

Value at Risk and the Cross-Section of Hedge Fund Returns^{*}

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ABSTRACT

Using two large hedge fund databases, this paper empirically tests the presence and significance of a cross-sectional relation between hedge fund returns and value at risk (VaR). The univariate and bivariate portfolio-level analyses as well as the fund-level regression results indicate a significantly positive relation between VaR and the cross-section of expected returns on live funds. During the period of January 1995 to December 2003, the live funds with high VaR outperform those with low VaR by an annual return difference of 9%. This risk-return tradeoff holds even after controlling for age, size, and liquidity factors. Furthermore, the risk profile of defunct funds is found to be different from that of live funds. The relation between downside risk and expected return is found to be negative for defunct funds because taking high risk by these funds can wipe out fund capital, and hence they become defunct. Meanwhile, voluntary closure makes some well performed funds with large assets and low risk fall into the defunct category. Hence, the risk-return relation for defunct funds is more complicated than what implies by survival. We demonstrate how to distinguish live funds from defunct funds on an ex ante basis. A trading rule based on buying the expected to live funds and selling the expected to disappear funds provides an annual profit of 8-10% depending on the investment horizons.

Key words: hedge fund, value at risk, cross-section of expected returns, liquidity, voluntary closure

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Using two large hedge fund databases, this paper empirically tests the presence and significance of a cross-sectional relation between hedge fund returns and value at risk (VaR). The univariate and bivariate portfolio-level analyses as well as the fund-level regression results indicate a significantly positive relation between VaR and the cross-section of expected returns on live funds. During the period of January 1995 to December 2003, the live funds with high VaR outperform those with low VaR by an annual return difference of 9%. This risk-return tradeoff holds even after controlling for age, size, and liquidity factors. Furthermore, the risk profile of defunct funds is found to be different from that of live funds. The relation between downside risk and expected return is found to be negative for defunct funds because taking high risk by these funds can wipe out fund capital, and hence they become defunct. Meanwhile, voluntary closure makes some well performed funds with large assets and low risk fall into the defunct category. Hence, the risk-return relation for defunct funds is more complicated than what implies by survival. We demonstrate how to distinguish live funds from defunct funds on an ex ante basis. A trading rule based on buying the expected to live funds and selling the expected to disappear funds provides an annual profit of 8-10% depending on the investment horizons.

1. Introduction

Due to flexible trading strategies, advantageous fee structure, low correlations with traditional asset classes, and light regulatory oversight, hedge funds have gained tremendous popularity lately. It is estimated that there are over 7,000 hedge funds worldwide with at least \$870 billion under management.¹ The NYSE market makers estimate that during 2004 about half of the daily trading volume comes from hedge funds. Although hedge funds are initially created for accredited investors, institutional investors such as investment banks, public and private pension funds, university endowments and foundations are heavily involved in investing in this alternative investment vehicle.² This increasing involvement by institutional investors has raised public concerns on the risk profile of hedge funds and the fiduciary duties of the financial institutions.

Academic literature on hedge funds has been largely focused on performance measures. For example, Fung and Hsieh (1997) extend Sharpe's (1992) style analysis framework by including dynamic hedge fund investment strategies and argue that the extended model can provide an integrated framework for style analysis. Brown, Goetzmann, and Ibbotson (1999) examine the performance of offshore hedge funds and attribute their performance to style effects rather than managerial skills. Ackermann, McEnally, and Ravenscraft (1999) conclude that hedge funds outperform mutual funds but find mixed results when comparing them with various benchmarks. Liang (1999) finds that hedge fund investment strategies are different from those of mutual funds. Recently, Agarwal and Naik (2004) propose a general asset class factor model comprising of option-based and buy-and-hold strategies to benchmark hedge fund performance.

All of the aforementioned studies analyze hedge fund performance relative to certain benchmarks. An equally important question, largely unanswered, is about the risk profile of hedge funds and how to relate risk to fund returns. The debacle of Long-Term Capital Management LP (LTCM) highlighted the need for more academic studies on hedge fund risk exposure. In this paper, we address the following primary questions: How to measure hedge fund risk? Can fund characteristics such as Value at Risk explain the cross-sectional variation in hedge fund returns? Do defunct funds have different risk profile from that of the live ones? Are other fund characteristics such as size, age, and liquidity factor proxies for fund risk?

Due to speculative bet and dynamic trading strategies, hedge fund returns often exhibit fat tails that are affected by event risk. For example, hedge funds suffered from huge losses during the

¹ See "Registration Under the Advisers Act of Certain Hedge Fund Advisers" by the US SEC, 2004.

² Harvard University invests 12% of the \$27 billion endowment in hedge funds. See Business Week, January 3, 2005.

1997 Asian Currency Crisis and the 1998 Russian Debt Crisis. Hence, the traditional risk measures such as standard deviation may not fully capture the risk characteristics of hedge funds. In fact, Jorion (2000) adopts a VaR approach to analyze LTCM's failure and concludes that LCTM underestimates its risk profile due to its reliance on short-term history. Gupta and Liang (2005) compare VaR and traditional risk measures in evaluating hedge fund risk and conclude that VaR is a better measure for hedge fund risk than standard deviation due to negative skewness and substantial kurtosis in hedge fund returns. Meanwhile, assuming normality can underestimate the true risk and is inappropriate in determining capital adequacy for the hedge fund industry. Furthermore, Bali and Gokcan (2004) estimate VaR for hedge fund portfolios using the thin-tailed normal distribution, the fat-tailed generalized error distribution, the Cornish-Fisher (CF, 1937) expansion, and the extreme value theory (EVT) based approach of Bali (2003) that considers higher-order moments like skewness and kurtosis. They find the EVT approach and the CF expansion capture the tail risk better than the other approaches. Finally, using a mean-conditional VaR framework, Agarwal and Naik (2004) demonstrate that the standard mean-variance framework can underestimate the tail risk of hedge funds.

The above papers indicate that VaR provides a better characterization of hedge fund risk than the traditional measures such as standard deviation. In addition to VaR, hedge fund returns can be affected by other risk factors such as liquidity risk. In fact, Liang (1999) indicates that the lockup feature is related to hedge fund returns. Recently, Aragon (2004) argues that the abnormal performance of hedge funds can be largely explained by liquidity risk premium that is measured by the lockup period. Many hedge funds have the lockup feature. Money invested in such funds is not allowed to withdraw immediately and fund managers have the flexibility to invest in illiquid securities. Aragon (2004) finds that the funds with lockup features outperform those without by 4% on an annual basis.³ In addition, Getmansky, Lo, and Makarov (2004) find that serial correlation in hedge fund returns is stronger compared to the traditional assets like mutual funds. They argue the autocorrelation pattern can be explained by return smoothing or illiquidity in asset returns.

One of the most important relations in the asset pricing literature is the link between expected return and risk of an asset. It is well documented that the expected asset returns are related to systematic risk or market risk (the CAPM model), factor risk such as macroeconomic variables (the

³ Compared with the liquidity risk premium, VaR measures market risk and event risk. In order to better understand the VaR-expected return relation, it is important to control for liquidity risk. As will be discussed later in the paper, the significantly positive relation between VaR and the cross-section of hedge fund returns holds with and without controlling for liquidity risk.

APT framework), and Fama-French (1992, 1993) factors such as size and book-to-market. Following the asset pricing literature, we examine the cross-sectional relation between expected return, risk, and other explanatory variables of hedge funds in this paper.⁴

Our main focus is to test the presence and significance of a relationship between VaR and expected returns on hedge funds. We estimate VaR using the empirical distribution as well as the Cornish-Fisher (CF) expansion to incorporate the higher-order moments in fund returns. The empirical results indicate that the average return difference between the high VaR and low VaR portfolios is both statistically and economically significant: Buying the higher VaR portfolio while short selling the low VaR portfolio generates an average annual return of 9% for the sample period of January 1995-December 2003. These results hold not only for univariate sorting based on historical VaRs but also for the bivariate sorting (first by age, asset size, or liquidity and then VaR). The cross-sectional regression results indicate that VaR indeed has significant power in predicting hedge fund returns, even after controlling for fund characteristics such as age, size, and liquidity risk.

Based on the observed risk changing patterns, we develop a trading rule to identify the expected to live funds and the expected to disappear funds. We expect that the future live funds will not have much change in their VaRs while the future defunct funds will most likely to face with a significant increase in their VaRs. The trading rule is to buy the expected to live funds and sell the expected to disappear funds. With this simple trading rule, we can generate an annual profit of 8-10% depending on the investment horizon.

To mitigate the survivorship bias issue, we analyze not only the live funds but also the defunct funds. We document that the risk profile of the defunct funds is different from that of the live funds. For the live funds, the risk-return relation is positive: the higher the tail risk, the higher the hedge fund return. However, this relation is reversed for the defunct funds: the higher the tail risk, the lower the realized return simply because high risk wipes out fund assets and makes them defunct. This makes intuitive sense. When a fund takes high risk, it may generate very high return so that the fund will survive. This is the exact relation for live funds. However, high risk may also wipe out fund asset; hence it causes the fund to disappear. Therefore, for the defunct funds, the inverse relationship is consistent with the market's experience: high risk funds will lose capital and hence become defunct. Interestingly, some large and low risk funds choose to voluntarily stop

⁴ Bali and Cakici (2004) examine the cross-sectional relation between VaR and expected returns on individual stocks trading at NYSE, AMEX, and Nasdaq.

reporting. Their performance is even better than the corresponding live funds. This risk-return relation for defunct funds is more complicated than what is implied by survivor conditioning.

To the best of our knowledge, this paper is the first that explores the cross-sectional relation between hedge fund risk and return at both the individual fund level and the portfolio level in an asset pricing framework. The paper also contributes to the literature by showing how to measure hedge fund risk and how to explain the cross-sectional variability in hedge fund returns.

The paper is organized as follows. Section 2 describes the data and methodology. Section 3 presents the empirical results. Section 4 provides some robustness checks. Section 5 concludes the paper.

2. Data and Methodology

2.1. Data

We obtain the data from Tremont TASS (hereafter, TASS) and Hedge Fund Research, Inc. (hereafter, HFR). These two databases are the most commonly utilized databases by researchers in academia and practitioners in hedge fund industry.⁵ As of December 2003, there are 2,012 live funds and 1,902 defunct funds in TASS. There are 2,375 live funds in HFR.⁶ These numbers exclude fund of hedge funds to avoid double counting. For each fund, HFR and TASS provide large array of information including net-of-fee monthly returns, investment strategy, assets under management, fee structure, whether or not a fund applies high water mark provision and hurdle rate, minimum investment, subscription and redemption information, lockup, etc.

To enlarge our sample we merge these two databases by eliminating those funds that appear twice. A fund might appear twice, because they choose to report to both databases. To merge the data, we do three way sorting: by firm name, fund name, and database. This helps us to identify the funds that appear on both databases. In most cases, monthly returns reported to both databases are identical. In this case selection of the reported data to the HFR versus TASS is random. However, in some cases one database may have a long return history than the other. In this case, we select the provider with a long history. After screening a total of 4,387 live funds, we find that there are 1,307

⁵ TASS is used by Fung and Hsieh (1997, 2000), Liang (2000), Lo (2001), Brown, Goetzmann, and Park (2002), Brown and Goetzmann (2003), Getmansky, Lo, and Makarov (2004), and Agarwal and Naik (2004). HFR is used by Ackermann et al. (1999) and Liang (2000).

