(1+c_i^2 - 2c_i\, a_{i-1,i}\right)}{\left(1-c_i\right)^2} \text{Var}\,[\,r_{0,t}\,]. \tag{29}$$

The approximate correlation between $r_{m,t}$ and any variable, *x*, is given by:

$$\rho_{r_{m,t},x} \equiv \text{Corr}\,[\,r_{m,t}, x\,] \approx \left(\prod_{i=1}^{m} \left(1+c_i^2 - 2c_i\, a_{i-1,i}\right)^{\frac{-1}{2}} \right) * \Phi, \tag{30}$$

where

$$\Phi = \rho_{r_{0,t},x} + (-1)^{-[2m]} \sum_{i=1}^{m} c_i\, \rho_{r_{0t-i},x}$$
$$+ (-1)^{-[2m-1]} \sum_{i=1}^{m-1} c_i \left(\sum_{j=i+1}^{m} c_j\, \rho_{r_{0,t-(i+j)},x} \right)$$
$$+ (-1)^{-[2m-2]} \sum_{i=1}^{m-2} c_i \left(\sum_{j=i+1}^{m-1} c_j \left(\sum_{k=i+2}^{m} c_k\, \rho_{r_{0,t-(i+j+k)},x} \right)\right)$$

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[12] Note that all of the approximations that follow would hold exactly if the iteration process were not necessary.

$$+ \bullet \bullet \bullet + (-1)^{-[2m-(m-1)]} *$$

$$\sum_{i=1}^{m-(m-1)} c_i \left(\sum_{j=i+1}^{m-(m-2)} c_j \left(\sum_{k=i+2}^{m-(m-3)} c_k \bullet \bullet \bullet \left(\sum_{p=m}^{m-(m-m)} c_p \rho_{r_{0,t-(i+j+k+\bullet\bullet\bullet+p)},x} \right) \bullet \bullet \bullet \right) \right)$$

Finally, when we remove the first *m* autocorrelations we implicitly assume:

$$r_{0,t} \approx \left[\prod_{i=1}^{m} (1-c_i) \right] r_{m,t} + (-1)^{2m} \sum_{i=1}^{m} c_i \, r_{0,t-i}$$

$$+ (-1)^{2m-1} \sum_{i=1}^{m-1} c_i \left(\sum_{j=i+1}^{m} c_j \, r_{0,t-(i+j)} \right)$$

$$+ (-1)^{2m-2} \sum_{i=1}^{m-2} c_i \left(\sum_{j=i+1}^{m-1} c_j \left(\sum_{k=i+2}^{m} c_k \, r_{0,t-(i+j+k)} \right) \right)$$

$$+ \bullet \bullet \bullet + (-1)^{2m-(m-1)} *$$

$$\left[\sum_{i=1}^{m-(m-1)} c_i \left(\sum_{j=i+1}^{m-(m-2)} c_j \left(\sum_{k=i+2}^{m-(m-3)} c_k \bullet \bullet \bullet \left(\sum_{p=m}^{m-(m-m)} c_p \, r_{0,t-(i+j+k+\bullet\bullet\bullet+p)} \right) \bullet \bullet \bullet \right) \right) \right], \tag{31}$$

where $r_{m,t}$ is the true unsmoothed return.

III.B. Determination of Hedge Fund Factors

We now wish to map (regress) the individual hedge fund index returns (adjusted to remove serial correlation) onto the potential risk factors detailed in Section II. For this part, we will closely follow the methodology of Agarwal and Naik (2001). Initially, for each *Index Factor* we will 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 will create the following two return series:

S&P 500 +	= S&P 500 return if S&P 500 return > 0
	= 0 otherwise
S&P 500 –	= S&P 500 return if S&P 500 return < 0

= 0 otherwise

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 realised returns. We will define the directional factor return series as *Directional* factors.

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 FHA Mortgage rate, and the U.S. 10 year swap rate. In addition, for the differences we use: the UBS Global return less the U.S. Treasury return, the Lehman high-yield return less U.S. Treasury, JPM Brady return less Treasury return, JPM Fixed return less JPM Float return, Baa rate less Treasury, FHA Mortgage rate less Treasury, the 10 year swap rate less Treasury, and the JPM non-U.S. government bond index return less Treasury. In addition, we also created 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 of a correlation or a regression coefficient will have opposite interpretations in these two cases.

Finally, we will 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 will define this third category of risk exposures as the *Trading Strategy* factors.

To model the *Trading Strategy* factors, we will 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 will 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 will create the payoffs for 3 call options and 3 put options.[13] 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 percent. 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 S&P 500, NASDAQ, EAFE, Nikkei, Salomon Brothers WGBI, U.S. Credit Bond index, UBS Warburg sub BBB and NR index, CME Commodity, Philadelphia Gold/Silver, U.S. Real Estate Inv Trst, NYBOT U.S. dollar, and the VIX index. We feel confident that this subset adequately spans the payoffs to options on the remaining *Index* factors.

We will 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.

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[13] 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 behaviour 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.

In order to overcome this potential dilemma, we will follow the procedure outlined in Agarwal and Naik (2001). We will use stepwise regressions to determine the underlying risk factors to the hedge fund returns.[14] For each of the hedge fund indices, we will 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 will 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 Table 3 and Table 4), we scale (divide) each return by its trailing 24 month standard deviation before we include the factor in the regression.[15] This should eliminate most concerns about heteroscedasticity in the resulting error terms to provide a more accurate fitting.[16]

III.C. 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-

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[14] 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.

[15] 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.

[16] 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 percent.

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 will 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. It may be the case that the dynamic trading style of the hedge fund manager is intended to counter any shift in return patterns on the underlying assets, however, we feel that such contentions would be fairly classified as "wishful thinking".

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.

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

$$\text{Return}_{\text{HFR Merger Arbitrage}} = 0.005 + 0.25 * [\text{S\&P 500}] + (-0.50) * [\text{EAFE}] \quad (32)$$

with a standard error of 0.02.

Instead of randomly simulating the actual historical (adjusted, excess) returns of the HFR *Merger 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).[17] Since our regression equation does not perfectly fit the HFR *Merger 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 percent, an EAFE return of 6 percent, and our random number generator gives us a value of 1.01 then the simulated return for month *t* from equation (3) would be:

$$\text{Simulated Return}_{\text{HFR Merger Arbitrage}}$$
$$= 0.005 + 0.25 * [0.04] + (-0.50) * [0.06] + 0.02 * 1.01$$
$$= 0.0052$$
$$= 0.52 \text{ percent}$$

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.[18] In order to estimate risk with fat-tails we will also conduct historical simulations using mapped factor returns and assuming the error distribution has a Student-t distribution with 4 degrees of freedom.[19] 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,

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[17] 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.

[18] 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 putrid 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.

[19] 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.

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 will 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 will 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 will estimate the value-at-risk using actual historical (adjusted, excess) returns.

IV. The Risk Factors to Hedge Fund Returns

IV.A. Simple Correlations of Risk Factors to Hedge Fund Returns

We are now ready to proceed with an analysis of the underlying risk factors for each of the hedge fund indices. Table 5 presents the top five and bottom five correlated factors to each of the hedge fund indices. In general, we find remarkable consistency in the factors within each hedge fund style and even across hedge fund styles when we examine the simple correlations. This will become even more apparent when we proceed with the more formal mapping process.

IV.A.1. Convertible Arbitrage

Table 5 clearly shows that all hedge fund indices in the *Convertible Arbitrage* style are highly correlated with the returns on high-yield debt. Only one of the *Convertible Arbitrage* indices had the convertible factor make the top five – the Hennessee index (UBS Convertible return less U.S. Treasury). We should note also that limited evidence exists for a small stock exposure with *Convertible Arbitrage*. As for negative correlations, we find all the indices are negatively correlated to changes in volatility and to mortgage yields.

IV.A.2. Fixed Income Arbitrage

While Table 2 doe show the correlations between the *Fixed Income Arbitrage* and the *Convertible Arbitrage* styles to be relatively low, we once again find evidence of a strong exposure to high-yield debt. In addition, we find for the FRM and the CSFB *Fixed Income Arbitrage* indices a negative exposure to the yen. In fact, it is quite clear from the CSFB correlations that the hedge funds in this index on balance were long U.S. dollar denominated assets and short yen-based assets during this time period. Given the differentials in yields between these two currencies, perhaps this result is not surprising. Our results are consistent with Fung and Hsieh (2002) who find a very high correlation with high-yield returns for this hedge fund style.

IV.A.3. Credit Trading

As we would expect, Table 5 shows the two indices within this style to be extremely highly correlated with high-yield debt. The FRM index appears to also have a strong correlation with international bonds. As with most of the hedge fund indices, we find a negative correlation with volatility. Fung and Hsieh (2002) reported the correlation between the same HFR index we use and the CSFB High-Yield bond index to be 0.853. We find very similar results by using the SSB High-Yield index (correlation equal to 0.847).

IV.A.4. Distressed Securities

We find extreme consistency in the factor correlations with this style for the FRM, HFR, and Zurich indices. *Distressed Securities* hedge funds tend to have a very strong exposure to small stock returns, a very negative exposure to volatility, and tend to behave more like growth stocks (low book-to-market). In addition, this style is positively correlated with JPM floating rate returns relative to JPM fixed rate returns. We also see that each of the indices are strongly correlated with the Lipper Mutual Funds which is used as a benchmark by some hedge funds.

IV.A.5. Merger Arbitrage

As with *Distressed Securities*, we find a small stock factor with *Merger Arbitrage*. Given that some have argued that the return premium to small stocks is at least in part to due to an implicit short put position on the overall market, this result is not surprising and is consistent with the findings of Mitchell and Pulvino (2001). Moreover, Mitchell and Pulvino (2001) also find a positive, significant loading on the SMB factor. Our finding for a positive correlation with small stocks is consistent with this work. We will examine this issue more closely when we run the step-wise regressions to determine the underlying factors to this hedge fund style.

IV.A.6. MultiProcess – Event Driven

Given the very broad definition for this style of hedge fund, it is quite interesting to find out actually what they do in aggregate. Table 5 begins to shed some light on this issue. We can clearly see from this table that as with *Distressed Securities* and *Merger Arbitrage*, this style has a very strong exposure to the returns on small stocks. In addition, we find limited evidence for a high-yield debt factor for the FRM and HFR indices and a non-U.S. bond factor for the CSFB index. As with most of the other styles, *MultiProcess – Event Driven* is strongly negatively correlated with volatility and HML returns. We also find a long exposure to international floating-yield debt relative to fixed-rate debt for all indices within this style.

IV.B. Mapping of Indices Using Only Index, Ken French, and Interest Rate Factors

In this section, 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 obtained from Table 6. We can compare the results of this section directly with the results in Section III.B. which are detailed in Table 5. In general, we find consistency between this mapping and the simple, univariate correlations examined earlier. In this section, we will also report a measure of the goodness of fit during two subperiods in-sample, 1994 – 1997 and 1998 – 2001. The measure we will use is straightforward:

$$\text{sub-period r-square} \;=\; 1 \;-\; \frac{\text{residual sum of squares in sub-period}}{\text{total sum of squares in sub-period}}. \qquad (33)$$

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.[20]

IV.B.1. Convertible Arbitrage

We find the dominant factor for *Convertible Arbitrage* to be the return on a high yield index. In fact, for the HFR index, the top two factors are high yield indices. For the individual hedge fund indices, we find varying levels of fit within sample and over the entire sample. Our procedures were the most successful with the HFR index, producing an adjusted r-square of 0.46 over the entire sample and with remarkable stability in the sub-period r-squares. On the other hand, we were unsuccessful in achieving a good fit with the FRM index.