⁶ We do not have the defunct fund information from HFR. However, Liang (2000) indicates that HFR carries much less defunct funds than TASS. Hence, including defunct funds from TASS will largely solve for the problem of survivorship bias.

funds that are appearing twice.⁷ After excluding one of the repeating funds, we end up with a total universe of 3,080 unique funds. However, not all of these funds are included in our analysis for several reasons. First, in order to estimate the VaR of these funds we need 60 months of returns. Where 60 months of data is not available, a minimum of 24 months is used. Therefore, we require at least 2 years of performance history starting from January 1995 to December 2003. This requirement leaves us with 2,043 funds. Second, we concentrate on the following strategies: equity hedge, macro, convertible arbitrage, distressed securities, merger arbitrage, event driven, fixed income, equity market neutral, statistical arbitrage, short selling, sector funds and relative value arbitrage strategies.⁸ According to HFR, these strategies cover 93.5% of all the assets managed by hedge funds as fourth quarter of 2003. Finally, we exclude the funds with assets under management less than \$10 million.⁹ This is to reduce any bias that might be caused by very small funds. After all these requirements we have 1,221 surviving (or live) funds left in our sample.

To mitigate survivorship bias, we also include defunct funds in our sample. There are 1,902 defunct funds from the TASS data. To be consistent, we select the defunct funds executing the aforementioned strategies and restrict them to have at least a 24-month return history for estimating the VaR. After these requirements, we have 843 defunct funds left in our data sample.¹⁰ Table I presents the number of observations for each hedge fund category, the average values of the sample mean, standard deviation, skewness, and excess kurtosis of individual hedge fund returns. Table I also reports the results of the normality tests that are presented as a percentage of rejection of the null hypothesis at the 1% significance level. It is well documented that hedge fund returns are not normally distributed (see Bali and Gokcan (2004), Agarwal and Naik (2004), Gupta and Liang (2005)). Table I clearly shows that zero skewness is rejected about 50% of the time, excess kurtosis of zero is rejected about 75% of the time, and the Jarque-Bera (JB) test rejects normality for at least

⁷ TASS expects 50% to 60% of hedge funds in their database to overlap with the funds in HFR. These numbers are in line with our findings.

⁸ We exclude funds of funds, managed futures, and emerging market funds. We want to focus on hedge funds, rather than funds of funds and CTAs. We eliminate emerging market funds as they are not a specific style but concentrating on emerging markets.

⁹ Some index builders such as Credit Suisse First Boston also require a minimum asset of \$10 million for the member funds. Recently, the SEC has passed a regulatory rule to require major hedge funds with at least \$25 million assets under management and less than two year lockup periods to register as investment advisors. Liang (2003) indicates that small funds are more likely to have ineffective auditing and the returns numbers are more likely to be problematic.

¹⁰ We include small funds with assets below \$10 million for defunct funds as nearly half of the defunct funds falls in this category. Plus, defunct funds drop out of the databases at different dates so it is hard to impose a common size cutoff point since sizes at different time points are not comparable.

90% of the funds in our sample no matter we look at the live, defunct, or the total sample.¹¹ This confirms that standard deviation is an inappropriate measure for hedge fund risk because it calculates “average” fluctuations around the mean and ignores “extreme” movements that generate significant skewness and kurtosis in the return distribution. We think that VaR provides a better characterization of price (or market) risk for hedge funds because it takes into account higher-order moments such as skewness and kurtosis along with the standard deviation.

2.2. Methodology

In this subsection, we present the methods of estimating VaRs and forming portfolios for our empirical tests.

Nonparametric VaR: There are three main decision variables that are required to estimate VaR – the confidence level, a target horizon, and an estimation model. In this paper, we use approximately 95% confidence level depending on data availability. The time horizon is 1 month. Estimation model for nonparametric VaR is based on the lower tail of the actual empirical distribution, i.e., we use monthly returns over the past 24 to 60 months (as available) to estimate nonparametric VaR from the empirical distribution of individual hedge fund returns.¹² When we have 60 observations, we use the third (57/59=96.6% VaR) and the fourth lowest (56/59=94.9% VaR) observations for interpolating the 95% VaR, while we have 24 observations, we interpolate between the second lowest and the third lowest observations (22/23=95.7% and 21/23=91.3%). We use similar interpolation for other return history in between 24 and 60 months.¹³

Parametric VaR (CF VaR): The traditional parametric approaches to VaR assume that returns follow a normal distribution. Hence, the VaR measure depends on the mean and standard deviation of the normal density, and the critical value corresponding to a confidence level. As shown in Jorion (2001) and others, the 1% normal VaR is calculated by the following formula:

$$\mathfrak{V}_{Normal} = \mu - 2.326\sigma \quad (1)$$

¹¹ The standard errors of skewness and excess kurtosis statistics are, respectively, $\sqrt{6/n}$ and $\sqrt{24/n}$, where n is the number of observations. The Jarque-Bera (JB) statistic is a formal statistic for testing non-normality based on the skewness (S) and kurtosis (K) estimates, $JB = n[(S^2/6)+(K-3)^2/24]$. The statistic has a Chi-square distribution with two degrees of freedom under the null of the normal return distribution, with the critical values at the 5% and 1% significance level are 5.99 and 9.21, respectively.

¹² If a fund has less than 24 observations for any month, it is not included in the portfolios or is not used in the cross-sectional regressions for that month.

¹³ We use the Microsoft Excel’s percentile function to automatically calculate the 95% VaR. We also use a more uniform VaR structure by restricting the sample to a set of hedge funds with 60 months of return data. In fact, we find a stronger relation between VaR and the cross-section of hedge fund returns from this restricted sample.

where μ and σ are, respectively, the sample mean and standard deviation of returns, and -2.326 is the critical value from the normal density corresponding to the confidence level of 99%.

However, since hedge fund returns are skewed and fat-tailed we cannot use the above VaR formula that assumes a normal distribution. To account for non-normality of returns, we estimate VaR using the Cornish-Fisher (1937) expansion in the following equation that adjusts \mathfrak{F}_{Normal} for the skewness and kurtosis of the empirical distribution:

$$\mathfrak{F}_{CF}(\alpha) = \mu - \Omega(\alpha) \times \sigma \quad (2)$$

$$\Omega(\alpha) = z(\alpha) + \frac{1}{6}(z(\alpha)^2 - 1)S + \frac{1}{24}(z(\alpha)^3 - 3z(\alpha))K - \frac{1}{36}(2z(\alpha)^3 - 5z(\alpha))S^2 \quad (3)$$

where μ is the mean, σ is the standard deviation of the past 24 to 60 monthly returns, and $\Omega(\alpha)$ is the critical value based on the loss probability level, skewness, and kurtosis of the past 24 to 60 monthly returns. In equation (3), $z(\alpha)$ is the critical value from the normal distribution for probability $(1-\alpha)$, S is the skewness, and K is the excess kurtosis.¹⁴ Equations (2) and (3) indicate that the Cornish-Fisher expansion allows us to compute VaR for distribution with asymmetry and leptokurtosis. Note that if the distribution is normal, S and K are equal to zero, which makes $\Omega(\alpha)$ be equal to $z(\alpha)$.

Note that the CF-VaR takes higher-order moments or extreme events into consideration, which is consistent with the extreme value theory approach applied by Gupta and Liang (2005). Recently, Bali and Theodossiou (2005) compare the risk measurement performance of alternative skewed fat-tailed distributions with the generalized Pareto (GPD) and generalized extreme value (GEV) distributions. Based on the unconditional and conditional coverage test results, they find that the skewed generalized t (SGT) distribution performs as well as the GPD and GEV distributions. That is, the unconditional and conditional VaR measures of SGT are very similar to those obtained from the GPD and GEV distributions. Bali and Theodossiou show that SGT yields an accurate characterization of the tails of the return distribution because of its additional skewness and kurtosis parameters. We should note that the Cornish-Fisher expansion used in the paper provides an approximation to the tails of the SGT density by taking into account the skewness and excess kurtosis of the empirical return distribution. Unfortunately, we cannot estimate VaR with SGT because of our limited number of observations.

¹⁴ For example, $z(\alpha)$ equals -2.326 (-1.960) [-1.645] for the 1% (2.5%) [5%] VaR.

Portfolio Formation Based on Univariate Sorting: Once we have the value-at-risk measures for each fund, we rank and place them into 10 decile portfolios based on their VaRs. Portfolio 1 has the lowest VaR and portfolio 10 has the highest VaR. The portfolio formation procedure is very similar to Fama and French (1992), except that they update their portfolios annually, whereas we update ours on a monthly basis. Our estimation period for VaR starts in January 1990 and the test period is from January 1995 to December 2003. For example, in January 1995 we estimate VaR for each fund based on the return history from January 1990 to December 1994 and rank all the funds according to the estimated VaRs. Then 10 equally weighted portfolios are formed based on the VaR rank. We calculate the one-month ahead portfolio returns in January 1995. Next month, by rolling over one month ahead, we re-estimate VaR for each fund, rank them based on the updated VaR, and form new portfolios. This procedure is repeated until December 2003 when we have no more data left. Therefore, we have 108 time series for the 10 equally weighted portfolios formed based on their VaRs. We generate these portfolios for both live and defunct funds.

The same procedure is conducted for the Age, Asset, and Liquidity portfolios. We have three age (or asset) portfolios and two lockup portfolios. We use the lockup dummy to measure liquidity risk. The dummy variable (*dlock*) equals 1 if the fund reports a nonzero lockup period and zero otherwise.¹⁵

Portfolio Formation Based on Bivariate Sorting: To examine whether VaR can generate enough cross-sectional difference between portfolio 1 and portfolio 10 after controlling for age, asset, and liquidity, we need to form portfolios first by age (asset or liquidity) and then VaR. Hence, in addition to the univariate sorting, we need to form portfolios based on bivariate sorts. For example, to separate the age effect from VaR, we first rank hedge funds based on age and then VaR. Specifically, every month we first rank funds based on their ages. Then, we form low, medium, and high age groups with an equal amount of funds in each group. Finally, within each age group, funds are further ranked based on their VaR and 10 equally weighted portfolios are formed based on the VaR. This procedure is repeated every month starting from January 1995 until December 2003. Similar to the univariate sorting procedure, we have 108 time series of 10 equally weighted portfolios formed on VaR within each of the age (asset or liquidity) subgroup¹⁶.

Cross-Sectional Regressions: Similar to Fama and French (1992), we run the cross-sectional one-month-ahead predictive regressions to examine the predictive power of VaR at the fund level.

¹⁵ For funds with lockup periods, they are clustered around one year. Since there is not enough variation for the lockup period we use a dummy variable instead of the number of months.

¹⁶ Note that we have only two liquidity groups.

In fact, we adopt the Fama-MacBeth (1973) cross-sectional regression framework. Specifically, we use the data from January 1990 to December 1994 to calculate VaR and then regress the cross-section of January 1995 returns on the calculated VaRs.

We continue to generate VaRs and run the cross-sectional regressions until we exhaust the whole sample in December 2003. Once we obtain the 108 time series of slope coefficients, we take the average of these coefficients and test their statistical significance using the standard t -statistics and the Newey-West (1987) t -statistics with 6 lags to correct for autocorrelation and heteroscedasticity. We conduct both univariate and multivariate regressions with VaR, CF VaR, Age, Asset and the Lockup dummy.

3. Empirical Results

3.1. Univariate Sort

3.1.1. Sort by VaR

We form 10 portfolios by sorting individual hedge funds based on their estimated VaR.¹⁷ Specifically, for each month from January 1995 to December 2003, we use the previous 24 to 60 monthly returns (as available) to estimate VaR for each fund and then assign the next month's return to the current month's VaR.¹⁸ Once the portfolios are formed and the one-month ahead returns are computed, the average return on portfolio i is calculated as the equal-weighted average of the one-month ahead returns on individual funds that are in portfolio i .¹⁹ In this setup, portfolio 1 has the lowest average VaR while portfolio 10 has the highest average VaR from 108 rolling time windows over the period of January 1995-December 2003.