IV.B.2. Fixed Income Arbitrage

It is somewhat difficult to interpret the results of Table 6 for the *Fixed Income Arbitrage* style. We find evidence of a strong exposure to high yield returns once again, but the additional factors vary markedly across the individual indices within this style. Moreover, the in-sample stability of the mappings is also relatively poor. Fung and Hsieh (2002) 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

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[20] 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.)

convertible bond less treasury returns. We did not find any evidence for a convertible bond exposure, nor for that matter with either the FRM or CSFB indices.

IV.B.3. Credit Trading

Consistent with Fung and Hsieh (2002), we were able to achieve a remarkably good fit with the HFR index, however, our procedure did not identify the High-Yield less Treasury factor as dominant. Instead, our results isolated on the SSB High-Yield index. We did find that the change in the Lehman U.S. High-Yield index less Treasury returns should be included as an additional risk factor.

Fung and Hsieh (2002) report they were able to achieve an r-square of 0.78 with the CSFB High-Yield bond less Treasury return factor. They report that their lookback option payoff produces an r-square of 0.79. It is not clear from their paper, that lookback options add much to any value in terms of fitting the fixed income hedge fund indices they consider.

Finally, we should note that the fit achieved with the FRM index was much less strong than that with HFR. The FRM index mapping was much less stable in-sample than that with HFR. We did find, though, the high-yield factor to once again dominate.

IV.B.4. Distressed Securities

As we found with the univariate correlations, the dominant factor for this style of hedge fund is simply small stocks. The incremental r-square explained by small stocks for each of the three indices is over 50 percent. With the exception of the HFR index, the second most important factor is once again the returns on a high-yield index. This did not show up with the univariate correlations of Table 5. In addition, we find remarkable stability in-sample for the chosen factors. The sub-period r-squares are quite high for all three indices in this category.

IV.B.5. Merger Arbitrage

As we would expect from the univariate correlations, small stocks are the dominant factor for this hedge fund style category. The explanatory power of small stocks, however, is not as great as with *Distressed Securities*. This is consistent with the results from the univariate correlations. Our small stock finding is also consistent with Mitchell and Pulvino (2001). One danger of using the Agarwal and Naik (2001) technique, is that factors may find their way through the step-wise process that have no intuitive relation to the dependent variable (hedge fund returns in this case). We may find such an instance here where the returns on health stocks are included for three out of four hedge fund indices. However, we feel confident that we can filter out logically irrelevant variables *ex-post* as well as we could *ex-ante*.

IV.B.6. MultiProcess – Event Driven

As with *Distressed Securities* and *Merger Arbitrage*, we find small stocks entering significantly in some manner for all five indices. We also find the high-yield index is relevant for FRM, CSFB, and Zurich. In general, we were able to attain reasonably good fits in all cases with reasonable in-sample stability.

IV.C. Mapping of Indices Using All Factors

All the results that follow are detailed in Table 7. In general, we found the most important risk factor for nearly all styles to be a short put position on high-yield debt. Consistent with Fung and Hsieh (2002), we found no real improvement with using non-linear payoff factors for *Fixed Income Arbitrage* and *Credit Trading*. However, we did find that using the non-linear factors resulted in moderate increases in explanatory power for the other hedge fund styles. One of our most significant findings is that the short put position on equities advocated by Mitchell and Pulvino (2001) as a risk factor for *Merger Arbitrage* should, in fact, be a short put on high-yield debt.

IV.C.1. Convertible Arbitrage

For three of the four indices, we found the most important risk factor to be the short put position on the UBS Warburg sub BBB / NR index. For the remaining index in this category, the most important factor was the UBS Warburg sub BBB / NR index itself. This remarkable consistency leads to believe that this is a true risk factor for this hedge fund strategy. Moreover, for the HFR and CSFB indices we see a high-yield index also enter into the step-wise regressions. In general, a comparison of Table 7 with Table 6 reveals a moderate improvement in explanatory power by including the non-linear payoff factors.

IV.C.2. Fixed Income Arbitrage

The results for this hedge fund strategy given on Table 7 are quite difficult to interpret. We do find evidence for a high-yield risk factor and, in fact, we find the short put on high-yield debt for the FRM index. For all three indices we do find evidence for a high-yield risk factor. Consistent with Fung and Hsieh (2002), we do not believe that adding non-linear factors to this hedge fund style provides any improvements in explanatory power. Moreover, the fits that we get are remarkably unstable in-sample.

IV.C.3. Credit Trading

Two factors enter quite strongly for the two indices in this style: the return on high-yield debt and, once again, the short put on high-yield debt. In particular, the fit we achieve with the HFR index is quite strong and stable in-sample. Unfortunately, it is not clear that adding this non-linearity provides much benefit to the remarkably good fit we were able to achieve in Table 6 for this style without non-linear and directional risk factors.

IV.C.4. Distressed Securities

While we found in Table 6 that the most important factor for this style of hedge fund was small stocks, it is interesting to note that, once again, the short put position on high-yield debt enters as the most important factor for two of the three indices considered and the second factor for Zurich. The small stock factor falls to second most important for FRM and HFR and remains the most important for Zurich. In addition, we find a strong negative exposure to volatility in the regressions – something we saw in the univariate correlations but have not seen in the regressions until now. We were able to achieve marginal improvements in fit by including non-linearities for this style with considerable stability in-sample.

IV.C.5. Merger Arbitrage

In Table 6 we found small stocks to be the most important factor for this hedge fund style. Once we include non-linear payoffs, we once again find the short put on high-yield debt dominates. This is interesting in that we did not find any evidence from Table 5 for the importance of high-yield debt. Our results here are consistent with Mitchell and Pulvino (2001), except that the risk in risk arbitrage (their words) would be more accurately akin to a short put on debt rather than equity. Finally, we find varying evidence for factor stability with this style – with the least stable mapping occurring with the HFR index.

IV.C.6. MultiProcess – Event Driven

For this hedge fund style we once again find the same dominant risk factor – a short put on high-yield debt. This enters first four of five hedge fund indices and second for HFR. In addition, we find that many of the indices have a strong negative exposure to changes in volatility. We find moderate improvement with including non-linear payoffs here with stability of the factors in-sample.

IV.C.7. A Discussion of the Short Put on High-Yield Debt

We have found that the short put on high-yield debt appears to replace small stocks as the most important factor when both are rival factors in a regression. To investigate the similarity between these two factors we calculated simple correlations between small stocks and the three candidate short put positions on the UBS Warburg sub BBB / NR index (at, shallow, and deep). We found the correlations to be: small and short put (at) 0.389, small and short put (shallow) 0.517, small and short put (deep)

0.635. In addition, we examined the correlations between puts constructed on the S&P 500 index and the NASDAQ index with the puts on the UBS Warburg index. In general, we found the greatest correlations to be between the NASDAQ and UBS Warburg with values of about 0.800. While these correlations are certainly high, we do feel that the UBS Warburg put returns are sufficiently distinct to warrant their designation as the actual risk factor.

V. Value-at-Risk Analysis

We wish to now examine the effect of using non-linearities as factor exposures on value-at-risk estimates for the different hedge fund styles. While the effect of unsmoothing returns documented in Section III may have some impact on our ability to detect significant underlying risk factors, the primary benefit to unsmoothing is in estimating risk. The magnitude, if not the significance, of the factor exposures will likely increase as we unsmooth reported returns. In addition, we wish to examine the congruity for value-at-risk estimates within each hedge fund style. That is, we have already found remarkable consistency in the underlying risk factors to each of the hedge fund styles. The question that remains is whether in-sample we can find this same consistency in value-at-risk estimates.

As previously stated, we will conduct five different value-at-risk estimations with each built from 50,000 simulations. Four of the estimations will be 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, 1994 through December, 2001. 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. As this is a time period during which equities have performed markedly well, we cannot assume that the future distribution will match this historical one. However, it will give us some insight into the magnitude of the value-at-risk estimates for the hedge fund returns.

Table 8 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. Table 9 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 Gov/Corp bond index with a one-year, one percent value-at-risk estimate of only − 5.73 percent. On the opposite end of the risk spectrum lie the commodity indices with one-year, one percent value-at-risk levels approaching − 50 percent and worse. On a purely reward-to-risk basis very little justification can be made for including a commodity position in one's portfolio.[21]

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 Table 8 and Table 9 which give downside risk estimates to the factors. Table 10 will give the value-at-risk estimates for every hedge fund style.

V.A. Convertible Arbitrage

The primary result we find here is that in spite of the remarkable homogeneity in underlying explanatory risk variables, we find a remarkable range in downside risk estimates. For instance, the CSFB estimates give value-at-risk estimates that are two to four times greater than that for FRM. This is somewhat surprising given that CFSB requires a minimum total assets under management of 10 million U.S. dollars and is value-weighted. The HFR and Hennessee index fall between these two extremes. While the estimated mean excess returns are relatively close, the estimated standard deviations vary substantially as we compare across the indices.

In addition, we find that limited evidence for slight increases in downside risk when we include the non-linear risk factors, however, the difference is remarkably small. To see this compare the Normal row with "All" and the Normal row with "Index, French" for each of the indices.

V.B. Fixed Income Arbitrage

In general, we find downside risk exposures to be much greater with *Fixed Income Arbitrage* than for *Convertible Arbitrage*. We find very marginal evidence that including non-linearities slightly increases downside exposure. While the value-at-risk estimates do somewhat vary across indices, they fall within a much tighter range than that with *Convertible Arbitrage*.

V.C. Credit Trading

While the estimated mean excess returns differ substantially for the two hedge fund indices in this category, the standard deviations and estimated value-at-risk levels are much closer. We also find strong evidence here that including non-linear factors leads to increased estimates for downside loss.

V.D. Distressed Securities

Recall that all indices in this style loaded very strongly on either small stocks or the short put on high-yield debt. In spite of the relative equality of mean excess return across the indices, we find a considerable range of possible value-at-risk estimates. Once again, even though we are fairly confident in our ability to determine the underlying factors to this style, this does not necessarily translate into any necessary consistency regarding the value-at-risk to this style – even in-sample. We also find that including non-linearities increases downside risk estimates.

V.E. Merger Arbitrage

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[21] Of course, the primary selling point for commodities is their diversification value.

Across all indices, *Merger Arbitrage* appears to be the safest and one of the strongest performing hedge fund styles. Downside risk estimates are far safer than that with the other indices and the mean excess returns are second only to *MultiProcess – Event Driven*. This, in fact, should not be surprising given that this strategy was documented to be one of the safest in Table 1 and required the least adjustment due to its low autocorrelation in original returns. As with the other indices, we find limited evidence that including the non-linear factors leads to more negative estimates for value-at-risk. The risk estimates appear to be relatively stable across the different hedge fund indices.

V.F. MultiProcess – Event Driven

This hedge fund category has outperformed all other categories during the sample period. We find, once again evidence that including non-linear payoffs marginally increases downside risk. As we found with *Convertible Arbitrage*, even though we have considerable stability in the underlying risk factors across indices, we find a substantial range for possible value-at-risk estimates.

VI. Conclusion

In this paper, we have shown a methodology to completely remove any order of autocorrelation from reported returns that may arise due to smoothing to find, in theory, the true underlying returns. We apply this method to 21 different hedge fund indices in six different styles – *Convertible Arbitrage*, *Fixed Income Arbitrage*, *Credit Trading*, *Distressed Securities*, *Merger Arbitrage*, and *MultiProcess – Event Driven*. After removing the autocorrelations from returns, we find increases in risk of between 60 and 100 percent for many of the individual indices. In particular, the autocorrelations were most severe for *Convertible Arbitrage* and *Fixed Income Arbitrage*.