We should also note that the original VaR measures are multiplied by -1 before forming the decile portfolios. The original maximum likely loss values are negative since they are obtained from the left tail of the return distribution, but the variables used in portfolio formation are defined as $-1 \times (\text{the maximum likely loss})$.

¹⁷ The portfolio breakpoints are determined in such a way that each portfolio contains 10% of the hedge funds sorted by estimated VaR.

¹⁸ The portfolios are formed to test the significance of a cross-sectional relation between VaR and the one-month ahead expected returns on hedge funds. We do not examine the “contemporaneous” cross-sectional relation between VaR and expected returns. Instead, following Fama and French (1992), we focus on the “predictive” relation between VaR and the cross-section of hedge fund returns.

¹⁹ For example, if a fund has 60 monthly return observations from January 1990 to December 1994. We first estimate the nonparametric 5% VaR as the third lowest return observation over the past 5 years (January 1990-December 1994) and then assign the return of January 1995 to this estimated VaR. This procedure is repeated rolling the sample by one month and for all funds in the sample with at least 24 monthly return observations. Final results are based on the average of these returns and VaRs obtained from the overlapping monthly intervals.

Since the VaR measures are constructed by moving one month ahead each time, the average returns and average VaRs of 10 portfolios are obtained from the overlapping monthly intervals. To correct for potential autocorrelation and heteroscedasticity, we calculate both the standard t -statistics and the Newey-West (1987) adjusted t -statistics with 6 lags.

Table II shows the cross-sectional relation between VaR and expected returns for all funds based on the pooled sample of both live and defunct funds. The results from the parametric (CF VaR) and nonparametric VaR measures are very similar except that CF VaR has a slightly wider range across the ten portfolios than that of nonparametric VaR. The result in Table II indicates that, moving from Decile 1 to Decile 9, there is a positive relation between VaR and expected returns on hedge funds. For example, the return difference between Decile 9 and Decile 1 is 0.32% per month when CF VaR is used, and the VaR-return relation is almost monotonic except for Decile 10, which represents the highest VaR group and consists of many defunct funds. Interestingly, Decile 10 offers a monthly return of only 0.82%, the lowest among all portfolios when the nonparametric VaR is used. Overall, the bottom panel in Table II shows that when both live and defunct funds are considered, there is no positive and statistically significant average return differential between Decile 10 (high VaR portfolio) and Decile 1 (low VaR portfolio). It seems that the monotonic risk-return relation is broken out by Decile 10. We conjecture that the risk-return relation is different for live and defunct funds as taking high risk can wipe out the assets for some funds that ultimately fall into the defunct category. Hence, analyzing the live and defunct funds together disguise the actual underlying relation between VaR and expected return on hedge funds, given the large proportion of the defunct funds in hedge fund databases. Remember, there are 2,012 live funds and 1,902 defunct funds in the TASS data. In contrast, the proportion of defunct funds in mutual funds is relatively small.²⁰

To test the above hypothesis and gain further insight into the difference between live and defunct funds as well as the nature of hedge fund closure, we need to examine the downside risk and return characteristics of live and defunct funds separately. Table III presents the portfolio returns of live and defunct funds based on their parametric (CF VaR) and nonparametric VaRs. For live funds, across 10 portfolios from low VaRs to high VaRs, returns generally increase with the portfolio rank. The relation is almost monotonic. Hence, the average return differential between portfolio 10 (high VaR portfolio) and portfolio 1 (low VaR portfolio) turns out to be positive, which

²⁰ The attrition rate for offshore hedge funds is 14% according to Brown, Gotzmann, and Ibbotson (1999), 8.3% for hedge funds in general according to Liang (2000). It is only 4.8% for mutual funds in Brown, Goetzman, Ibbotson, and Ross (1992).

gives the central result of the paper that there is a statistically significant “positive” relation between VaR and the cross-section of expected returns on hedge funds, i.e, the more a fund can potentially fall in value the higher should be the expected return.

The highest portfolio return (1.65%) is corresponding to the highest VaR (11.7%). The average return difference between portfolio 10 and portfolio 1 is 0.72% per month, or 9% per year, which is significant at the 5% level regardless we use the standard *t*-statistic or the Newey-West *t*-statistic. The result based on the parametric VaR (CF VaR) is even a little stronger than that from the nonparametric VaR: There is a slightly wider VaR distribution (from -0.57% to 12.07%) across 10 portfolios and the average return difference between the two extreme portfolios is slightly higher (0.73%) than that from the nonparametric VaR. The difference is also significant at the 5% level. Based on the above result, if one invests in the riskiest portfolio while short selling the least risky portfolio she will realize an annual profit of 9%.

Interestingly as shown in Table III, for defunct funds the results are almost reversed. This confirms our conjecture that the risk-return relation is different between live and defunct funds. With a wider range in the VaR distribution, defunct funds are riskier than live funds. Although the returns are somehow similar across the first nine portfolios, the negative return from portfolio 10 is dramatically different from the others. In fact, portfolio 10 (with the highest VaR of 15.74%) has a -0.06% monthly return while portfolio 1 (with the lowest VaR of 0.04% across the 108 time windows) earns 0.81%. Hence, the average return difference between portfolios 10 and 1 is about -0.87% per month (or -10.95% per year) and significant at the 10% level based on either the standard *t*-statistic or the Newey-West *t*-statistic. Liang (2000) indicates that the main reason for a fund to disappear from a database is poor performance although funds could get delisted from the database due to other reasons such as mergers and acquisitions, voluntary withdraw, or name changes.²¹ When a fund takes high risk, it can make sizeable profit hence it survives, or it can lose significant amount of capital hence it is wiped out. As a result, the ex-post VaR-return relationship is positive for live funds, but it is negative for defunct funds. The parametric VaR (CF VaR) result for defunct funds is similar to that of the nonparametric VaR.

Previous literature on mutual funds indicates that conditioning on survival the risk-return relation is positive for live funds but negative for dead funds (see Brown, Goetzmann, and Ross (1995)). However, the situation here is more complicated than survival conditioning. Note that we do not call the defunct funds “dead” as funds are closed down for nine different reasons according

²¹ Getmansky, Lo, and Mei (2004) indicate that there are nine reasons why a fund may drop out of the TASS data.

to by Getmansky, Lo, and Mei (2004). Survival conditioning can explain why the riskiest funds are wiped out in the defunct group but fails to explain why the least risky funds earn the highest return.²² This is quite unique for hedge fund data: some well performed funds voluntarily withdraw from the data as they may not need more investors and want to stay away from the public. These funds are usually large with low VaRs.²³ The fact that the returns from all portfolios are similar except for portfolio 10 may indicate that only portfolio 10 contains really “dead” funds.

Overall, the results in Table III provide evidence for a positive and significant relation between VaR and expected returns on live funds, whereas the relation is negative and significant for defunct funds. Further, the nature of voluntary closure complicates the risk-return relation for defunct funds. In contrast, Table II clearly shows that when we pool the live and defunct funds together, the average return differential between the high VaR and low VaR portfolios is not statistically different from zero; particularly, the monotonic relation is destroyed by the riskiest portfolio. Hence, when all funds are considered simultaneously, the actual underlying relation is canceled out as the proportion of defunct funds is very large, and it becomes difficult to identify a positive and significant relation between downside risk and expected returns on hedge funds.

We must point it out that the above risk-return relations for both live and defunct funds are ex post instead of ex ante. In reality, how can an investor distinguish future live funds from defunct funds before she makes the investment decision? In other words, if an investor takes high value at risk for a high expected return, how can she achieve a high realized return while avoiding a low return from funds that eventually become defunct?

Liang (2000) indicates that the main reason for a fund to disappear is poor performance.²⁴ He observes that returns for defunct funds display a decreasing pattern in the last 24 months toward the exit dates. In the mean time, Gupta and Liang (2005) show that VaR is an extremely useful measure for capturing the dynamics of hedge fund risk. They demonstrate that for defunct funds VaR increases dramatically for the last five years toward their exit dates while there is no such a changing risk pattern for live funds.

Figure 1 is basically consistent with the results of Liang (2000) and Gupta and Liang (2005). In Figure 1 returns for defunct funds show a clearly declining pattern in the last 24 months while

²² The CF VaR approach indeed shows that portfolio 1 with the lowest risk earns the highest return at 0.82%.

²³ We indeed show that the largest defunct funds have the highest return of 1.39% which is even higher than the corresponding return (0.98%) for live funds (see Table IV).

²⁴ Although some funds exit the databases due to superior performance as they don't need any more marketing channels, majority of funds leave the databases for reasons other than superior performance. Hence, the aggregate result for a fund to disappear is poor performance.

VaR shows a strong increasing pattern during the same time period. However, for live funds, VaR displays a declining pattern. Note that the sharp drop in VaR for the live funds is observed in the 4th month before December 2003, which is the first month when August 1998 is excluded from the five-year estimation period. Therefore, the strong decreasing VaR pattern for the live funds is mainly caused by an outlier in August 1998 which corresponds to the Russian debt crisis.

Therefore, a practical investment strategy for investors is to invest in the expected to live funds with no significant change in their VaRs in the past. A fund with dramatic increase in risk together with decrease in returns may indicate that the fund has a high chance to become defunct and deliver inferior returns.

To form this simple trading rule *ex ante*, we decompose funds into two groups based on the result in Figure 1: expected to live and expected to become defunct. In Figure 1, defunct funds show an increased VaR pattern over time while live funds show a decreased pattern, mainly caused by the month of August 1998.²⁵ Therefore, we form ten VaR portfolios according to the percentage changes in VaRs. Specifically, we estimate the 95% VaR (in December 1994) from 24-60 monthly return observations (as available) during the period from January 1990 to December 1994. By moving one month ahead, we estimate these VaRs in a rolling sample. In December 1995, we compare the annual percentage change in VaRs from December 1994 to December 1995. Based on these VaR changes, we rank each fund and form ten portfolios. Portfolio 1 contains the funds with the most declining VaRs, portfolio 10 contains the funds with the most increasing VaRs, and portfolio 5 contains funds with no changes in VaRs. We then examine the portfolio performance in January 1996 to see if the trading strategy based on buying the expected to live funds (portfolio 5) and selling the expected to drop funds (portfolio 10) can make any profit. We repeat the above process by moving one month ahead each time. This way, we have 96 monthly profits (the last monthly profit occurs on December 2003) to compute the average trading profit and conduct the formal *t*-test. For robustness, we also calculate the three-month average profit (from 94 monthly profits) based on a similar trading rule. The results are reported in Table IV. The average one (three) month ahead profit based on this *ex ante* trading rule is 0.78% (0.61%) per month or 9.8% (7.6%)

²⁵ Gupta and Liang (2005) show a similar result with increasing risk pattern for defunct funds, but they find VaR is basically not changing for the live funds. We attribute the different results to different databases over different time periods.

per year, which is significant at the conventional level. This result demonstrates that investors can make profit by buying the expected to live funds and selling the expected to drop funds ex ante.²⁶

The above profits are not adjusted for the trading costs. Even we include a round-trip trading cost of 1%, the profits will remain economically significant.²⁷

3.1.2. Sort by Age, Size, and Lockup

The hedge fund literature indicates that fund characteristics such as age, size, and lockup are related to the cross-section of hedge fund returns (see Liang (1999)). Therefore, VaR may not be the only factor that can explain return variations. Table V displays the return pattern when portfolios are formed by fund age, asset size, and lockup. When forming 10 portfolios by fund age, we find that fund returns generally decrease with age: younger funds on average outperform older funds by 0.28% per month or 3.4% per year in the live fund group. This result is consistent with Chevalier and Ellison (1999) that young mutual fund managers tend to take higher risk and are more eager to establish their career record than the seasoned managers. Compared to the live funds, defunct funds have much shorter life. Portfolio 10 has an average age of only 2.6 months, in contrast to 26.3 months for live funds. The age effect is much stronger for defunct funds: the low age portfolio (with a return of 1.82%) outperforms the high age portfolio (with a return of only 0.5%) by 1.32% per month, which is significant at the 1% level.