Once we have unsmoothed returns find 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

indicies have a very strong exposure to high-yield credit, small stocks with negative exposures to volatility.
When we map the hedge fund returns to non-linear payoff factors, we find that one particular risk factor is common to 17 of the 21 indices – a short put position on the UBS Warburg BBB / NR index. To put this more succinctly – a short put on high-yield debt. While earlier research has certainly identified non-linear risk factors, none have isolated on this particular one across a wide a range of hedge fund indices and trading styles.

Finally, we conduct value-at-risk analyses using the individual mappings onto risk factors. For many hedge fund styles we find a wide range of downside risk estimates. In addition, we find that the inclusion of non-linear factors marginally increases the magnitude of the downside risk estimate, but the effect is relatively slight.

We feel that future work should focus on the autocorrelation adjustment process introduced in this paper. We feel this methodology may have a number of important applications beyond the purposes of this paper. Perhaps it is a method that can be used to quickly rescale the reported autocorrelations of earnings if it is suspected that one company's reported results are inordinately smooth. While we do believe that the method will apply across a wide variety of time series processes, this has not been properly examined and much work in this area remains.

Hedge funds provide fertile ground for many interesting avenues of research due to their sheer diversity and inherent opaqueness. The mapping methodology used in this paper is gaining in acceptance, but we must be careful as we proceed down this path. For industry, the ultimate aim of mapping is to estimate and simulate risk distributions. Unfortunately, the trading practices of hedge funds are highly fluid and prior sensitivities may poorly reflect future risk. Even within a given style category with common underlying risk factors, the estimated magnitude of the exposures across different indices may result in widely varying estimates of risk for a given strategy. Needless to say, we must proceed cautiously when examining the true risk underlying hedge fund returns.

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Appendix A

Definitions of Hedge Fund Strategies

Note: In all cases these definitions are taken directly from the stated source.

1. Convertible Arbitrage

Convertible arbitrage involves taking positions in convertibles hedged by the issuers equity in situations in which the manager discerns that the market price reflects a lower level of stock volatility than the manager anticipates will actually be the case for the underlying stock over some specified time horizon. This means the manager anticipates the convertible bond to be more valuable than its current market price. The equity risk is hedged by shorting the underlying stock to realize a profitable cash flow as the stock's price changes. The hedging process, in effect, realizes the cheapness of the convertible bond. The credit risk of the convertibles is either explicitly hedged, or actively mitigated (either by investing in a very diversified portfolio of convertibles, or by finding convertibles with high hedge ratios trading far above their bond floor, thus having little or no credit spread risk).

(Manager Guide to Fund Classification, MSCI, July 2002)

2. Fixed Income Arbitrage

Fixed income arbitrage managers seek to exploit pricing anomalies within and across global fixed income markets and their derivatives, using leverage to enhance returns. In most cases, fixed income arbitrageurs take offsetting long and short positions in similar fixed income securities that are mathematically, fundamentally, or historically interrelated. The relationship can be distorted by market events . . .

(UBS Warburg, In Search of Alpha, October 2000)

3. Credit Trading (High yield fixed income)

Fixed income high-yield managers invest in non-investment grade debt. Objectives may range from high current income to acquisition of undervalued instruments. Emphasis is placed on assessing credit risk of the issuer. Some of the available high-yield instruments include extendible/reset securities, increasing-rate notes, pay-in-kind securities, step-up coupon securities, split-coupon securities and usable bonds.

(www.hfr.com)

4. Distressed Securities

Distressed Securities strategies invest in, and may sell short, the securities of companies where the security's price has been, or is expected to be, affected by a distressed situation. This may involve reorganizations, bankruptcies, distressed sales and other corporate restructurings. Depending on the manager's style, investments may be made in bank debt, corporate debt, trade claims, common stock, preferred stock and warrants. Strategies may be sub-categorized as "high-yield" or "orphan equities." Leverage may be used by some managers. Fund managers may run a market hedge using S&P put options or put options spreads.

(www.hfr.com)

5. Merger Arbitrage

Merger arbitrageurs seek to capture the price spread between current market prices of securities and their value upon successful completion of a takeover, merger, restructuring or similar corporate action. Normally, the principal determinant of success of a merger arbitrage is the consummation of the transaction. Typically, merger arbitrage managers wait until a merger is announced before taking a merger arbitrage position; they do not generally speculate on stocks that are expected to become takeover targets, or trade in instruments that are mispriced relative to others.

In mergers involving an offer of stock in the acquiring company, the spread is the difference between the current values of the target company stock and the acquiring company stock. Capturing this spread typically involves buying the stock of the target company and shorting an appropriate amount of the acquiring company's stock. In straight stock for stock deals, the relationship between the two companies' stock prices is linear. In collared stock for stock transactions, the cash value of the amount of stock to be exchanged within the transaction has upper and / or lower limits; this means that the relationship between the two companies' stock prices is non-linear, and the manager will often make use of options or actively manage the short stock position to retain an appropriate hedge.

In mergers involving cash only transactions, the spread is the difference between the current market price and the offered price. Capturing the spread in these transactions is possible by just purchasing the stock of the target company; the manager may or may not take a short position in the stock of the acquiring company.

(Manager Guide to Fund Classification, MSCI, July 2002)

6. MultiProcess – Event Driven

Event-Driven is also known as "corporate life cycle" investing. This involves investing in opportunities created by significant transactional events, such as spin-offs, mergers and acquisitions, bankruptcy reorganizations, recapitalizations and share buybacks. The portfolio of some Event-Driven managers may shift in majority weighting between Risk Arbitrage and Distressed Securities, while others may take a broader scope. Instruments include long and short common and preferred stocks, as well as debt securities and options. Leverage may be used by some managers. Fund managers may hedge against market risk by purchasing S&P put options or put option spreads.

(www.hfr.com)

TABLE 1
Hedge Fund Indices
Excess and Adjusted Monthly Returns
January, 1994 – December, 2001

		Excess Returns			Autocorrelations				Adjusted Returns			Autocorrelations			
		Mean	Std Dev	Info Ratio	First	Second	Third	Fourth	Mean	Std Dev	Info Ratio	First	Second	Third	Fourth
Arbitrage Convertible	FRM	0.682	1.065	0.640	0.399**	0.249*	-0.020	0.034	0.670	1.624	0.413	0.000	0.000	0.000	0.000
	HFR	0.524	1.033	0.507	0.508**	0.198	-0.076	-0.094	0.503	1.594	0.315	0.000	0.000	0.000	0.000
	CSFB	0.494	1.371	0.361	0.604**	0.470**	0.147	0.126	0.485	2.618	0.185	0.000	0.000	0.000	0.000
	Henn	0.357	1.235	0.289	0.503**	0.133	-0.026	-0.094	0.349	1.865	0.187	0.000	0.000	0.000	0.000
Arbitrage Fixed Income	FRM	0.470	1.370	0.343	0.527**	0.358**	0.069	0.087	0.439	2.574	0.171	0.000	0.000	0.000	0.000
	HFR	0.045	1.320	0.034	0.373**	0.029	0.120	0.030	0.037	1.931	0.019	0.000	0.000	0.000	0.000
	CSFB	0.166	1.176	0.141	0.403**	0.133	0.049	0.100	0.162	1.882	0.086	0.000	0.000	0.000	0.000
Credit Trading	FRM	0.415	1.572	0.264	0.319**	0.150	-0.033	0.088	0.409	2.295	0.178	0.000	0.000	0.000	0.000
	HFR	0.103	1.447	0.071	0.309**	0.144	-0.030	0.028	0.091	2.001	0.046	0.000	0.000	0.000	0.000
Distressed Securities	FRM	0.561	1.515	0.371	0.401**	0.074	-0.085	-0.042	0.540	2.036	0.265	0.000	0.000	0.000	0.000
	HFR	0.476	1.656	0.287	0.410**	0.089	-0.065	-0.001	0.444	2.364	0.188	0.000	0.000	0.000	0.000
	Zurich	0.437	1.731	0.253	0.320**	0.174	-0.003	0.020	0.432	2.513	0.172	0.000	0.000	0.000	0.000
Merger Arbitrage	FRM	0.676	1.117	0.605	0.170	-0.040	-0.082	-0.125	0.675	1.130	0.597	0.000	0.000	0.000	0.000
	HFR	0.612	1.064	0.575	0.104	0.047	0.078	-0.170	0.616	1.135	0.543	0.000	0.000	0.000	0.000
	Henn	0.556	1.024	0.543	0.153	-0.053	-0.007	-0.178	0.556	0.986	0.564	0.000	0.000	0.000	0.000
	Zurich	0.555	1.079	0.514	0.235*	0.034	-0.062	-0.102	0.548	1.237	0.443	0.000	0.000	0.000	0.000
MultiProcess (Event Driven)	FRM	0.891	1.585	0.562	0.210*	0.115	0.004	-0.061	0.891	1.930	0.462	0.000	0.000	0.000	0.000
	HFR	0.792	1.904	0.416	0.215*	-0.031	-0.040	0.010	0.784	2.120	0.370	0.000	0.000	0.000	0.000
	CSFB	0.563	1.804	0.312	0.326**	0.126	0.009	-0.001	0.550	2.511	0.219	0.000	0.000	0.000	0.000
	Henn	0.645	1.700	0.379	0.396**	0.098	-0.050	-0.108	0.620	2.129	0.291	0.000	0.000	0.000	0.000
	Zurich	0.469	1.223	0.384	0.242*	0.098	-0.033	-0.080	0.463	1.488	0.311	0.000	0.000	0.000	0.000

TABLE 2
Hedge Fund Indices
Correlations
January, 1994 – December, 2001

		Arbitrage Convertible				Arbitrage Fixed Income			Credit Trading		Distressed Securities		
		FRM	HFR	CSFB	Henn	FRM	HFR	CSFB	FRM	HFR	FRM	HFR	Zurich
Arbitrage Convertible	FRM	1.000	**0.785**	**0.706**	**0.742**	0.451	0.265	0.336	0.489	0.480	0.429	0.434	0.432
	HFR		1.000	**0.719**	**0.812**	0.539	0.152	0.300	0.588	0.656	0.643	0.623	0.628
	CSFB			1.000	**0.599**	0.584	0.262	0.464	0.652	0.630	0.483	0.455	0.447
	Henn				1.000	0.388	0.204	0.205	0.431	0.438	0.528	0.502	0.488
Arbitrage Fixed Income	FRM					1.000	**0.570**	**0.642**	0.590	0.688	0.529	0.517	0.475
	HFR						1.000	**0.532**	0.263	0.373	0.233	0.226	0.113
	CSFB							1.000	0.436	0.474	0.312	0.318	0.274
Credit Trading	FRM								1.000	**0.717**	0.572	0.566	0.575
	HFR									1.000	0.770	0.727	0.715
Distressed Securities	FRM										1.000	**0.947**	**0.864**
	HFR											1.000	**0.872**
	Zurich												1.000

TABLE 2 – *continued*
Hedge Fund Indices
Correlations
January, 1994 – December, 2001