When formed by asset size, portfolio returns are generally declining with asset size for live funds. For example, the smallest fund group earns 1.71% per month while the largest one earns only 0.98%. The 0.72% return difference is significant at the 1% level. This is consistent with Berk and Green (2004) that funds display a decreasing return to scale due to capacity limit or restrictions on certain investment strategies. It is well known that some mutual funds/hedge funds are closed to new investors because managers do not want their funds to become too large to manage.²⁸ Funds belonging to a certain investment style usually invest in securities that meet the criteria for that particular investment style. Limited choices for super securities together with the implementation difficulty from large block trading can result in limited asset size for the funds. Funds need to maintain this limited size for exercising their niche. When fund assets are small, the manager can

²⁶ We also form a trading strategy of buying portfolio 1 with the largest decrease in VaRs and selling portfolio 10 with the largest increase in VaRs, the results are weaker (5.4% and 3.9% profits for one- and three-month holding periods, respectively) and available upon request.

²⁷ Jegadeesh and Titman (1993) use a one-way trading cost of 0.5%. The trading cost now should be even lower than 0.5%.

²⁸ One popular example is Fidelity Magelin that is closed to new investors.

fully invest fund assets into their favorable securities and move quickly between different market sectors when needed. However, when fund assets grow due to superior performance or marketing efforts, fund managers may run out of favorable choices and be forced to invest in some relatively inferior securities. Therefore, there may exist an optimal fund size.

However, for defunct funds, the relation between return and asset size is reversed: the smallest fund group suffers an average loss of 0.02% while the largest group has a gain of 1.39% on a monthly basis. The -1.41% difference is significant at the 1% level. As we mentioned earlier, funds may drop out of the database due to voluntary withdraw. The best performed funds in the defunct fund group can grow significantly in asset size and withdraw from the data vendors as they no longer need to report to the vendors for the purpose of seeking potential investors.²⁹ They may also want to stay away from the public to protect their proprietary trading strategies. In contrast, the smallest funds can disappear because of lacking critical asset mass to outweigh the operating costs or their asset sizes get shrunk as a result of poor performance. Interestingly, the largest portfolio here earns the highest return of 1.39% per month, even higher than 0.98% from the corresponding live funds. This confirms our conjecture that well performed funds may voluntarily withdraw from data vendors since they do not need to disclose themselves in order to attract investors. Again, this type of voluntary closure is totally different from forced liquidation due to poor performance.

Finally, as shown in Table V, liquidity risk measured by the lockup dummy variable plays a very important role in explaining returns for both live funds and defunct funds. On average, funds with the lockup feature earn much higher return than funds without. The differences are all significant at the 1% level for both the live and defunct funds. This is consistent with Aragon (2004) that funds with the lockup feature invest in illiquid assets and hence outperform those without the lockup feature.

The above results demonstrate that hedge fund returns are related to fund age, size, and liquidity risk. Hence, in order to study the relationship between risk and return for hedge funds, we need to control for age, size, and lockup. In addition, age, size, and lockup may intertwine with VaR as we do not expect funds with different age, size, or liquidity characteristics have the same value-at-risk profile. To separate one effect from another, in the following analysis, we conduct bivariate sorting to form portfolios: we first sort funds by their ages (asset or lockup), and then form 10 portfolios by sorting funds based on their estimated VaRs within each age (asset or lockup) group.

²⁹ Some funds such as the Long Term Capital Management never reports to any data vendor. Other names include Caxton, Moore, and Tudor.

By doing so, we can separate the age (size or liquidity) effect from VaR and see if the VaR-expected return relation still holds within each age (size or lockup) group.

3.2. Bivariate Sort

Tables VI-VIII report the results based on bivariate sorts.³⁰ In Table VI we first form three age groups with equal amount of funds in each group, then we form 10 portfolios within each age group based the estimated VaRs. For live funds in Panel A, although the relation between VaR and return is similar across all three groups, it is the strongest in the low age group, where the average return difference between the two extreme portfolios is statistically significant. The difference is insignificant in other two age groups. The VaR distribution in the low age group is also the widest among all three groups. In other words, young funds are generally riskier than old funds. In the low age group, the portfolio with the highest VaR earns an average monthly return of 1.86% during the period from January 1995 to December 2003. In contrast, the portfolio with the lowest VaR in the high age group earns only 0.96%. The difference is 0.9% per month or 11.4% per year, which is significant at the 5% (or 10% according to the Newey-West t -statistic) level.

The results for defunct funds are reported in Panel B, where portfolios with the highest VaRs still earn the lowest returns, similar to the result in Table III. This is true across all age groups. However, the average return difference between the two extreme portfolios is significant (at the 1% level) only for the low age group. The average return difference between the high VaR and low VaR portfolios is -1.72% per month and significant at the 1% level. Young and highly risky funds are more likely to become defunct due to poor performance.

Table VII shows the results based on sorting by asset size and then VaR. Similar to the results in Table VI where portfolios are formed by age then VaR, the VaR-return relation in Panel A for live funds is especially strong for the low asset group. Small and risky funds earn the highest return of 2.3%. The cross-sectional return difference from the two extreme size portfolios is 1.36% per month and significant at the 1% level. For the medium asset group, the relation is insignificant. For the high asset group, the VaR-return relation is almost flat: the difference between the two extreme size portfolios is near zero. For defunct funds in Panel B, the VaR-return relation is reversed and strong only for the low asset group: the average return difference between the two extreme size portfolios is -2.43% per month and is significant at the 5% level. Overall, small and risky funds suffer a loss of 1.95% per month.

³⁰ The CF VaR versions are presented in Appendices A through C.

Table VIII reports the results from sorting first by lockup dummy and then VaR. It seems that VaR is significant in explaining returns only in the no lockup group ($dlock=0$) for both the live (only marginally significant) and defunct funds. The direction of the relation between VaR and expected returns is positive for the lockup fund group ($dlock=1$), but the relation is statistically insignificant for this group partially because of relatively small sample size, especially for the defunct funds.

The above analyses indicate that VaR-return relation holds even after we control for age, size, and lockup. However, the strength of the risk-return relation is complicated by fund age, size, and liquidity risk. The VaR-return relation is especially strong for small and young funds, probably because these funds are more risky and exhibit higher tail risk than other funds.

3.3. Cross-Sectional Regressions

The above analyses are all done at the portfolio level. Although aggregating may give us more power in statistical tests, we lose fund specific information. To consider different risk factors in one model and include fund specific information, we use the fund-level cross-sectional regression analysis in this section. We present time-series averages of the slope coefficients from the cross-sectional regressions of the one-month ahead returns on nonparametric VaR, parametric VaR, age, asset, and liquidity risk. The average slopes provide the standard Fama-MacBeth (1973) tests for determining which explanatory variables on average have non-zero expected premiums. Monthly cross-sectional regressions are conducted for the following univariate specifications as well as their multivariate versions:

$$R_{i,t+1} = \gamma_{0,t} + \gamma_{1,t}VaR_{i,t} + \varepsilon_{i,t+1} \quad (4)$$

$$R_{i,t+1} = \gamma_{0,t} + \gamma_{2,t}CFVaR_{i,t} + \varepsilon_{i,t+1} \quad (5)$$

$$R_{i,t+1} = \gamma_{0,t} + \gamma_{3,t}Age_{i,t} + \varepsilon_{i,t+1} \quad (6)$$

$$R_{i,t+1} = \gamma_{0,t} + \gamma_{4,t} \log(Asset_{i,t}) + \varepsilon_{i,t+1} \quad (7)$$

$$R_{i,t+1} = \gamma_{0,t} + \gamma_{5,t}dlock_{i,t} + \varepsilon_{i,t+1} \quad (8)$$

where $R_{i,t+1}$ is the realized return on fund i in month $t+1$, $VaR_{i,t}$ is the nonparametric VaR for fund i in month t , $CFVaR_{i,t}$ is the parametric VaR (CF VaR) for fund i in month t , $Age_{i,t}$ is the age of fund i in month t , $\log(Asset_{i,t})$ is the natural logarithm of asset size of fund i in month t , and

$dlock_{i,t}$ is the dummy variable for lockup period of fund i in month t . $dlock = 1$ if the lockup period is non-zero and $dlock = 0$ otherwise.

Tables IX and X report the cross-sectional regression results from univariate (models 1 through 5) and multivariate regressions (models 6 through 13) of the one-month ahead returns on a set of fund characteristics such as VaR, CF VaR, age, size, and lockup dummy for live and defunct funds. For each regression model in Tables IX and X, the first row presents the time series averages of the slope coefficients $\gamma_{i,t}$ ($i = 1, \dots, 5$) over the 108 months from January 1995 to December 2003. The second row shows the standard t -statistics in parentheses. The third row displays the Newey-West adjusted t -statistics in square brackets.

The univariate regression results on VaR (model 1) show that there is a significant relation between nonparametric VaR and the expected returns for both the live (Table IX) and defunct funds (Table X). However, the signs for the two groups are in the opposite direction. For live funds, the higher the risk, the higher the expected return. For defunct funds it is the opposite. Turning to CF VaR (model 2), the regression result is even stronger for the live funds, but it is insignificant for the defunct funds.³¹ These regression results are basically consistent with the portfolio results in Table III based on univariate sorting.

The age regression (model 3) indicates that younger funds have significantly higher returns than old funds. This is true for both the live and defunct funds. The coefficients are all significant at the 1% level. In the size regression (model 4), we have significant (at 1% level) average slope coefficients for both the live and defunct funds. Again, the signs are in the opposite direction: for live funds the smaller the fund, the higher the return; for defunct funds the result is reversed. Small funds drop out of the database because of poor performance while large funds get out may be due to self-withdraw. This is consistent with the portfolio results in Table V based on univariate sorting.

For lockup dummy (model 5), the result is significant at either 1% or 5% level for both the live and defunct funds. In other words, funds with lockup feature outperform those funds without due to liquidity premium. This is consistent with Aragon (2004).

Note that in the univariate regressions, the average R^2 values are much higher for VaR/CF VaR regressions (above 4%) than those from age, asset, or liquidity regressions (below 1%),

³¹ This could be caused by the lack of enough observations on defunct funds as we mentioned earlier that the defunct funds are generally much younger than the live funds.

indicating that VaR/CF VaR is a more important factor than the others in explaining the cross-sectional variation in hedge fund returns.³²

The multiple regression results are reported in models 6 through 13 in Tables IX and X for the live and defunct funds, respectively.³³ As VaR/CF VaR is more important than other variables, we keep them in all the sub-regressions. For live funds in Table IX, VaR (or CF VaR) is significant across all models. For all regression specifications, the asset variable is significant at the conventional significance level. However, the age variable and lockup dummy are significant only in some of the models; they are subdued by factors such as VaR/CF VaR and size. Therefore, VaR and fund size are more important variables than age and liquidity measure in explaining the cross-sectional differences for live funds based on the multi-factor regression analysis. Overall, small, young, and risky funds with lockup feature earn higher returns than other funds.

For defunct funds in Table X, the results are slightly different. The liquidity premium and size variable are more significant factors in explaining fund returns (they have higher t -statistics than other variables) than VaR/CF VaR and age. Overall, less risky, large, and young funds with lockup feature earn higher returns than other funds. These funds become defunct probably because of voluntary withdraw.

In summary, our regression analyses on individual funds confirm the portfolio results based on univariate and bivariate sorting. Factors in explaining hedge fund return variability are slightly different in between the live and defunct funds. For live funds, VaR/CF VaR and fund size are the most significant factors. Live funds with higher risk, smaller assets, younger age, and lockup periods outperform the other funds. For defunct funds, important factors are liquidity premium and size. The significance of the size variable may be consistent with the nature of voluntary closure. Overall, in the defunct fund category, large, less risky, and young funds with lockup feature outperform the other funds. Small and risky funds disappear due to poor performance. Those large and less risky funds delivering superior returns choose to withdraw from the databases.

4. Robustness Check

³² Note that earlier studies on individual stocks show that the average R^2 values from the cross-sectional regressions using all stocks (or only nonfinancial firms) traded on the NYSE, AMEX, and Nasdaq are in the range of 1% to 2%. Hence, the average R^2 values presented in the paper for hedge fund returns are greater than those obtained from individual stocks.

³³ We have repeated our analysis for live funds by including small funds with assets under \$10 million. The results are even stronger. VaR/CF VaR remains as the only significant variable in the multiple regressions.

To assure that our empirical results are not affected by how we estimate VaRs, we present several robustness checks in this subsection.

4.1. 95% VaR Based on 60 Month Return History Only

In the previous sections, we have used 95% VaR estimated from 24 to 60 monthly return observations (as available). Although these VaRs are all 95% VaRs, they are obtained from different return histories. To check whether using different number of observations in the estimation of VaR affects our conclusions, we re-run our portfolio-level and fund-level analyses by requiring all funds having a minimum return history of 60 months. We use the third and fourth lowest observations to interpolate the 95% VaR for all funds. In this way, we restrict all funds to have the same confidence level (i.e., 95%) for the VaR estimates. Although this may induce more survivorship bias due to the minimum 60-month requirement, we find the VaR results to be stronger than those reported in Tables I through IX. For example, from the univariate sort of the VaR portfolios, we find the average return difference between the high VaR and low VaR portfolios to be about 1% per month as compared to 0.72% per month in Table III. To save space, we do not report the results from these 95% VaRs. They are available upon request.

4.2. 95% CF VaR

To make sure that our results are not biased towards the way we estimate nonparametric VaR from the empirical return distribution, we repeat our analyses in Tables V through VI by using the parametric VaR (CF VaR) to capture higher-order moments in returns. Appendices A through C present the CF VaR results from bivariate sorts. They are very similar to the results in Tables V through VII where we use the nonparametric VaRs.

4.3. Long-Term Predictability of VaR

Previously, we use the one-month-ahead return to test the predictability of VaR. To check the long-run predictive power of VaR, we form portfolios using one-year ahead returns. For example, we take the sample from January 1990 to December 1994 and calculate the 95% VaR. Instead of assigning the one-month-ahead return (i.e., return of January 1995), we assign the one-year-ahead return (i.e., the return of January 1996) to the estimated VaR. Then, we roll the sample for one month and calculate the VaR using the sample period of February 1990-January 1995. Then we assign the return of February 1996 to this estimated VaR. We repeat this procedure till we

exhaust the entire sample. This way, we generated 10 VaR portfolios and instead of having 108 months of observations we have 96 months of observations. Based on the one-year ahead returns from 96 rolling window results, the average return difference on the high and low VaR portfolios is still significant at the conventional levels for the live funds. Although the return difference for the two extreme portfolios is insignificant for the defunct funds, the inverse relation between VaR and expected return still holds.

5. Conclusion

In this paper, using two large hedge fund databases from HFR and TASS, we analyze the cross-sectional relationship between VaR and expected return with and without controlling for age, size, and liquidity factors. To the best of our knowledge, this is the first paper that addresses the cross-sectional relation between VaR, return, and other fund characteristics for hedge funds at both the fund level and the portfolio level. The empirical results can be summarized as follows:

First, based on sorting on the estimated VaR, we form 10 portfolios. We find that the risk-return relation is almost monotonic across portfolios except for the riskiest portfolio. Further examination by breaking down the sample into live versus defunct funds reveals different risk-return behavior between the two fund groups. For the live funds, the high VaR portfolio outperforms the low VaR portfolio by 0.72% per month (or 9% per annum) during the period from January 1995 to December 2003. This result is both statistically and economically significant. Investors who buy the high VaR portfolio while short selling the low VaR portfolio can realize a 9% gain on an annual basis. Our results provide support for the existence of a relation between downside risk and expected return on hedge funds.

Second, the above risk-return relationship is almost reversed for defunct funds: the higher the VaR the lower the expected return. Taking high risk by the defunct funds can wipe out fund capital, and hence they become defunct. In contrast, taking high risk by the ex-post live funds can only deliver them superior returns. This different risk-return relation between live and defunct funds is important in hedge fund studies as hedge funds have high attritions compared with traditional asset classes such as stocks or mutual funds. More importantly, due to voluntary closure of hedge funds, the risk-return relation is different from that is implied by the simple survivor conditioning, which can explain why the riskiest funds are wiped out but fails to explain why the least risky funds earn the highest return. We conclude that those funds with large assets and low risk choose to voluntarily withdraw from the databases.

Third, we develop a trading rule of buying the expected to live funds and selling the expected to disappear funds based on the changing VaR patterns over time. This simple trading rule generates an average annual profit of 8-10% depending on the investment horizon. Transaction costs are unlikely to affect our results.

Fourth, the VaR-return relation is complicated by fund age, size, and liquidity risk factor. For live funds, we find that small and young funds are especially promising than the other funds in delivering higher returns. Based on bivariate sort by age then VaR, (by size or liquidity then VaR), we find that the strong link between VaR and expected return still holds for both live and defunct funds even after we control for other factors. This relation is especially strong for small and young live funds due to high risk taken by these funds. For defunct funds, large and young funds have higher returns than other funds.

Finally, the fund-level regression analyses show that VaR is the most important factor in explaining the cross-sectional differences in hedge fund returns even we include the fund characteristics such as age, size, and liquidity risk. The regression analyses based on individual funds confirm our portfolio results from univariate and bivariate sorting. However, risk factors are different for live and defunct funds: for live funds the important factors are VaR and size, while for defunct funds the significant factors are size and liquidity. The different risk profiles for defunct funds from those of the live funds have important implications to the valuation of individual hedge funds and hedge fund portfolios.

References

- Ackermann, Carl, Richard McEnally, and David Ravenscraft, 1999, The performance of hedge funds: risk, return, and incentives, *Journal of Finance* 54, 833-874.
- Agarwal, Vikas, and Narayan Naik, 2004, Risks and portfolio decisions involving hedge funds, *Review of Financial Studies* 17, 63-98.
- Alexander, Gordon, and Alexandre Baptista, 2003, Portfolio performance evaluation using value at risk, *Financial Analysts Journal* 59, 93-102.
- Aragon, George, 2004, Share restriction and asset pricing: Evidence from the hedge fund industry, Working Paper, Boston College.
- Bali, Turan G., 2003, An extreme value approach to estimating volatility and value at risk, *Journal of Business* 76, 83-108.
- Bali, Turan G., and Nusret Cakici, 2004, Value at Risk and Expected Stock Returns, *Financial Analysts Journal* 60, 57-73.
- Bali, Turan G., and Suleyman Gokcan, 2004, Alternative approaches to estimating VaR for hedge fund portfolios, Edited by Barry Schachter, *Intelligent Hedge Fund Investing*, pp. 253-277, Risk Books, Publisher: Incisive Media PLC.
- Bali, Turan G., and Panayiotis Theodossiou, 2005, A Conditional-SGT-VaR approach with alternative GARCH models, *Annals of Operations Research* forthcoming.
- Berk, Jonathan, Richard Green, 2004, Mutual fund flows and performance in rational markets, *Journal of Political Economy* 112, 1269-1295.
- Brown, Stephen J., William N. Goetzmann, 2003, Hedge funds with style, *Journal of Portfolio Management* 29, 101-112.
- Brown, Stephen J., William N. Goetzmann, Roger Ibbotson, 1999, Offshore hedge funds: survival and performance, *Journal of Business* 72, 91-117.
- Brown, Stephen J., William N. Goetzmann, and James Park, 2001, Careers and survival: Competition and risk in the hedge fund and CTA industry, *Journal of Finance* 56, 1869-1886.
- Brown, Stephen J., William N. Goetzmann, and Stephen A. Ross, 1995, Survival, *Journal of Finance* 50, 853-873.
- Brown, S. J., W. N. Goetzmann, R. G. Ibbotson, and S. A. Ross. 1992. "Survivorship Bias in Performance Studies." *Review of Financial Studies*, vol. 5, no. 4 (Winter):553-580.
- Chevalier, Judith, and Glenn Ellison, 1999, Are some mutual fund managers better than others? Cross-sectional patterns in behavior and performance, *Journal of Finance* 54, 875-899.
- Cornish, E.A., and . Fisher, R.A., 1937, Moments and cumulants in the specification of distributions, *Review of the International Statistical Institute*, 307-320.

Fama, Eugene, and Kenneth French, 1992, Cross-section of expected stock returns, *Journal of Finance* 47, 427-465.

Fama, Eugene, and Kenneth French, 1993, Common risk factors in the returns on bonds and stocks, *Journal of Financial Economics* 23, 3-56.

Fama, Eugene, and James MacBeth, 1973, Risk, return and equilibrium: Empirical test, *Journal of Political Economy* 81, 607-636.

Fung, William, and David Hsieh, 1997, Empirical characteristics of dynamic trading strategies: the case of hedge funds, *Review of Financial Studies* 10, 275-302.

Fung, William, and David Hsieh, 2000, Performance characteristics of hedge funds and commodity funds: natural versus spurious biases, *Journal of Financial and Quantitative Analysis* 35, 291-307.

Getmansky, Mila, Andrew Lo, and Igor Makarov, 2004, An econometric model of serial correlation and illiquidity in hedge funds returns, *Journal of Financial Economics* 74, 529-610.

Getmansky, Mila, Andrew Lo, and Shauna Mei, 2004, Shifting through the wreckage: Lessons from recent hedge-fund liquidations, forthcoming, *Journal of Investment Management*.

Gupta, Anurag, and Bing Liang, 2005, Do Hedge Funds Have Enough Capital? A Value at Risk Approach, *Journal of Financial Economics* 77, 219-253..

Jagadeesh, Narasimhan, and Sheridan Titman, 1993, Returns to buying winners and selling losers: Implications for stock market efficiency, *Journal of Finance* 48, 65-91.

Jorion, Philippe, 2000, Risk management lessons from Long Term Capital Management, *European Financial Management* 6, 277-300.

Jorion, Philippe, 2001. *Value-at-Risk: The New Benchmark for Controlling Market Risk*. McGraw-Hill: Chicago.

Liang, Bing, 1999, On the performance of hedge funds, *Financial Analysts Journal* 55, 72-85.

Liang, Bing, 2000, Hedge fund: the living and the dead, *Journal of Financial and Quantitative Analysis* 35, 309-326.

Liang, Bing, 2003, Hedge fund returns: Auditing and accuracy". *Journal of Portfolio Management* 29, 111-122.

Lo, Andrew, 2001, Risk management for hedge funds: Introduction and overview, *Financial Analysts Journal* 57, 16-33.

Newey, Whitney K., and Kenneth D. West, 1987, A simple, heteroskedastic and autocorrelation consistent covariance matrix, *Econometrica* 55, 703-708.

Sharpe, William F., 1992, Asset allocation, management style and performance measurement, *Journal of Portfolio Management* 18, 7-19.