		Merger Arbitrage				MultiProcess (Event Driven)				
		FRM	HFR	Henn	Zurich	FRM	HFR	CSFB	Henn	Zurich
Arbitrage Convertible	FRM	0.322	0.329	0.398	0.430	0.436	0.450	0.470	0.418	0.427
	HFR	0.502	0.497	0.575	0.620	0.595	0.610	0.649	0.598	0.628
	CSFB	0.407	0.446	0.489	0.528	0.513	0.506	0.562	0.496	0.553
	Henn	0.290	0.271	0.391	0.421	0.531	0.540	0.513	0.483	0.460
Arbitrage Fixed Income	FRM	0.350	0.319	0.383	0.475	0.455	0.516	0.599	0.462	0.483
	HFR	0.093	0.071	0.161	0.158	0.143	0.212	0.220	0.161	0.138
	CSFB	0.166	0.096	0.208	0.297	0.324	0.348	0.309	0.321	0.272
Credit Trading	FRM	0.421	0.419	0.446	0.557	0.537	0.566	0.631	0.500	0.540
	HFR	0.579	0.559	0.608	0.709	0.628	0.721	0.784	0.701	0.720
Distressed Securities	FRM	0.667	0.632	0.725	0.795	0.803	0.872	0.847	0.858	0.854
	HFR	0.632	0.582	0.687	0.774	0.770	0.838	0.850	0.827	0.831
	Zurich	0.650	0.623	0.694	0.775	0.797	0.822	0.830	0.763	0.847
Merger Arbitrage	FRM	1.000	**0.902**	**0.939**	**0.900**	0.746	0.739	0.704	0.746	0.805
	HFR		1.000	**0.887**	**0.853**	0.706	0.682	0.710	0.695	0.802
	Henn			1.000	**0.910**	0.773	0.768	0.731	0.794	0.855
	Zurich				1.000	0.831	0.839	0.838	0.841	0.933
MultiProcess (Event Driven)	FRM					1.000	**0.909**	**0.811**	**0.806**	**0.844**
	HFR						1.000	**0.859**	**0.858**	**0.854**
	CSFB							1.000	**0.819**	**0.873**
	Henn								1.000	**0.853**
	Zurich									1.000

TABLE 3
Index Factors
Excess Monthly Returns
January, 1994 – December, 2001

	Mean Return	Std Dev Return	Info Ratio	Standard Deviation 94 – 95	96 – 97	98 – 99	00 – 01	Autocorrelation First	Second
SP500	0.795	4.402	0.181	2.614	3.792	4.941	5.144	-0.041	-0.079
DJIA	0.799	4.568	0.175	3.198	3.986	5.122	5.131	-0.048	-0.064
NASDAQ	0.936	8.526	0.110	3.329	5.345	8.442	12.558	0.047	-0.035
Russell 2000	0.423	5.572	0.076	3.049	4.304	6.534	7.269	0.038	-0.118
Wilshire 5000	0.576	4.524	0.127	2.692	3.618	5.255	5.382	0.011	-0.104
SP Barra Growth	0.765	5.028	0.152	2.537	4.225	5.122	6.389	-0.027	-0.01
SP Barra Value	0.499	4.285	0.117	2.879	3.480	5.172	4.909	-0.033	-0.107
MSCI World	0.370	4.041	0.092	2.859	3.222	4.517	4.553	-0.027	-0.094
Nikkei	-0.742	5.980	-0.124	6.509	5.161	5.551	6.017	-0.009	-0.026
FTSE	0.118	3.862	0.030	3.499	3.323	4.063	3.975	-0.006	-0.068
EAFE	-0.038	4.195	-0.009	3.582	3.456	4.566	4.294	-0.043	-0.122
Lipper Mut Funds	0.626	4.362	0.144	2.515	3.673	4.957	5.352	-0.023	-0.117
MSCI AAA	-0.090	2.780	-0.032	2.505	2.113	2.611	3.489	0.177	-0.041
MSCI 10 Yr +	0.237	2.322	0.102	2.586	2.535	1.860	2.148	0.177	-0.051
MSCI Wrld Sov Ex-USA	-0.084	2.342	-0.036	2.493	1.851	2.335	2.433	0.110	-0.061
UBS Warburg AAA / AA	0.680	3.616	0.188	1.282	2.982	4.815	4.120	0.021	-0.237*
UBS Warburg sub BBB / NR	0.765	5.946	0.129	2.834	2.754	6.970	7.975	0.060	0.063
UBS Warburg Conv. Global	0.279	3.393	0.082	2.706	2.065	3.760	4.060	0.038	-0.035
CBT Municipal Bond	-0.422	2.234	-0.189	3.043	2.072	1.415	1.967	0.088	-0.065
Lehman U.S. Aggregate	-0.423	1.113	-0.380	1.383	1.150	0.865	0.913	0.253*	-0.025
Lehman U.S. Credit Bond	-0.430	1.411	-0.305	1.734	1.491	1.150	1.086	0.165	0.009
Lehman Mortgage Backed Secs	-0.416	0.918	-0.453	1.245	0.868	0.576	0.785	0.288**	-0.003
Lehman U.S. High Yield	-0.571	2.130	-0.268	1.538	1.144	1.810	3.302	0.021	-0.085
Lehman Gov / Corp	0.134	0.910	0.147	1.052	0.956	0.761	0.786	0.262*	-0.025
SSB High Yield Index	0.094	1.943	0.048	1.381	0.821	2.003	2.827	0.015	-0.104
US Credit Bond	-0.439	1.410	-0.311	1.733	1.491	1.151	1.085	0.165	0.008
Salomon WGBI	-0.029	1.740	-0.017	1.692	1.317	1.812	1.967	0.195	-0.050
JPM Non-U.S. Govt Bond	-0.057	2.274	-0.025	2.322	1.818	2.282	2.432	0.116	-0.067
JPM Brady Broad	0.646	5.066	0.127	5.560	4.081	6.735	2.885	-0.010	-0.131
JPM Brady Broad Fixed	0.650	4.935	0.132	6.099	4.686	5.412	2.713	0.031	-0.086
JPM Brady Broad Float	0.675	5.409	0.125	5.318	3.813	7.871	3.334	-0.023	-0.148
CME Goldman Commodity	-0.248	5.116	-0.049	2.950	4.332	6.262	6.080	-0.048	-0.143
Dow Jones Commodity	-0.739	5.056	-0.146	2.540	2.980	8.324	4.042	-0.001	-0.191
Philadelphia Gold / Silver	-0.789	10.559	-0.075	8.271	9.588	15.217	7.174	-0.239*	-0.135
Wrld Ex-U.S. Real Estate	-0.166	6.111	-0.027	6.214	5.496	7.177	4.896	-0.035	0.046
U.S. Real Estate	0.338	4.952	0.068	3.973	4.248	6.011	4.604	-0.024	-0.01
CME Yen Futures	-0.487	4.040	-0.121	4.071	3.014	4.864	3.554	-0.020	0.058
NYBOT Dollar Index	-0.186	2.140	-0.087	1.968	2.019	1.868	2.419	-0.006	-0.092
NYBOT Orange Juice	-0.182	8.778	-0.021	7.845	8.363	10.636	7.747	-0.374**	0.244*
% Chg VXN	1.764	15.202	0.116	13.334	9.698	18.992	16.873	-0.075	-0.193
% Chg VIX	1.981	19.190	0.103	20.412	16.585	22.923	15.816	-0.153	-0.211*

TABLE 4
Ken French Factors
Excess Monthly Returns
January, 1994 – December, 2001

	Mean Return	Std Dev Return	Info Ratio	Standard Deviation 94 – 95	96 – 97	98 – 99	00 – 01	Autocorrelation First	Second
SMB	-0.334	4.036	-0.083	1.818	3.456	3.522	5.987	-0.007	-0.006
HML	-0.413	4.897	-0.084	2.126	2.624	4.492	7.638	0.097	0.023
Low	0.764	4.893	0.156	2.691	4.103	5.489	5.887	0.000	-0.059
High	0.728	4.051	0.180	2.729	2.929	4.575	5.278	0.110	-0.269**
Big	0.765	4.527	0.169	2.585	3.698	5.132	5.457	-0.013	-0.083
Small	0.732	5.944	0.123	3.012	4.801	6.588	8.073	0.125	-0.198
Momentum	0.592	5.511	0.107	1.641	2.344	4.667	9.493	-0.108	-0.079
Europe High BM	0.908	5.354	0.170	3.382	4.147	6.286	6.500	-0.024	-0.052
Europe Low BM	0.412	4.672	0.088	3.092	3.489	5.106	5.737	-0.024	-0.011
Europe HML	0.105	3.321	0.032	1.716	2.412	3.748	4.520	0.222*	0.062
UK High BM	0.504	4.693	0.107	4.203	2.728	4.946	6.004	0.024	-0.172
UK Low BM	0.422	3.943	0.107	3.993	2.935	3.594	4.314	-0.052	0.017
UK HML	-0.308	3.610	-0.085	1.787	2.024	4.325	5.008	0.083	0.104
Pacific Rim High BM	0.104	7.520	0.014	4.862	5.659	10.439	6.891	0.050	-0.114
Pacific Rim Low BM	-0.785	5.787	-0.136	4.724	5.398	5.942	5.492	0.070	-0.018
Pacific Rim HML	0.498	5.210	0.096	1.649	3.180	7.425	5.962	0.025	0.010
Japan High BM	0.238	8.598	0.028	5.969	6.331	11.728	7.931	0.012	-0.136
Japan Low BM	-0.850	6.428	-0.132	5.671	5.886	6.267	6.087	0.089	-0.010
Japan HML	0.697	6.209	0.112	1.858	3.957	8.818	7.091	-0.026	-0.029
NoDurbl	0.672	4.098	0.164	2.455	3.777	5.172	4.188	0.092	-0.115
Durbl	0.926	5.737	0.161	3.683	4.370	6.049	7.370	-0.061	-0.013
Manuf	0.522	4.407	0.118	3.070	3.481	5.466	4.871	0.024	-0.095
Enrgy	0.664	5.085	0.130	3.352	3.680	6.516	5.912	-0.039	-0.069
HiTec	1.439	9.122	0.158	4.187	6.692	8.769	13.004	-0.027	-0.015
Telcm	0.392	6.554	0.060	3.015	4.678	7.225	7.890	0.068	-0.017
Shops	0.759	4.825	0.157	3.076	3.819	5.620	5.874	0.045	-0.269**
Hlth	1.291	4.785	0.270	3.851	4.681	5.699	4.627	-0.176	-0.027
Utils	0.430	4.369	0.098	3.280	3.267	4.322	5.929	0.001	-0.160
Other	0.858	4.868	0.176	3.123	3.810	6.097	5.581	-0.045	-0.094

TABLE 5
Top and Bottom Correlated Factors to Hedge Fund Indices
January, 1994 – December, 2001