Table I. Basic Statistics and the Test of Normality for Hedge Funds Returns

This table shows the number of observations (N) for each hedge fund category, the average values of the sample mean, standard deviation, skewness and excess kurtosis of individual hedge fund returns. The sample period is from January 1994 to December 2003. Live funds are from the combined TASS/HFR database. Defunct funds are from TASS database. The results of the normality tests are presented as a percentage of rejection of the null hypothesis at the significance level of 1%. Funds with a minimum 24 months of return history are included in the analysis. Emerging markets funds, managed futures, and funds of funds are excluded. Live funds with less than \$10 million of assets under management are excluded.

Category	N	Mean	Std Dev	Skew	Kurt	% Rejection of Normality at the 1% significance level		
						skewness (H_0 :Skew=0)	kurtosis (H_0 :Ex Kurt=0)	JB test (H_0 :Normality)
Live Funds	1221	1.04	3.31	0.05	2.32	45.4%	77.8%	93.9%
Defunct Funds	843	0.86	5.24	-0.14	4.09	52.8%	73.2%	91.8%
All Funds	2064	0.97	4.06	-0.02	3.02	48.3%	76.0%	93.1%

Table II. Average Return on the Portfolios of Combined Live and Defunct Funds Sorted by Nonparametric and Parametric VaRs (January 1995 to December 2003)

The first panel presents the average returns of the nonparametric VaR and the parametric VaR (CF VaR) portfolios for Deciles 1 to 10 for both live and defunct funds in our sample. The VaR and CF VaR values are calculated using the past 24 to 60 monthly returns (as available) for each month from January 1995 to December 2003. The original VaR values are multiplied by -1 so that we expect a positive relation between expected return and downside risk. The second panel presents the average return differential between Deciles 10 and 1, the standard t -statistics for the average return differential, and the Newey-West (1987) adjusted t -statistics for both live and defunct funds.

VaR for All Funds			CF VaR for All Funds		
Decile	VaR	Return	Decile	CF VaR	Return
Low VaR	0.04%	0.89%	Low VaR	-0.60%	0.87%
2	0.98%	0.84%	2	1.12%	0.86%
3	1.71%	0.85%	3	1.91%	0.80%
4	2.54%	0.92%	4	2.72%	0.92%
5	3.38%	1.01%	5	3.66%	1.04%
6	4.27%	1.01%	6	4.63%	1.02%
7	5.27%	1.05%	7	5.72%	1.05%
8	6.49%	1.10%	8	7.04%	1.04%
9	8.29%	1.14%	9	8.89%	1.19%
High VaR	13.90%	0.82%	High VaR	14.43%	0.82%

Average Return Differential for VaR		Average Return Differential for CF VaR	
High VaR - Low VaR	-0.07%	High CF VaR - Low CF VaR	-0.05%
standard t -statistic	-0.17	standard t -statistic	-0.14
Newey-West t -statistic	-0.16	Newey-West t -statistic	-0.13

Table III. Average Return of Live and Defunct Fund Portfolios Sorted by Nonparametric and Parametric VaRs (January 1995 to December 2003)

The first panel shows the average returns of the nonparametric VaR and the parametric VaR (CF VaR) portfolios for Deciles 1 to 10 for both live and defunct funds. The VaR and CF VaR values are calculated using the past 24 to 60 monthly returns (as available) for each month from January 1995 to December 2003. The original VaR values are multiplied by -1 so that we expect a positive relation between expected return and downside risk. The second panel presents the average return differential between Deciles 10 and 1, the standard t -statistics for the average return differential, and the Newey-West (1987) adjusted t -statistics for both live and defunct funds. ***, **, * denotes significance level at least at the 1%, 5%, and 10% level, respectively.

VaR						CF VaR					
Live			Defunct			Live			Defunct		
Decile	VaR	Return	Decile	VaR	Return	Decile	CF VaR	Return	Decile	CF VaR	Return
Low VaR	0.08%	0.93%	Low VaR	0.04%	0.81%	Low CF VaR	-0.57%	0.90%	Low CF VaR	-0.66%	0.82%
2	0.91%	0.85%	2	1.08%	0.80%	2	1.05%	0.86%	2	1.19%	0.68%
3	1.59%	0.92%	3	1.88%	0.63%	3	1.77%	0.93%	3	2.07%	0.63%
4	2.31%	1.06%	4	2.75%	0.60%	4	2.53%	0.99%	4	2.94%	0.76%
5	3.15%	1.19%	5	3.64%	0.67%	5	3.36%	1.17%	5	3.96%	0.63%
6	3.98%	1.21%	6	4.60%	0.78%	6	4.26%	1.30%	6	5.05%	0.72%
7	4.91%	1.16%	7	5.63%	0.84%	7	5.31%	1.09%	7	6.20%	0.63%
8	6.05%	1.46%	8	6.96%	0.50%	8	6.45%	1.33%	8	7.60%	0.67%
9	7.50%	1.29%	9	9.10%	0.67%	9	8.05%	1.51%	9	9.80%	0.62%
High VaR	11.70%	1.65%	High VaR	15.74%	-0.06%	High CF VaR	12.07%	1.63%	High CF VaR	16.65%	0.08%

Average Return Differential for VaR		Average Return Differential for VaR		Average Return Differential for CF VaR		Average Return Differential for CF VaR	
High VaR - Low VaR	0.72%	High VaR - Low VaR	-0.87%	High CF VaR - Low CF VaR	0.73%	High CF VaR - Low CF VaR	-0.74%
standard t -statistic	2.15**	standard t -statistic	-1.90*	standard t -statistic	2.26**	standard t -statistic	-1.60
Newey-West t -statistic	2.03**	Newey-West t -statistic	-1.89*	Newey-West t -statistic	2.05**	Newey-West t -statistic	-1.67*

Table IV. Average Trading Profits Based on Buying the Expected to Live Funds and Selling the Expected to Disappear Funds (January 1990 to December 2003)

The first panel presents the average annual percentage changes in risk and the one month look-ahead returns for nonparametric VaR and the parametric VaR (CF VaR) portfolios for Deciles 1 to 10 for both live and defunct funds in our sample. The VaR and CF VaR values are calculated using the past 24 to 60 monthly returns (as available) for each month from January 1990 to November 2003. The original VaR values are multiplied by -1 so that we expect a positive relation between expected return and downside risk. The percentage change in the annual VaR is used to predict the future live funds (with no risk change) and the future defunct funds (with large VaR increase). The second panel presents the average profit differential between Deciles 5 and 10, representing a trading rule of buying the expected to live funds (portfolio 5) and the expected to disappear funds (portfolio 10). The standard t -statistics for the average return differential, and the Newey-West (1987) adjusted t -statistics for both live and defunct funds are also reported.

VaR Change for All Funds			CF VaR Change for All Funds		
Decile	VaR Change (%)	Return (%)	Decile	CF VaR Change (%)	Return (%)
Low VaR Chg	-219.01	0.86	Low VaR Chg	-220.81	0.81
2	-15.95	0.82	2	-15.36	0.84
3	-8.52	0.96	3	-8.06	0.86
4	-3.58	1.02	4	-3.20	0.98
5	0.74	1.19	5	1.09	1.10
6	5.46	0.94	6	5.82	0.96
7	11.31	1.03	7	11.71	0.98
8	19.56	0.99	8	20.05	0.95
9	35.70	0.76	9	36.43	0.65
High VaR Chg	249.81	0.41	High VaR Chg	254.02	0.49

Average Profit Differential for Changing VaR		Average Profit Differential for Changing CF VaR	
Exp Live (5) – Exp Defunct (10)	0.78%	Exp Live (5) – Exp Defunct (10)	0.61%
Standard t -statistic	3.46**	Standard t -statistic	4.22**
Newey-West t -statistic	3.32**	Newey-West t -statistic	2.88*

**Table V. Average Return of the Hedge Fund Portfolios Sorted on Age, Asset, and Lockup
(January 1995 to December 2003)**

The first panel shows the average returns of the Age and Asset portfolios for Deciles 1 to 10 for both live and defunct funds. The second panel presents the average return differential between Deciles 10 and 1, the standard t -statistics for the average return differential, and the Newey-West (1987) adjusted t -statistics for both live and defunct funds. The third and fourth panels display the corresponding results for the Lockup portfolios. ***, **, * denotes significance level at least at the 1%, 5%, and 10% level, respectively.

Live			Defunct			Live			Defunct		
Decile	Age (in months)	Return	Decile	Age (in months)	Return	Decile	Ln (Asset)	Return	Decile	Ln (Asset)	Return
High Age	112.6	1.12%	High Age	102.6	0.50%	High Ln(Asset)	20.34	0.98%	High Ln(Asset)	20.09	1.39%
2	101.36	1.12%	2	74.0	0.64%	2	19.36	1.04%	2	18.88	0.93%
3	86.88	1.26%	3	56.9	0.64%	3	18.83	0.99%	3	18.31	0.79%
4	74.19	1.18%	4	44.2	0.67%	4	18.42	1.02%	4	17.84	0.55%
5	63.19	1.19%	5	34.5	0.77%	5	18.05	1.12%	5	17.42	0.53%
6	53.84	1.21%	6	26.8	0.57%	6	17.71	1.22%	6	16.98	0.43%
7	45.58	1.30%	7	20.0	0.87%	7	17.31	1.44%	7	16.57	0.70%
8	38.53	1.30%	8	13.9	0.86%	8	16.88	1.49%	8	16.04	0.30%
9	32.05	1.37%	9	8.2	1.23%	9	16.36	1.56%	9	15.43	0.70%
Low Age	26.31	1.40%	Low Age	2.6	1.82%	Low Ln (Asset)	15.31	1.71%	Low Ln(Asset)	14.09	-0.02%

Average Return Differential for Age		Average Return Differential for Age		Average Return Differential for Asset		Average Return Differential for Asset	
Low Age - High Age	0.28%	Low Age - High Age	1.32%	Low Asset - High Asset	0.72%	Low Asset - High Asset	-1.41%
standard t -statistic	2.52**	standard t -statistic	7.03***	standard t -statistic	5.31***	standard t -statistic	-3.19***
Newey-West t -statistic	2.08**	Newey-West t -statistic	5.66***	Newey-West t -statistic	4.49***	Newey-West t -statistic	-3.85***

Live Funds			Defunct Funds		
Portfolio	dlock	Return	Portfolio	dlock	Return
No Lockup	0	1.15%	No Lockup	0	0.76%
Lockup	1	1.36%	Lockup	1	1.44%

Average Return Differential for Lockup		Average Return Differential for Lockup	
Lockup - No Lockup	0.20%	Lockup - No Lockup	0.68%
standard t -statistic	3.16***	standard t -statistic	6.52***
Newey-West t -statistic	2.92***	Newey-West t -statistic	5.31***

**Table VI. Average Return of the Hedge Fund Portfolios from Bivariate Sorts:
First Sorted by Age and then VaR (January 1995 to December 2003)**

This table shows the average returns of the hedge fund portfolios first sorted by three Age groups and then VaR. The table also reports the average return differential between Deciles 10 and 1, the standard t -statistics for the average return differential, and the Newey-West (1987) adjusted t -statistics. Panels A and B present results for live and defunct funds, respectively. ***, **, * denotes significance level at least at the 1%, 5%, and 10% level, respectively.

Panel A. Live Funds

<i>Low Age Group</i>			<i>Medium Age Group</i>			<i>High Age Group</i>		
Decile	VaR	Return	Decile	VaR	Return	Decile	VaR	Return
Low VaR	-0.05%	0.96%	Low VaR	0.09%	0.94%	Low VaR	0.22%	0.84%
2	0.71%	0.91%	2	0.89%	0.74%	2	1.08%	0.86%
3	1.41%	1.05%	3	1.57%	0.83%	3	1.80%	1.07%
4	2.09%	0.91%	4	2.23%	1.09%	4	2.59%	1.18%
5	2.93%	1.08%	5	3.02%	1.12%	5	3.50%	1.14%
6	3.79%	1.28%	6	3.72%	1.39%	6	4.39%	1.03%
7	4.75%	1.32%	7	4.59%	1.39%	7	5.34%	1.15%
8	5.83%	1.49%	8	5.77%	1.24%	8	6.44%	1.19%
9	7.34%	1.42%	9	7.35%	1.48%	9	8.01%	1.36%
High VaR	11.88%	1.86%	High VaR	11.61%	1.63%	High VaR	11.45%	1.18%

<i>Low Age Group</i>		<i>Medium Age Group</i>		<i>High Age Group</i>	
High VaR - Low VaR	0.90%	High VaR - Low VaR	0.69%	High VaR - Low VaR	0.34%
standard t -statistic	1.97**	standard t -statistic	1.57	standard t -statistic	1.04
Newey-West t -statistic	1.95*	Newey-West t -statistic	1.50	Newey-West t -statistic	0.98

Panel B. Defunct Funds

<i>Low Age Group</i>			<i>Medium Age Group</i>			<i>High Age Group</i>		
Decile	VaR	Return	Decile	VaR	Return	Decile	VaR	Return
Low VaR	0.01%	1.00%	Low VaR	-0.03%	0.89%	Low VaR	0.24%	0.55%
2	0.99%	0.80%	2	1.06%	0.65%	2	1.14%	0.90%
3	1.91%	0.57%	3	1.95%	0.57%	3	1.84%	0.60%
4	2.79%	0.70%	4	2.84%	0.69%	4	2.63%	0.69%
5	3.58%	0.67%	5	3.73%	0.76%	5	3.48%	0.66%
6	4.42%	0.67%	6	4.72%	0.85%	6	4.60%	0.67%
7	5.43%	0.91%	7	5.76%	0.95%	7	5.80%	0.41%
8	6.80%	0.75%	8	7.02%	0.53%	8	7.09%	0.60%
9	9.16%	0.48%	9	9.26%	0.98%	9	9.27%	0.69%
High VaR	16.09%	-0.72%	High VaR	15.59%	0.05%	High VaR	15.39%	0.03%

<i>Low Age Group</i>		<i>Medium Age Group</i>		<i>High Age Group</i>	
High VaR - Low VaR	-1.72%	High VaR - Low VaR	-0.83%	High VaR - Low VaR	-0.52%
standard <i>t</i> -statistic	-2.83***	standard <i>t</i> -statistic	-1.57	standard <i>t</i> -statistic	-0.89
Newey-West <i>t</i> -statistic	-3.27***	Newey-West <i>t</i> -statistic	-1.28	Newey-West <i>t</i> -statistic	-0.83

**Table VII. Average Return of the Hedge Fund Portfolios from Bivariate Sorts:
First Sorted by Asset and then VaR (January 1995 to December 2003)**

This table shows the average returns of the hedge fund portfolios first sorted by three Asset groups and then VaR. The table also reports the average return differential between Deciles 10 and 1, the standard t -statistics for the average return differential, and the Newey-West (1987) adjusted t -statistics. Panels A and B present results for live and defunct funds, respectively. ***, **, * denotes significance level at least at the 1%, 5%, and 10% level, respectively.

Panel A: Live Funds

<i>Low Asset Group</i>			<i>Medium Asset Group</i>			<i>High Asset Group</i>		
Decile	VaR	Return	Decile	VaR	Return	Decile	VaR	Return
Low VaR	0.43%	0.94%	Low VaR	0.08%	0.98%	Low VaR	-0.02%	0.87%
2	1.42%	0.98%	2	0.87%	0.87%	2	0.61%	0.82%
3	2.42%	1.12%	3	1.57%	0.73%	3	1.33%	0.90%
4	3.49%	1.53%	4	2.23%	1.02%	4	1.94%	1.07%
5	4.41%	1.46%	5	2.96%	0.95%	5	2.53%	1.15%
6	5.23%	1.40%	6	3.71%	1.27%	6	3.14%	1.12%
7	6.25%	1.42%	7	4.76%	1.07%	7	3.89%	1.14%
8	7.46%	1.37%	8	5.88%	1.48%	8	4.98%	0.82%
9	9.08%	1.91%	9	7.18%	1.24%	9	6.21%	1.39%
High VaR	13.97%	2.30%	High VaR	10.79%	1.40%	High VaR	8.98%	0.88%

<i>Low Asset Group</i>		<i>Medium Asset Group</i>		<i>High Asset Group</i>	
High VaR - Low VaR	1.36%	High VaR - Low VaR	0.42%	High VaR - Low VaR	0.01%
standard t -statistic	2.79***	standard t -statistic	1.00	standard t -statistic	0.04
Newey-West t -statistic	2.59**	Newey-West t -statistic	0.94	Newey-West t -statistic	0.03

Panel B: Defunct Funds

<i>Low Asset Group</i>			<i>Medium Asset Group</i>			<i>High Asset Group</i>		
Decile	VaR	Return	Decile	VaR	Return	Decile	VaR	Return
Low VaR	0.99%	0.48%	Low VaR	0.60%	0.72%	Low VaR	-0.07%	0.36%
2	2.01%	0.81%	2	1.49%	0.77%	2	0.73%	0.65%
3	3.28%	0.52%	3	2.33%	0.78%	3	1.64%	1.00%
4	3.45%	0.79%	4	3.49%	0.30%	4	2.00%	0.93%
5	4.42%	0.18%	5	3.69%	0.23%	5	3.04%	1.44%
6	5.71%	0.11%	6	4.66%	0.96%	6	3.97%	1.02%
7	7.13%	0.48%	7	5.60%	0.49%	7	5.06%	1.19%
8	8.87%	0.43%	8	6.77%	0.88%	8	6.74%	1.50%
9	11.28%	0.18%	9	9.60%	0.71%	9	8.70%	0.60%
High VaR	18.64%	-1.95%	High VaR	14.29%	-0.84%	High VaR	12.98%	0.82%

<i>Low Asset Group</i>		<i>Medium Asset Group</i>		<i>High Asset Group</i>	
High VaR - Low VaR	-2.43%	High VaR - Low VaR	-1.56%	High VaR - Low VaR	0.46%
standard <i>t</i> -statistic	-2.00**	standard <i>t</i> -statistic	-1.72*	standard <i>t</i> -statistic	0.65
Newey-West <i>t</i> -statistic	-2.04**	Newey-West <i>t</i> -statistic	-1.60	Newey-West <i>t</i> -statistic	0.77

**Table VIII. Average Return of the Hedge Fund Portfolios from Bivariate Sorts:
First Sorted by Lockup and then VaR (January 1995 to December 2003)**

This table shows the average returns of the hedge fund portfolios first sorted by two lockup groups and then VaR. The table also reports the average return differential between Deciles 10 and 1, the standard t -statistics for the average return differential, and the Newey-West (1987) adjusted t -statistics. Panels A and B present results for live and defunct funds, respectively. ***, **, * denotes significance level at least at the 1%, 5%, and 10% level, respectively. Note that there are not enough observations for defunct funds with lockup periods during the first twelve months (January 1995 – December 1995), we present the average of the following 96 months (January 1996-December 2003).

Panel A: Live Funds

<i>Non-Lockup Funds (dlock=0)</i>			<i>Lockup Funds (dlock=1)</i>		
Decile	VaR	Return	Decile	VaR	Return
Low VaR	0.02%	0.92%	Low VaR	0.32%	1.05%
2	0.73%	0.79%	2	1.32%	0.92%
3	1.42%	0.90%	3	1.93%	1.09%
4	2.11%	1.02%	4	2.71%	1.06%
5	2.95%	1.08%	5	3.58%	1.35%
6	3.75%	1.29%	6	4.57%	1.42%
7	4.61%	1.03%	7	5.68%	1.73%
8	5.66%	1.24%	8	7.05%	1.34%
9	6.96%	1.32%	9	8.96%	1.49%
High VaR	10.82%	1.59%	High VaR	12.86%	1.52%

<i>Non-Lockup Funds (dlock=0)</i>		<i>Lockup Funds (dlock=1)</i>	
High VaR - Low VaR	0.67%	High VaR - Low VaR	0.47%
standard t -statistic	1.70*	standard t -statistic	1.42
Newey-West t -statistic	1.59	Newey-West t -statistic	1.38

Panel B: Defunct Funds

<i>Non-Lockup Funds (dlock=0)</i>			<i>Lockup Funds (dlock=1)</i>		
Decile	VaR	Return	Decile	VaR	Return
Low VaR	0.06%	0.76%	Low VaR	-0.09%	1.44%
2	1.05%	0.68%	2	0.95%	0.71%
3	1.81%	0.62%	3	1.84%	0.58%
4	2.63%	0.66%	4	3.17%	0.42%
5	3.49%	0.63%	5	4.18%	1.34%
6	4.42%	0.78%	6	5.25%	1.32%
7	5.45%	0.73%	7	6.73%	0.71%
8	6.72%	0.63%	8	8.24%	0.33%
9	8.88%	0.52%	9	9.94%	1.47%
High VaR	15.99%	-0.22%	High VaR	14.28%	0.65%

<i>Non-Lockup Funds (dlock=0)</i>		<i>Lockup Funds (dlock=1)</i>	
High VaR - Low VaR	-0.98%	High VaR - Low VaR	-0.79%
standard <i>t</i> -statistic	-2.00**	standard <i>t</i> -statistic	-1.28
Newey-West <i>t</i> -statistic	-1.96**	Newey-West <i>t</i> -statistic	-1.58

Table IX. Cross-Sectional Regressions of Hedge Fund Returns on VaR, CF VaR, Age, Assets, and Lockup (Live Funds)

This table presents the time-series averages of the slope coefficients obtained from the monthly Fama-MacBeth (1973) regressions for live funds. The standard t -statistics given in parentheses are the average slope divided by its time-series standard error. The Newey-West (1987) adjusted t -statistics are given in square brackets. The average adjusted R^2 values are reported in the last column. ***, **, * denotes significance level at least at the 1%, 5%, and 10% level, respectively.

	$VaR_{i,t}$	$CFVaR_{i,t}$	$Age_{i,t}$	$Asset_{i,t}$	$dlock_{i,t}$	Average R^2
1	0.0717 (2.35)** [2.39]**					5.61%
2		0.0696 (2.69)*** [2.78]***				4.56%
3			-0.00003 (-3.44)*** [-2.68]***			0.13%
4				-0.0016 (-6.52)*** [-5.42]***		0.62%
5					0.0020 (3.16)*** [2.92]**	0.32%
6	0.0734 (2.39)** [2.42]**		-0.00004 (-2.61)** [-2.09]**			5.75%
7	0.0757 (2.07)** [2.11]*			-0.0009 (-2.73)*** [-2.64]***		7.22%
8	0.0692 (2.25)** [2.29]**				0.0011 (1.82)* [1.43]	5.70%
9	0.0754 (2.06)** [2.06]**		-0.00003 (-1.50) [-1.38]	-0.0007 (-2.22)** [-2.12]**	0.0011 (1.73)* [1.48]	7.44%
10		0.0708 (2.73)*** [2.80]***	-0.00004 (-2.50)** [-2.02]**			4.69%
11		0.0735 (2.39)** [2.51]**		-0.0009 (-3.01)*** [-3.09]***		6.01%
12		0.0678 (2.62)** [2.70]***			0.0013 (2.11)** [1.69]*	4.68%
13		0.0736 (2.48)** [2.48]**	-0.00002 (-1.27) [-1.22]	-0.0007 (-2.43)** [-2.45]**	0.0014 (2.15)** [1.84]*	6.24%

Table X. Cross-Sectional Regressions of Hedge Fund Returns on VaR, CF VaR, Age, Assets, and Lockup (Defunct Funds)

This table presents the time-series averages of the slope coefficients obtained from the monthly Fama-MacBeth (1973) regressions for defunct funds. The standard t -statistics given in parentheses are the average slope divided by its time-series standard error. The Newey-West (1987) adjusted t -statistics are given in square brackets. The average adjusted R^2 values are reported in the last column. ***, **, * denotes significance level at least at the 1%, 5%, and 10% level, respectively.