		Arbitrage Convertible				Arbitrage Fixed Income			Credit Trading	
		FRM	HFR	CSFB	Hennessee	FRM	HFR	CSFB	FRM	HFR
Top Five	1	Lehman U.S. High Yield	SSB High Yield Index	SSB High Yield Index	UBS Warburg sub BBB / NR	JPM Brady Broad Float	Chg in 10 Yr. US Swap Rate	Lehman U.S. High Yield	SSB High Yield Index	SSB High Yield Index
		0.475	0.627	0.578	0.619	0.535	0.287	0.381	0.631	0.847
	2	Leh. High Yld Ret – Treas.	Lehman U.S. High Yield	Lehman U.S. High Yield	UBS Warburg Conv. Global	SSB High Yield Index	Leh High Yld Ret – Treas.	Leh High Yld Ret – Treas.	JPM Brady Broad	Lehman U.S. High Yield
		0.475	0.589	0.531	0.543	0.510	0.272	0.381	0.611	0.779
	3	SSB High Yield Index	Leh High Yld Ret – Treas.	Leh High Yld Ret – Treas.	UBS Conv. Global – Treas	JPM Brady Broad – Treas.	Lehman U.S. High Yield	SSB High Yield Index	JPM Brady Broad – Treas.	Leh High Yld Ret – Treas.
		0.467	0.589	0.531	0.543	0.503	0.272	0.337	0.611	0.779
	4	Small	JPM Brady Broad	JPM Brady Broad Float	Small	JPM Brady Broad	SSB High Yield Index	Chg in Leh High Yld Ret – Treas	JPM Brady Broad Fixed	Small
		0.368	0.563	0.426	0.516	0.502	0.255	0.317	0.598	0.625
	5	UBS Warburg sub BBB / NR	JPM Brady Broad – Treas.	JPM Brady Broad	NASDAQ	Leh High Yld Ret – Treas.	SMB	NYBOT Dollar Index	JPM Brady Broad Float	Lipper Mutual Funds
		0.353	0.563	0.423	0.512	0.477	0.238	0.305	0.593	0.623
Bottom Five	1	Mortgage Rate – Treas.	% Chg VXN	JPM Non-U.S. Gov–Treasury	% Chg VXN	JPM Fixed – JPM Float	Salomon WGBI	CME Yen Futures	Chg in U.S. Corp Baa Rate	% Chg VXN
		-0.207	-0.386	-0.190	-0.263	-0.330	-0.280	-0.476	-0.282	-0.433
	2	Swap Rate – Treas.	% Chg VIX	% Chg VXN	% Chg VIX	% Chg VXN	Lehman Treasury	MSCI Wrld Sov Ex-USA	% Chg VIX	% Chg VIX
		-0.204	-0.386	-0.176	-0.250	-0.284	-0.256	-0.340	-0.282	-0.417
	3	Momentum	Chg in FHA Mortgage	Chg in FHA Mortgage	Chg in FHA Mortgage	% Chg VIX	CME Yen Future	JPM Non-U.S. Govt. Bond	Chg in JPM Non-US Gov Bd	JPM Fixed – JPM Float
		-0.195	-0.293	-0.172	-0.240	-0.276	-0.255	-0.312	-0.268	-0.250
	4	JPM Non-U.S. Gov–Treasury	Swap Rate – Treas.	Chg in JPM Fixed – Float	HML	HML	MSCI Wrld Sov Ex-USA	Salomon WGBI	% Chg VXN	Chg in U.S. Corp Baa Rate
		-0.188	-0.245	-0.166	-0.206	-0.243	-0.241	-0.308	-0.254	-0.232
	5	Chg in JPM Non-US Gov Bd	Chg in JPM Non-US Gov Bd	Swap Rate – Treasury	Chg in U.S. Corp Baa Rate	CME Yen Futures	JPM Non-U.S. Govt. Bond	Japan HML	CME Yen Futures	Chg in JPM Fixed – Float
		-0.180	-0.241	-0.162	-0.204	-0.218	-0.237	-0.207	-0.228	-0.210

TABLE 5 – *continued*
Top and Bottom Correlated Factors to Hedge Fund Indices
January, 1994 – December, 2001

		Distressed Securities			Merger Arbitrage			
		FRM	HFR	Zurich	FRM	HFR	Hennessee	Zurich
Top Five	1	Small	Small	Small	Lipper Mutual Funds	Small	Russell 2000	Lipper Mutual Funds
		0.809	0.753	0.775	0.612	0.553	0.647	0.702
	2	Russell 2000	Russell 2000	Russell 2000	Russell 2000	Russell 2000	Small	Small
		0.800	0.750	0.770	0.601	0.550	0.642	0.700
	3	Lipper Mutual Funds	Lipper Mutual Funds	Lipper Mutual Funds	Small	Manuf	Lipper Mutual Funds	Russell 2000
		0.732	0.706	0.720	0.591	0.547	0.636	0.686
	4	Wilshire 5000	Wilshire 5000	Wilshire 5000	Manuf	Lipper Mutual Funds	Manuf	Wilshire 5000
		0.681	0.674	0.702	0.570	0.540	0.572	0.657
	5	Nasdaq	JPM Brady Broad Float	Big	Wilshire 5000	JPM Brady Broad Float	Wilshire 5000	SP Barra Value
		0.677	0.662	0.670	0.563	0.524	0.570	0.635
Bottom Five	1	% Chg VIX	% Chg VIX	% Chg VIX	% Chg VIX	% Chg VIX	% Chg VIX	% Chg VIX
		-0.583	-0.586	-0.547	-0.462	-0.456	-0.508	-0.533
	2	% Chg VXN	% Chg VXN	% Chg VXN	% Chg VXN	% Chg VXN	% Chg VXN	% Chg VXN
		-0.575	-0.583	-0.505	-0.419	-0.393	-0.474	-0.485
	3	HML	HML	HML	HML	JPM Fixed – JPM Float	HML	HML
		-0.390	-0.360	-0.338	-0.250	-0.275	-0.247	-0.237
	4	JPM Fixed – JPM Float	JPM Fixed – JPM Float	JPM Fixed – JPM Float	Chg in JPM Fixed – Float	Chg in JPM Fixed – Float	JPM Fixed – JPM Float	Chg in JPM Fixed – Float
		-0.332	-0.318	-0.228	-0.217	-0.266	-0.234	-0.228
	5	Chg in JPM Fixed – Float	Chg in JPM Fixed – Float	Chg in JPM Fixed – Float	JPM Fixed – JPM Float	Momentum	Chg in U.S. Baa – Treas.	Chg in U.S. Corp Baa Rate
		-0.282	-0.228	-0.178	-0.195	-0.167	-0.197	-0.223

TABLE 5 – *continued*
Top and Bottom Correlated Factors to Hedge Fund Indices
January, 1994 – December, 2001

		MultiProcess (Event Driven)				
		FRM	HFR	CSFB	Hennessee	Zurich
Top Five	1	Russell 2000	Small	JPM Brady Broad Float	Small	Small
		0.775	0.835	0.742	0.709	0.747
	2	Small	Russell 2000	JPM Brady Broad – Treas.	Russell 2000	Russell 2000
		0.775	0.826	0.730	0.696	0.741
	3	Lipper Mutual Funds	Lipper Mutual Funds	JPM Brady Broad	Lipper Mutual Funds	Lipper Mutual Funds
		0.744	0.772	0.730	0.690	0.718
	4	Wilshire 5000	UBS Warburg sub BBB / NR	Lipper Mutual Funds	Wilshire 5000	Wilshire 5000
		0.709	0.736	0.716	0.657	0.674
	5	UBS Warburg sub BBB / NR	Wilshire 5000	Small	JPM Brady Broad Float	Low
		0.695	0.715	0.701	0.636	0.647
Bottom Five	1	% Chg VIX	% Chg VIX	% Chg VIX	% Chg VIX	% Chg VIX
		-0.507	-0.517	-0.564	-0.518	-0.550
	2	% Chg VXN	% Chg VXN	% Chg VXN	% Chg VXN	% Chg VXN
		-0.449	-0.504	-0.532	-0.487	-0.502
	3	HML	HML	JPM Fixed – JPM Float	HML	HML
		-0.373	-0.363	-0.301	-0.268	-0.344
	4	Chg in U.S. Corp Baa Rate	JPM Fixed – JPM Float	HML	JPM Fixed – JPM Float	JPM Fixed – JPM Float
		-0.260	-0.230	-0.296	-0.240	-0.260
	5	Japan HML	Chg in U.S. Corp Baa Rate	Chg in JPM Fixed – Float	Chg in U.S. Corp Baa Rate	Chg in JPM Fixed – Float
		-0.169	-0.204	-0.268	-0.199	-0.234

TABLE 6
Mapping of Hedge Fund Indices Using Only Index, French, and Interest Rate Factors
January, 1994 – December, 2001

	Int	Factor 1	Factor 2	Factor 3	Factor 4	Factor 5	R^2 94 – 97	R^2 98 – 01
Arbitrage Convertible								
FRM		UBS Warburg sub BBB / NR					0.2514	0.1220
coef:	0.0053	0.0062						
t-stat:	3.4276	4.4922						
inc. adj R^2:		0.1680						
HFR		SSB High Yield Index	UBS Warburg sub BBB / NR	Dow Jones Commodity			0.5047	0.5100
coef:	0.0036	0.0054	0.0049	0.0033				
t-stat:	2.8865	4.3297	3.7409	2.8520				
inc. adj R^2:		0.3279	0.4201	0.4614				
CSFB		SSB High Yield Index					0.2009	0.3017
coef:	0.0028	0.0111						
t-stat:	1.1700	5.4324						
inc. adj R^2:		0.2308						
Henn		UBS Warburg sub BBB / NR					0.3999	0.3800
coef:	0.0011	0.0106						
t-stat:	0.7329	7.7356						
inc. adj R^2:		0.3825						
Arbitrage Fixed Income								
FRM		Lehman U.S. High Yield	Lehman U.S. Treasury	US Credit Bond			0.1036	0.4616
coef:	0.0062	0.0062	– 0.0216	0.0181				
t-stat:	2.7561	2.3314	– 5.1961	3.5692				
inc. adj R^2:		0.1951	0.3089	0.3864				
HFR		Chg in 10 Yr. US Swap Rate	Lehman Mortgage Backed Secs	SSB High Yield Index	U.S. Real Estate		– 0.0099	0.5750
coef:	0.0097	0.0209	0.0145	0.0063	– 0.0047			
t-stat:	3.9831	7.1353	5.0697	3.8844	– 2.9352			
inc. adj R^2:		0.0978	0.3095	0.3550	0.4043			
CSFB		CME Yen Futures	Lehman U.S. High Yield				0.1875	0.3193
coef:	0.0030	– 0.0065	0.0063					
t-stat:	1.6733	– 4.3337	4.2798					
inc. adj R^2:		0.1425	0.2759					
Credit Trading								
FRM		SSB High Yield Index	JPM Brady Broad Fixed	Utils			0.3657	0.5039
coef:	0.0014	0.0090	0.0081	– 0.0045				
t-stat:	0.7735	4.8513	3.6629	– 2.6876				
inc. adj R^2:		0.3686	0.4217	0.4580				
HFR		SSB High Yield Index	JPM Fixed – JPM Float	Chg in U.S. High Yld Ind – Treas.	Chg in 10 Yr. US Swap Rate	US Credit Bond	0.7243	0.7986
coef:	0.0015	0.0114	– 0.0014	0.0044	0.0105	0.0065		
t-stat:	1.1562	9.6687	– 1.0031	3.6936	4.7327	3.0569		
inc. adj R^2:		0.6120	0.7034	0.7221	0.7524	0.7732		

TABLE 6 – *continued*

Mapping of Hedge Fund Indices Using Only Index, French, and Interest Rate Factors

January, 1994 – December, 2001

	Int	Factor 1	Factor 2	Factor 3	Factor 4	Factor 5	R^2 94 – 97	R^2 98 – 01
Distressed Securities								
FRM		Small	SSB High Yield Index	JPM Fixed – JPM Float	Chg in UBS Global – Treas	JPM Brady Broad Fixed	0.5704	0.7769
coef:	0.0024	0.0076	0.0045	– 0.0047	0.0037	0.0040		
t-stat:	2.1040	5.5665	3.5358	– 4.3205	2.9980	2.6896		
inc. adj R^2:		0.5721	0.6294	0.6698	0.6983	0.7177		
HFR		Small	JPM Brady Broad Float	Chg in UBS Global – Treas.			0.6216	0.6191
coef:	0.0011	0.0102	0.0065	0.0051				
t-stat:	0.7093	5.7433	3.5316	3.0780				
inc. adj R^2:		0.5207	0.5747	0.6102				
Zurich		Small	SSB High Yield Index				0.6795	0.6644
coef:	0.0005	0.0152	0.0056					
t-stat:	0.3040	9.6139	3.6835					
inc. adj R^2:		0.6189	0.6638					
Merger Arbitrage								
FRM		Small	Hlth				0.3708	0.4462
coef:	0.0048	0.0049	0.0032					
t-stat:	5.1244	5.5430	3.4892					
inc. adj R^2:		0.3401	0.4102					
HFR		Small	Hlth	Momentum			0.0375	0.4709
coef:	0.0048	0.0043	0.0031	– 0.0024				
t-stat:	4.8509	4.6243	3.1930	– 2.7543				
inc. adj R^2:		0.2594	0.3081	0.3539				
Hennessee		Small	Hlth				0.3894	0.4336
coef:	0.0040	0.0046	0.0022					
t-stat:	4.8311	5.9782	2.7976					
inc. adj R^2:		0.3610	0.4043					
Zurich		Small	SP Barra Value				0.4687	0.5105
coef:	0.0038	0.0056	0.0033					
t-stat:	4.1175	5.5077	3.1887					
inc. adj R^2:		0.4414	0.4910					

TABLE 6 – *continued*
Mapping of Hedge Fund Indices Using Only Index, French, and Interest Rate Factors
January, 1994 – December, 2001

	Int	Factor 1	Factor 2	Factor 3	Factor 4	Factor 5	R^2 94 – 97	R^2 98 – 01
MultiProcess (Event Driven)								
FRM		UBS Warburg sub BBB / NR	Lipper Mutual Funds	JPM Brady Broad	SMB	HiTec	0.6786	0.7872
coef:	0.0067	0.0065	0.0100	0.0036	0.0038	– 0.0058		
t-stat:	6.0896	4.1120	5.1673	2.7015	3.7883	– 3.5592		
inc. adj R^2:		0.5783	0.6451	0.6721	0.6968	0.7312		
HFR		Small	JPM Brady Broad Fixed	UBS Warburg AAA / AA			0.4889	0.7888
coef:	0.0037	0.0115	0.0058	0.0038				
t-stat:	2.9355	8.9383	4.1595	3.1280				
inc. adj R^2:		0.6087	0.6673	0.6960				
CSFB		JPM Brady Ind. – Treas.	Small	SSB High Yield Index	MSCI 10 Yr +	Chg in UBS Global Ind. – Treas.	0.5880	0.6799
coef:	0.0023	0.0090	0.0051	0.0061	– 0.0047	0.0049		
t-stat:	1.4340	4.4835	2.7219	3.5358	– 3.1348	2.8593		
inc. adj R^2:		0.4286	0.5471	0.5838	0.6133	0.6416		
Hennessee		Small	JPM Brady Broad Fixed				0.3008	0.5576
coef:	0.0030	0.0091	0.0073					
t-stat:	1.8677	5.5156	3.9733					
inc. adj R^2:		0.3933	0.4758					
Zurich		Small	Chg in U.S. High Yld. Ind. – Treas.				0.3535	0.6308
coef:	0.0031	0.0082	0.0037					
t-stat:	2.9362	8.1162	3.6981					
inc. adj R^2:		0.4808	0.5425					

TABLE 7
Mapping of Hedge Fund Indices Using All Factors
January, 1994 – December, 2001

	Int	Factor 1	Factor 2	Factor 3	Factor 4	Factor 5	R^2 94 – 97	R^2 98 – 01
Arbitrage Convertible								
FRM		UBS Warburg sub BBB / NR Put At					0.2288	0.2157
coef:	0.0066	– 0.0075						
t-stat:	4.4674	– 5.1001						
inc. adj R^2:		0.2084						
HFR		UBS Warburg sub BBB / NR Dir (–)	SSB High Yield Index	SP500 Put Deep			0.5211	0.5606
coef:	0.0081	0.0091	0.0038	– 0.0041				
t-stat:	5.3799	3.3306	3.1281	– 2.7633				
inc. adj R^2:		0.4058	0.4750	0.5100				
CSFB		UBS Warburg sub BBB / NR Put Shallow	SSB High Yield Index	VIX Put At			0.3517	0.5358
coef:	0.0037	– 0.0113	0.0076	– 0.0069				
t-stat:	1.8053	– 5.1229	3.8691	– 3.4017				
inc. adj R^2:		0.3046	0.3742	0.4380				
Henn		UBS Warburg sub BBB / NR	Wrld Ex-U.S. Real Estate	NoDur			0.4706	0.4908
coef:	0.0059	0.0103	0.0079	– 0.0044				
t-stat:	3.1587	7.4949	3.6034	– 3.0301				
inc. adj R^2:		0.3825	0.4201	0.4670				
Arbitrage Fixed Income								
FRM		UBS Warburg sub BBB / NR Put Shallow	Nikkei	Phil Gold/Silver Call Deep	SSB High Yield Index		0.0085	0.5404
coef:	0.0046	– 0.0097	0.0054	– 0.0062	0.0054			
t-stat:	2.2336	– 4.3357	2.7808	– 3.0992	2.7326			
inc. adj R^2:		0.2756	0.3381	0.3852	0.4255			
HFR		Phil Gold/Silver Call Deep	EAFE Put Shallow	SP Barra Growth Dir (+)	UBS Warburg sub BBB / NR Dir (+)	Nikkei Call Shallow	0.1710	0.5840
coef:	0.0049	– 0.0080	– 0.0056	– 0.0124	0.0081	0.0046		
t-stat:	2.1385	– 5.2221	– 3.5134	– 4.4889	2.9894	2.9892		
inc. adj R^2:		0.1863	0.2587	0.3087	0.3626	0.4138		
CSFB		CME Yen Futures Dir (+)	Lehman U.S. High Yield				0.1829	0.3729
coef:	0.0084	– 0.0126	0.0061					
t-stat:	4.4466	– 5.0148	4.2699					
inc. adj R^2:		0.1894	0.3150					
Credit Trading								
FRM		SSB High Yield Index	UBS Warburg sub BBB / NR Put Deep				0.3250	0.5278
coef:	0.0028	0.0098	– 0.0079					
t-stat:	1.5937	6.1585	– 4.3989					
inc. adj R^2:		0.3686	0.4717					
HFR		SSB High Yield Index	UBS Warburg sub BBB / NR Put Deep	Chg in 10 Yr. US Swap Rate	Chg in U.S. High Yield – Treas.	Phil Gold / Silver Put Deep	0.7778	0.8357
coef:	–0.0002	0.0111	– 0.0031	0.0054	0.0045	– 0.0034		
t-stat:	–0.2504	10.8868	– 2.9021	5.8319	4.4774	– 3.3067		
inc. adj R^2:		0.6120	0.7068	0.7561	0.7967	0.8167		

TABLE 7 – *continued*
Mapping of Hedge Fund Indices Using All Factors
January, 1994 – December, 2001

	Int	Factor 1	Factor 2	Factor 3	Factor 4	Factor 5	R^2 94 – 97	R^2 98 – 01
Distressed Securities								
FRM		UBS Warburg sub BBB / NR Put At	Small	VIX Call Deep	UBS Warburg sub BBB / NR Dir (–)	SSB High Yield Index	0.5596	0.8491
coef:	–0.0012	– 0.0127	0.0088	– 0.0036	– 0.0142	0.0031		
t-stat:	–0.6014	– 5.1373	6.7764	– 2.9152	– 3.2286	2.9219		
inc. adj R^2:		0.5795	0.7036	0.7360	0.7535	0.7724		
HFR		UBS Warburg sub BBB / NR Put At	Small	UBS Warburg sub BBB / NR Dir (–)	VIX Call Deep	Salomon WGBI Put Shallow	0.6199	0.7912
coef:	–0.0026	– 0.0162	0.0099	– 0.0177	– 0.0058	– 0.0037		
t-stat:	–1.0950	– 5.3215	6.1948	– 3.2873	– 3.7787	– 2.9311		
inc. adj R^2:		0.5487	0.6532	0.6928	0.7207	0.7422		
Zurich		Small	UBS Warburg sub BBB / NR Put Deep	Chg in U.S. High Yield – Treas.	Europe HML		0.6611	0.8598
coef:	0.0025	0.0139	– 0.0086	0.0036	0.0028			
t-stat:	1.9619	10.9207	– 6.5710	3.0341	2.6556			
inc. adj R^2:		0.6189	0.7362	0.7606	0.7754			
Merger Arbitrage								
FRM		UBS Warburg sub BBB / NR Put At	UBS Warburg AAA / AA Dir (+)	EAFE Put Deep			0.3506	0.6367
coef:	0.0049	– 0.0051	0.0038	– 0.0030				
t-stat:	4.7900	– 5.3108	3.3493	– 3.1623				
inc. adj R^2:		0.4190	0.4781	0.5241				
HFR		UBS Warburg sub BBB / NR Put At	EAFE Put Deep				– 0.0131	0.5873
coef:	0.0065	– 0.0045	– 0.0039					
t-stat:	7.3344	– 4.3459	– 3.7366					
inc. adj R^2:		0.3528	0.4312					
Hennessee		UBS Warburg sub BBB / NR Put At	VIX Call At	UBS Warburg AAA / AA Dir (+)			0.4413	0.5943
coef:	0.0046	– 0.0045	– 0.0029	0.0026				
t-stat:	5.1053	– 5.4683	– 3.5397	2.6626				
inc. adj R^2:		0.4413	0.5105	0.5406				
Zurich		UBS Warburg sub BBB / NR Put At	VIX Call At	U.S. Real Estate Call Deep	Small		0.6283	0.7073
coef:	0.0053	– 0.0048	– 0.0035	0.0022	0.0026			
t-stat:	6.9490	– 4.7748	– 3.9380	2.9718	2.9331			
inc. adj R^2:		0.5228	0.6005	0.6433	0.6706			

TABLE 7 – *continued*
Mapping of Hedge Fund Indices Using All Factors
January, 1994 – December, 2001

	Int	Factor 1	Factor 2	Factor 3	Factor 4	Factor 5	R^2 94 – 97	R^2 98 – 01
MultiProcess (Event Driven)								
FRM		UBS Warburg sub BBB / NR	VIX Call At	Small	NASDAQ	EAFE Put Deep	0.6832	0.8209
coef:	0.0078	0.0093	– 0.0035	0.0106	– 0.0081	– 0.0043		
t-stat:	7.3212	5.7979	– 2.7075	5.4002	– 3.8480	– 3.6557		
inc. adj R^2:		0.5783	0.6498	0.6824	0.7158	0.7498		
HFR		Small	UBS Warburg sub BBB / NR Put At	UBS Warburg AAA / AA Dir (+)	JPM Brady Broad Fixed		0.5119	0.8717
coef:	0.0022	0.0079	– 0.0072	0.0060	0.0040			
t-stat:	1.6354	5.8624	– 5.0407	3.7844	3.0798			
inc. adj R^2:		0.6087	0.7041	0.7389	0.7610			
CSFB		UBS Warburg sub BBB / NR Put At	JPM Brady Broad	Europe High BM	UBS Warburg sub BBB / NR Dir (–)	UBS Warburg sub BBB / NR Call At	0.5924	0.8972
coef:	–0.0076	–0.0269	0.0072	0.0039	–0.0266	0.0046		
t-stat:	–3.5288	–10.4792	5.1674	3.4199	–5.5171	3.4892		
inc. adj R^2:		0.6571	0.7219	0.7576	0.7969	0.8191		
Hennessee		UBS Warburg sub BBB / NR Put At	U.S. Real Estate Call Deep	VIX Call At	UBS Warburg sub BBB / NR Call At	Pacific Rim HML	0.4765	0.7325
coef:	0.0028	–0.0001	0.0053	–0.0030	0.0037	–0.0056		
t-stat:	2.5568	–0.0541	4.5413	–2.8725	2.9826	–2.7124		
inc. adj R^2:		0.4705	0.5375	0.5871	0.6128	0.6401		
Zurich		UBS Warburg sub BBB / NR Put At	Russell 2000	VIX Call Shallow	UBS Warburg AAA / AA Dir (+)	UBS Warburg sub BBB / NR Put Deep	0.5129	0.8029
coef:	0.0028	– 0.0001	0.0053	– 0.0030	0.0037	– 0.0056		
t-stat:	2.5568	– 0.0541	4.5413	– 2.8725	2.9826	– 2.7124		
inc. adj R^2:		0.5275	0.6219	0.6597	0.6839	0.7045		

TABLE 8
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	4.68	11.09	-43.09	-21.25	-13.63	9.82	16.52	-48.37	-26.07	-16.42
DJIA	5.10	11.61	-42.78	-21.52	-13.96	10.37	17.11	-50.60	-26.62	-16.80
NASDAQ	5.26	21.85	-64.56	-39.97	-28.58	10.92	33.04	-74.62	-49.51	-36.57
Russell 2000	2.79	13.97	-49.46	-28.90	-19.72	5.48	20.37	-56.68	-36.42	-25.82
Wilshire 5000	3.54	11.33	-40.08	-23.16	-15.34	7.08	16.62	-51.46	-29.09	-19.43
SP Barra Growth	4.48	12.64	-41.34	-24.27	-16.11	9.20	18.82	-49.25	-30.06	-20.06
SP Barra Value	3.01	10.66	-44.46	-22.21	-14.77	6.22	15.68	-47.40	-27.91	-18.52
MSCI World	2.22	10.01	-37.22	-21.19	-14.32	4.53	14.58	-46.74	-27.06	-18.50
Nikkei	-4.00	14.20	-48.19	-32.45	-25.44	-7.64	19.43	-64.10	-44.07	-35.94
FTSE	0.82	9.44	-32.68	-21.02	-14.69	1.49	13.43	-47.44	-27.10	-19.75
EAFE	-0.10	10.27	-39.54	-23.10	-16.76	-0.33	14.58	-50.10	-30.89	-22.91
Lipper Mut Funds	3.79	10.97	-41.25	-22.44	-14.57	7.66	16.16	-48.13	-27.91	-18.11
MSCI AAA	-0.61	6.71	-24.24	-14.46	-10.87	-1.29	9.41	-32.82	-20.46	-15.55
MSCI 10 Yr +	1.30	5.82	-20.31	-11.81	-8.15	2.66	8.27	-28.70	-15.50	-10.42
MSCI Wld Sov Ex-USA	-0.57	5.62	-23.91	-12.62	-9.32	-1.14	7.92	-30.17	-17.67	-13.34
UBS Warburg AAA / AA	4.18	9.10	-34.22	-15.58	-9.83	8.43	13.32	-38.14	-18.89	-11.78
UBS Warburg sub BBB / NR	4.55	15.11	-48.50	-27.20	-18.69	9.18	22.28	-60.85	-34.57	-23.52
CBT Municipal Bond	-2.51	5.37	-28.16	-15.12	-11.33	-4.91	7.45	-39.01	-21.62	-16.99
Leh Bros Gov/Corp	0.80	2.25	-7.87	-4.34	-2.85	1.58	3.24	-10.82	-5.73	-3.66
US Credit Bond	-2.64	3.38	-15.35	-10.43	-8.17	-5.10	4.67	-23.11	-15.54	-12.62
Salomon WGBI	-0.27	4.22	-17.71	-9.33	-6.92	-0.48	5.95	-22.67	-13.26	-9.74
CME Goldman Commodity	-0.33	12.91	-40.71	-25.81	-19.45	-0.56	18.28	-51.14	-35.15	-26.89
Dow Jones Commodity	-3.55	12.13	-66.89	-43.03	-33.19	-6.98	16.65	-80.39	-50.83	-41.07
Philadelphia Gold / Silver	-2.86	25.42	-65.95	-46.73	-37.16	-5.56	35.61	-79.38	-60.09	-49.90
Wld Ex-US Real Estate	-0.86	14.72	-59.14	-36.17	-25.19	-1.76	20.66	-71.94	-45.60	-33.86
U.S. Real Estate	2.45	12.33	-40.28	-24.38	-17.02	4.93	17.91	-51.50	-31.16	-22.19
CME Yen Futures	-2.86	9.51	-32.80	-21.04	-16.49	-5.52	13.21	-45.55	-29.90	-24.24
NYBOT Dollar Index	-0.95	5.16	-21.07	-12.26	-9.11	-1.84	7.28	-27.15	-17.49	-13.22
NYBOT Orange Juice	-1.01	21.31	-64.08	-41.72	-31.82	-1.65	30.13	-74.32	-53.52	-42.77

TABLE 9
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	-1.89	9.59	-35.49	-21.67	-16.30	-3.82	13.28	-42.80	-30.09	-23.37
HML	-2.39	11.67	-50.91	-31.44	-22.62	-4.74	16.12	-66.99	-40.62	-30.67
Low	4.60	12.31	-42.01	-23.61	-15.77	9.35	18.26	-54.23	-29.50	-19.47
High	4.32	10.06	-37.94	-17.89	-11.77	8.84	15.00	-45.03	-22.49	-14.36
Big	4.62	11.29	-43.58	-21.86	-14.00	9.33	16.80	-54.30	-27.19	-17.35
Small	4.32	14.91	-52.45	-29.24	-19.70	9.05	22.12	-60.07	-36.52	-24.73
Momentum	3.55	13.70	-55.56	-30.65	-19.40	7.09	20.16	-63.66	-37.10	-24.64
Europe High BM	5.46	13.53	-50.76	-25.95	-16.79	11.05	20.41	-55.74	-32.18	-20.57
Europe Low BM	2.42	11.51	-41.65	-23.11	-16.10	4.91	16.74	-57.93	-29.86	-20.97
Europe HML	0.60	8.07	-39.68	-18.68	-12.59	1.13	11.48	-45.80	-24.40	-17.18
UK High BM	2.93	11.56	-38.66	-22.80	-15.64	6.03	16.96	-48.87	-29.01	-20.08
UK Low BM	2.51	9.71	-33.17	-19.06	-13.15	5.00	14.20	-40.52	-25.02	-17.30
UK HML	-1.79	8.61	-35.12	-21.13	-15.36	-3.55	11.88	-42.54	-28.76	-22.04
Pacific Rim High BM	0.68	18.34	-46.53	-32.15	-24.71	1.17	26.39	-62.15	-43.12	-34.03
Pacific Rim Low BM	-4.53	13.51	-47.15	-31.39	-25.02	-8.80	18.37	-60.81	-43.30	-35.49
Pacific Rim HML	3.00	12.90	-48.59	-24.46	-16.73	5.79	18.92	-51.14	-31.40	-21.93
Japan High BM	1.24	21.16	-52.11	-34.89	-27.21	2.90	30.81	-62.41	-47.03	-36.83
Japan Low BM	-4.81	14.98	-48.91	-33.77	-26.97	-9.49	20.19	-62.51	-46.25	-38.14
Japan HML	4.21	15.61	-47.22	-27.01	-18.77	8.33	22.87	-53.33	-34.22	-23.98
NoDurbl	3.94	10.29	-37.81	-19.69	-12.83	8.10	15.08	-46.03	-24.35	-15.67
Durbl	5.48	14.46	-39.47	-24.55	-16.68	11.29	21.72	-56.39	-31.21	-20.88
Manuf	3.09	10.89	-46.44	-21.96	-14.57	6.23	15.98	-53.93	-28.02	-18.78
Enrgy	3.93	12.70	-33.89	-21.20	-14.94	7.95	18.73	-45.90	-27.42	-19.28
HiTec	8.69	23.79	-63.03	-39.99	-27.97	18.07	37.23	-75.36	-48.84	-34.86
Telcm	2.24	16.13	-52.43	-32.26	-22.97	4.63	23.54	-64.64	-41.67	-30.27
Shops	4.58	12.07	-38.96	-21.60	-14.44	9.18	18.02	-47.35	-27.34	-18.20
Hlth	7.71	12.30	-39.27	-19.35	-12.08	16.06	18.90	-46.20	-23.13	-13.14
Utils	2.55	10.82	-34.46	-20.45	-14.35	5.12	15.71	-47.13	-26.47	-18.77
Other	5.19	12.26	-46.45	-24.34	-14.85	10.50	18.39	-57.02	-29.64	-18.51

TABLE 10
Value-at-Risk Estimation
Excess 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
Arbitrage Convertible	FRM	Index, French	Normal	4.09	4.14	-11.14	-5.20	-2.63	8.34	6.10	-17.37	-5.22	-1.40
			T-dist	4.10	5.63	-71.06	-9.12	-4.71	8.28	8.22	-50.33	-10.44	-4.68
		All	Normal	4.08	4.14	-14.31	-5.98	-2.79	8.31	6.10	-18.32	-5.93	-1.65
			T-dist	4.04	5.53	-37.21	-9.55	-4.94	8.31	8.21	-52.34	-10.63	-4.68
		Historical		4.05	4.10	-15.82	-5.62	-2.63	8.33	6.05	-16.55	-5.46	-1.46
	HFR	Index, French	Normal	3.06	4.06	-13.64	-6.42	-3.64	6.19	5.91	-17.96	-7.26	-3.34
			T-dist	3.07	5.04	-43.26	-8.80	-5.04	6.25	7.33	-56.24	-10.38	-5.42
		All	Normal	3.06	4.02	-16.26	-7.16	-3.86	6.19	5.89	-18.87	-7.94	-3.70
			T-dist	3.06	4.91	-31.81	-8.94	-5.08	6.17	7.16	-44.28	-10.57	-5.43
		Historical		3.11	3.87	-16.93	-7.32	-3.80	6.26	5.66	-21.35	-7.92	-3.42
	CSFB	Index, French	Normal	2.90	6.60	-24.06	-11.74	-7.67	5.95	9.66	-29.45	-14.88	-9.21
			T-dist	2.99	8.78	-99.61	-17.06	-10.72	6.07	12.76	-97.37	-21.67	-13.69
		All	Normal	2.93	6.66	-29.81	-14.36	-8.56	5.99	9.66	-35.24	-17.17	-10.05
			T-dist	2.96	8.28	-72.27	-17.33	-10.60	5.90	12.03	-57.70	-21.66	-13.14
		Historical		2.93	7.27	-31.81	-16.42	-9.77	5.96	10.57	-44.07	-19.54	-11.67
	Henn	Index, French	Normal	2.07	4.68	-15.71	-8.32	-5.42	4.22	6.80	-20.40	-10.61	-6.60
			T-dist	2.15	5.98	-45.26	-11.68	-7.24	4.30	8.67	-99.74	-15.24	-9.27
		All	Normal	2.09	4.68	-17.11	-8.86	-5.59	4.27	6.79	-21.95	-11.09	-6.71
			T-dist	2.09	5.81	-76.74	-11.56	-7.26	4.27	8.39	-49.07	-14.82	-9.03
		Historical		2.18	4.52	-18.58	-9.18	-5.48	4.40	6.48	-22.72	-10.95	-6.30

TABLE 10 - *continued*
Value-at-Risk Estimation
Excess Returns

50,000 simulations				Six Month Analysis					One Year Analysis				
				Mean	Std Dev	Min	1 Percentile	5 Percentile	Mean	Std Dev	Min	1 Percentile	5 Percentile
Arbitrage Fixed Income	FRM	Index, French	Normal	2.66	6.55	-27.22	-12.81	-7.93	5.44	9.56	-32.68	-16.16	-9.96
			T-dist	2.65	8.24	-51.27	-16.70	-10.59	5.43	12.06	-95.22	-21.44	-13.37
		All	Normal	2.69	6.55	-29.90	-14.10	-8.48	5.42	9.49	-36.07	-17.09	-10.22
			T-dist	2.68	8.19	-62.24	-17.13	-10.77	5.36	11.90	-73.17	-21.84	-13.66
		Historical		2.68	6.23	-32.24	-15.55	-9.22	5.40	9.02	-38.69	-18.30	-10.69
	HFR	Index, French	Normal	0.23	4.80	-19.26	-10.72	-7.55	0.45	6.82	-30.45	-14.75	-10.50
			T-dist	0.26	6.11	-43.01	-14.00	-9.47	0.47	8.58	-85.42	-18.61	-12.94
		All	Normal	0.22	4.80	-23.14	-11.99	-7.96	0.43	6.82	-33.38	-15.96	-10.80
			T-dist	0.20	6.11	-73.96	-14.81	-9.76	0.42	8.63	-51.77	-19.58	-13.37
		Historical		0.18	4.59	-27.55	-12.30	-8.23	0.47	6.51	-32.03	-16.26	-10.75
	CSFB	Index, French	Normal	0.97	4.68	-16.16	-9.58	-6.60	1.97	6.77	-22.96	-12.87	-8.82
			T-dist	1.03	6.15	-47.45	-13.39	-8.75	1.95	8.77	-69.18	-17.77	-11.73
		All	Normal	0.98	4.69	-20.42	-9.96	-6.75	1.94	6.69	-25.41	-13.14	-8.85
			T-dist	0.95	6.14	-50.84	-13.57	-8.81	1.98	8.71	-43.67	-17.71	-11.78
		Historical		0.95	4.13	-21.45	-10.82	-6.85	1.87	5.94	-25.13	-13.68	-8.64
Credit Trading	FRM	Index, French	Normal	2.44	5.77	-19.80	-10.80	-6.96	5.02	8.43	-24.36	-13.45	-8.39
			T-dist	2.44	7.14	-54.16	-14.13	-8.92	5.04	10.45	-63.00	-17.84	-11.32
		All	Normal	2.49	5.80	-28.28	-12.68	-7.46	5.02	8.36	-35.10	-15.44	-9.05
			T-dist	2.52	7.13	-51.46	-15.28	-9.17	5.03	10.31	-48.36	-19.05	-11.65
		Historical		2.42	5.32	-26.32	-12.24	-7.21	4.90	7.67	-30.68	-14.28	-8.16
	HFR	Index, French	Normal	0.56	4.95	-23.96	-11.88	-7.97	1.10	7.09	-32.71	-15.72	-10.66
			T-dist	0.56	5.48	-23.63	-13.07	-8.61	1.12	7.83	-45.20	-17.04	-11.66
		All	Normal	0.56	4.93	-33.95	-13.00	-8.32	1.11	7.07	-32.75	-16.80	-11.11
			T-dist	0.53	5.36	-28.40	-13.68	-8.81	1.14	7.68	-34.05	-18.07	-11.95
		Historical		0.50	4.85	-27.67	-13.39	-8.67	1.04	6.91	-37.49	-17.28	-11.12

TABLE 10 – *continued*
Value-at-Risk Estimation
Excess 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
Distressed Securities	FRM	Index, French	Normal	3.29	5.17	-19.52	-9.34	-5.41	6.69	7.55	-25.03	-11.16	-5.77
			T-dist	3.31	5.87	-29.91	-10.89	-6.35	6.70	8.49	-30.05	-12.67	-7.10
		All	Normal	3.31	5.14	-26.86	-11.84	-6.30	6.65	7.57	-32.79	-13.56	-6.86
			T-dist	3.29	5.71	-52.91	-12.66	-7.03	6.69	8.31	-35.54	-14.49	-7.72
		Historical		3.29	4.91	-26.32	-11.70	-6.01	6.71	7.15	-29.03	-12.60	-6.24
	HFR	Index, French	Normal	2.67	5.99	-26.58	-10.98	-7.09	5.44	8.65	-36.79	-13.83	-8.39
			T-dist	2.68	6.99	-71.05	-13.38	-8.56	5.44	10.19	-42.66	-17.11	-10.70
		All	Normal	2.65	5.97	-34.85	-15.21	-8.59	5.50	8.67	-41.38	-17.42	-9.94
			T-dist	2.68	6.67	-37.49	-15.77	-9.23	5.44	9.79	-71.59	-19.17	-11.36
		Historical		2.67	5.40	-33.59	-13.55	-7.38	5.43	7.87	-39.60	-15.48	-8.68
	Zurich	Index, French	Normal	2.65	6.33	-22.37	-11.78	-7.66	5.31	9.22	-30.63	-15.15	-9.43
			T-dist	2.68	7.33	-43.69	-14.16	-9.12	5.27	10.69	-82.58	-18.34	-11.61
		All	Normal	2.68	6.32	-40.82	-15.12	-8.65	5.26	9.23	-41.73	-18.01	-10.70
			T-dist	2.64	7.01	-41.79	-16.26	-9.36	5.28	10.19	-51.65	-19.79	-11.99
		Historical		2.61	6.35	-31.17	-16.06	-9.65	5.34	9.22	-38.97	-19.03	-11.30

TABLE 10 – *continued*
Value-at-Risk Estimation
Excess 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
Merger Arbitrage	FRM	Index, French	Normal	4.14	2.89	-7.05	-2.50	-0.57	8.44	4.27	-9.87	-1.29	1.49
			T-dist	4.10	3.63	-20.01	-4.51	-1.70	8.43	5.36	-31.35	-3.97	-0.16
		All	Normal	4.12	2.89	-12.64	-4.13	-1.02	8.40	4.28	-12.57	-2.81	0.97
			T-dist	4.13	3.52	-30.46	-5.17	-1.86	8.39	5.14	-17.72	-4.32	-0.25
		Historical		4.10	3.02	-17.83	-4.67	-1.66	8.39	4.48	-19.19	-3.83	0.33
	HFR	Index, French	Normal	3.76	2.90	-7.37	-2.87	-1.00	7.67	4.26	-8.86	-2.00	0.77
			T-dist	3.74	3.72	-32.51	-5.04	-2.21	7.68	5.45	-32.75	-4.75	-0.99
		All	Normal	3.76	2.88	-12.83	-4.40	-1.40	7.63	4.23	-14.64	-3.40	0.25
			T-dist	3.75	3.63	-24.77	-5.83	-2.40	7.66	5.31	-26.12	-5.36	-1.08
		Historical		3.71	3.36	-16.20	-6.68	-2.98	7.62	4.94	-26.95	-6.14	-1.46
	Henn	Index, French	Normal	3.37	2.50	-7.45	-2.44	-0.75	6.87	3.67	-7.54	-1.42	0.89
			T-dist	3.39	3.17	-21.71	-4.16	-1.68	6.88	4.62	-15.19	-3.90	-0.54
		All	Normal	3.37	2.50	-10.29	-3.50	-1.05	6.89	3.67	-11.42	-2.68	0.58
			T-dist	3.38	3.04	-14.27	-4.61	-1.80	6.88	4.40	-39.41	-4.00	-0.51
		Historical		3.38	2.88	-13.75	-5.17	-2.16	6.83	4.23	-17.04	-4.78	-0.79
	Zurich	Index, French	Normal	3.34	3.15	-10.43	-4.04	-1.84	6.76	4.59	-11.55	-3.68	-0.75
			T-dist	3.32	3.85	-38.08	-5.86	-2.88	6.77	5.65	-33.75	-6.28	-2.23
		All	Normal	3.31	3.14	-15.54	-5.38	-2.26	6.78	4.58	-20.12	-4.77	-1.20
			T-dist	3.36	3.60	-19.01	-6.14	-2.85	6.83	5.27	-23.25	-6.29	-2.04
		Historical		3.34	3.32	-17.53	-6.86	-3.21	6.80	4.83	-21.75	-6.93	-2.03

TABLE 10 – *continued*
Value-at-Risk Estimation
Excess 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
MultiProcess (Event Driven)	FRM	Index, French	Normal	5.48	4.97	-14.69	-6.04	-2.66	11.19	7.48	-18.30	-5.75	-0.96
			T-dist	5.49	5.57	-32.92	-7.28	-3.60	11.18	8.38	-26.78	-7.65	-2.16
		All	Normal	5.46	4.97	-22.06	-7.10	-3.00	11.26	7.41	-20.37	-6.34	-1.12
			T-dist	5.48	5.57	-28.54	-8.27	-3.91	11.20	8.36	-40.35	-8.47	-2.43
		Historical		5.49	5.42	-24.09	-8.88	-3.70	11.30	8.05	-27.34	-8.05	-2.04
	HFR	Index, French	Normal	4.83	5.46	-16.85	-7.90	-4.15	9.86	8.05	-19.00	-8.16	-3.11
			T-dist	4.77	6.21	-37.58	-9.66	-5.27	9.75	9.18	-43.40	-10.85	-4.90
		All	Normal	4.80	5.44	-23.32	-9.25	-4.48	9.86	8.06	-25.68	-9.64	-3.65
			T-dist	4.81	6.02	-35.74	-10.09	-5.30	9.83	8.96	-50.27	-11.43	-4.87
		Historical		4.80	5.38	-23.33	-10.21	-4.61	9.84	8.05	-29.88	-10.51	-3.94
	CSFB	Index, French	Normal	3.35	6.42	-25.67	-12.26	-7.45	6.80	9.31	-31.45	-14.24	-8.34
			T-dist	3.33	7.38	-41.63	-14.23	-8.74	6.84	11.00	-58.39	-17.83	-10.70
		All	Normal	3.42	6.32	-36.23	-17.44	-9.85	6.73	9.38	-42.40	-19.60	-11.78
			T-dist	3.33	6.96	-38.27	-18.28	-10.61	6.80	10.09	-45.44	-20.67	-12.11
		Historical		3.33	6.47	-36.21	-18.59	-12.45	6.85	9.41	-45.03	-20.38	-12.72
	Henn	Index, French	Normal	3.76	5.45	-19.05	-8.74	-5.14	7.68	7.98	-19.65	-10.07	-5.11
			T-dist	3.83	6.67	-51.35	-11.73	-6.86	7.67	9.87	-67.22	-14.10	-7.86
		All	Normal	3.78	5.46	-21.96	-10.80	-5.56	7.67	8.05	-32.66	-11.82	-5.92
			T-dist	3.80	6.35	-39.64	-12.28	-6.86	7.70	9.29	-49.14	-14.34	-7.52
		Historical		3.79	6.05	-32.64	-13.44	-6.98	7.75	8.89	-33.75	-14.52	-7.58
	Zurich	Index, French	Normal	2.79	3.79	-13.20	-5.97	-3.42	5.69	5.49	-18.34	-6.65	-3.20
			T-dist	2.83	4.57	-56.39	-7.79	-4.55	5.68	6.61	-41.37	-9.31	-4.93
		All	Normal	2.79	3.77	-20.86	-8.50	-4.23	5.70	5.49	-22.09	-8.94	-4.10
			T-dist	2.81	4.28	-46.74	-9.06	-4.77	5.67	6.25	-29.30	-10.46	-5.06
		Historical		2.80	4.04	-22.47	-9.89	-5.20	5.71	5.84	-23.12	-10.50	-5.14