	$VaR_{i,t}$	$CFVaR_{i,t}$	$Age_{i,t}$	$Asset_{i,t}$	$dlock_{i,t}$	Average R^2
1	-0.0524 (-2.01)** [-2.10]**					4.29%
2		-0.04 (-1.64) [-1.58]				4.12%
3			-0.00009 (-6.18)** [-4.39]**			0.46%
4				0.0009 (3.41)** [3.33]**		0.44%
5					0.0069 (7.23)** [5.86]**	0.27%
6	-0.0540 (-2.07)** [-2.17]**		-0.00002 (-1.24) [-0.88]			4.42%
7	-0.0172 (-0.62) [-0.66]			0.0020 (5.54)** [5.02]**		5.26%
8	-0.0533 (-2.04)** [-2.14]**				0.0045 (4.55)** [4.34]**	4.34%
9	-0.0191 (-0.68) [-0.73]		-0.00005 (-2.29)** [-1.96]*	0.0021 (5.46)** [5.05]**	0.0024 (2.12)** [2.08]**	5.33%
10		-0.0418 (-1.72)* [-1.67]*	-0.00002 (-1.26) [-0.90]			4.22%
11		-0.0109 (-0.42) [-0.44]		0.0020 (5.58)** [5.23]**		4.96%
12		-0.0409 (-1.68)* [-1.63]			0.0044 (4.44)** [4.12]**	4.17%
13		-0.0132 (-0.52) [-0.54]	-0.00004 (-2.24)** [-1.92]**	0.0021 (5.46)** [5.18]**	0.0025 (2.14)** [2.02]**	4.99%

**Appendix A. Average Return of the Hedge Fund Portfolios from Bivariate Sorts:
First Sorted by Age and then CF VaR (January 1995 to December 2003)**

This table shows the average returns of the hedge fund portfolios first sorted by three Age groups and then CF VaR. The table also reports the average return differential between Deciles 10 and 1, the standard t -statistics for the average return differential, and the Newey-West (1987) adjusted t -statistics. Panels A and B present results for live and defunct funds, respectively. ***, **, * denotes significance level at least at the 1%, 5%, and 10% level, respectively.

Panel A: Live Funds

<i>Low Age Group</i>			<i>Medium Age Group</i>			<i>High Age Group</i>		
Decile	CF VaR	Return	Decile	CF VaR	Return	Decile	CF VaR	Return
Low CF VaR	-0.60%	0.98%	Low CF VaR	0.17%	0.94%	Low CF VaR	-1.30%	0.85%
2	0.93%	0.89%	2	1.05%	0.77%	2	1.13%	0.84%
3	1.67%	1.09%	3	1.73%	0.78%	3	1.96%	0.98%
4	2.34%	1.02%	4	2.49%	1.14%	4	2.72%	1.03%
5	3.20%	0.98%	5	3.24%	1.07%	5	3.59%	1.03%
6	4.11%	1.24%	6	3.97%	1.43%	6	4.75%	1.01%
7	5.08%	1.32%	7	4.90%	1.57%	7	5.82%	1.17%
8	6.15%	1.31%	8	6.25%	1.05%	8	6.94%	1.18%
9	7.83%	1.49%	9	8.02%	1.44%	9	8.39%	1.53%
High CF VaR	12.21%	1.96%	High CF VaR	11.97%	1.65%	High CF VaR	11.93%	1.39%

<i>Low Age Group</i>		<i>Medium Age Group</i>		<i>High Age Group</i>	
High CF VaR - Low CF VaR	0.98%	High CF VaR - Low CF VaR	0.71%	High CF VaR - Low CF VaR	0.54%
standard t -statistic	2.22**	standard t -statistic	1.45	standard t -statistic	1.54
Newey-West t -statistic	2.12**	Newey-West t -statistic	1.44	Newey-West t -statistic	1.36

Panel B: Defunct Funds

<i>Low Age Group</i>			<i>Medium Age Group</i>			<i>High Age Group</i>		
Decile	CF VaR	Return	Decile	CF VaR	Return	Decile	CF VaR	Return
Low CF VaR	-0.74%	1.03%	Low CF VaR	-1.38%	0.98%	Low CF VaR	0.18%	0.48%
2	1.17%	0.66%	2	1.16%	0.69%	2	1.20%	0.72%
3	2.07%	0.66%	3	2.16%	0.60%	3	2.05%	0.76%
4	2.99%	0.68%	4	3.02%	0.55%	4	2.91%	0.72%
5	4.00%	0.62%	5	3.88%	0.75%	5	3.86%	0.74%
6	5.03%	0.54%	6	5.09%	1.06%	6	5.02%	0.56%
7	6.12%	0.96%	7	6.41%	0.52%	7	6.16%	0.22%
8	7.56%	0.78%	8	7.71%	0.72%	8	7.58%	0.59%
9	9.92%	0.56%	9	10.08%	0.80%	9	9.81%	0.78%
High CF VaR	17.29%	-0.66%	High CF VaR	16.31%	0.29%	High CF VaR	16.01%	0.24%

<i>Low Age Group</i>		<i>Medium Age Group</i>		<i>High Age Group</i>	
High CF VaR - Low CF VaR	-1.69%	High CF VaR - Low CF VaR	-0.69%	High CF VaR - Low CF VaR	-0.24%
standard <i>t</i> -statistic	-2.76***	standard <i>t</i> -statistic	-1.29	standard <i>t</i> -statistic	-0.40
Newey-West <i>t</i> -statistic	-3.10***	Newey-West <i>t</i> -statistic	-1.02	Newey-West <i>t</i> -statistic	-0.35

**Appendix B. Average Return of the Hedge Fund Portfolios from Bivariate Sorts:
First Sorted by Asset and then CF VaR (January 1995 to December 2003)**

This table shows the average returns of the hedge fund portfolios first sorted by three Asset groups and then CF VaR. The table also reports the average return differential between Deciles 10 and 1, the standard *t*-statistics for the average return differential, and the Newey-West (1987) adjusted *t*-statistics. Panels A and B present results for live and defunct funds, respectively. ***, **, * denotes significance level at least at the 1%, 5%, and 10% level, respectively.

Panel A: Live Funds

<i>Low Asset Group</i>			<i>Medium Asset Group</i>			<i>High Asset Group</i>		
Decile	CF VaR	Return	Decile	CF VaR	Return	Decile	CF VaR	Return
Low CF VaR	-0.12%	1.07%	Low CF VaR	-1.76%	0.89%	Low CF VaR	0.04%	0.84%
2	1.57%	0.95%	2	0.94%	0.88%	2	0.83%	0.77%
3	2.53%	1.24%	3	1.67%	0.90%	3	1.59%	0.86%
4	3.61%	1.34%	4	2.38%	0.75%	4	2.17%	1.03%
5	4.66%	1.37%	5	3.16%	1.19%	5	2.73%	0.92%
6	5.66%	1.22%	6	3.95%	1.01%	6	3.47%	1.20%
7	6.59%	1.55%	7	5.06%	1.10%	7	4.35%	1.28%
8	7.80%	1.46%	8	6.21%	1.46%	8	5.38%	0.77%
9	9.61%	1.78%	9	7.68%	1.33%	9	6.81%	1.38%
High CF VaR	14.29%	2.46%	High CF VaR	10.97%	1.55%	High CF VaR	9.69%	1.09%

<i>Low Asset Group</i>		<i>Medium Asset Group</i>		<i>High Asset Group</i>	
High CF VaR - Low CF VaR	1.39%	High CF VaR - Low CF VaR	0.65%	High CF VaR - Low CF VaR	0.24%
standard <i>t</i> -statistic	2.80***	standard <i>t</i> -statistic	1.45	standard <i>t</i> -statistic	0.66
Newey-West <i>t</i> -statistic	2.53**	Newey-West <i>t</i> -statistic	1.32	Newey-West <i>t</i> -statistic	0.67

Panel B: Defunct Funds

<i>Low Asset Group</i>			<i>Medium Asset Group</i>			<i>High Asset Group</i>		
Decile	CF VaR	Return	Decile	CF VaR	Return	Decile	CF VaR	Return
Low CF VaR	-1.17%	0.63%	Low CF VaR	0.75%	0.77%	Low CF VaR	0.12%	0.48%
2	1.94%	0.66%	2	1.72%	0.83%	2	0.91%	0.58%
3	3.17%	1.05%	3	2.64%	0.76%	3	1.84%	1.27%
4	3.35%	0.98%	4	3.85%	0.40%	4	2.25%	0.96%
5	4.35%	-0.48%	5	4.09%	0.50%	5	3.30%	1.49%
6	5.74%	-0.14%	6	5.24%	0.67%	6	4.47%	1.04%
7	7.01%	0.46%	7	6.18%	0.63%	7	5.80%	0.88%
8	8.76%	0.57%	8	7.50%	0.96%	8	7.52%	1.08%
9	10.81%	0.46%	9	10.26%	-0.42%	9	9.66%	0.66%
High CF VaR	18.58%	-1.85%	High CF VaR	15.13%	0.18%	High CF VaR	14.15%	1.32%

<i>Low Asset Group</i>		<i>Medium Asset Group</i>		<i>High Asset Group</i>	
High CF VaR - Low CF VaR	-2.48%	High CF VaR - Low CF VaR	-0.59%	High CF VaR - Low CF VaR	0.84%
standard <i>t</i> -statistic	-1.81*	standard <i>t</i> -statistic	-0.81	standard <i>t</i> -statistic	1.17
Newey-West <i>t</i> -statistic	-1.94*	Newey-West <i>t</i> -statistic	-0.80	Newey-West <i>t</i> -statistic	1.56

**Appendix C. Average Return of the Hedge Fund Portfolios from Bivariate Sorts:
First Sorted by Lockup and then CF VaR (January 1995 to December 2003)**

This table shows the average returns of the hedge fund portfolios first sorted by two lockup groups and then CF VaR. The table also reports the average return differential between Deciles 10 and 1, the standard t -statistics for the average return differential, and the Newey-West (1987) adjusted t -statistics. Panels A and B present results for live and defunct funds, respectively. ***, **, * denotes significance level at least at the 1%, 5%, and 10% level, respectively. Note that there are not enough observations for defunct funds with lockup periods during the first twelve months (January 1995 – December 1995), we present the average of the following 96 months (January 1996-December 2003).

Panel A: Live Funds

<i>Non-Lockup Funds (dlock=0)</i>			<i>Lockup Funds (dlock=1)</i>		
Decile	CF VaR	Return	Decile	CF VaR	Return
Low CF VaR	-0.02%	0.88%	Low CF VaR	-1.89%	1.05%
2	0.91%	0.80%	2	1.34%	0.88%
3	1.65%	0.87%	3	2.07%	1.01%
4	2.40%	0.97%	4	2.76%	1.19%
5	3.20%	1.02%	5	3.74%	1.40%
6	4.00%	1.20%	6	5.00%	1.42%
7	4.94%	1.15%	7	6.15%	1.32%
8	6.06%	1.26%	8	7.47%	1.38%
9	7.45%	1.54%	9	9.41%	1.78%
High CF VaR	11.31%	1.46%	High CF VaR	13.10%	1.46%

<i>Non-Lockup Funds (dlock=0)</i>		<i>Lockup Funds (dlock=1)</i>	
High CF VaR - Low CF VaR	0.58%	High CF VaR - Low CF VaR	0.42%
standard t -statistic	1.52	standard t -statistic	1.15
Newey-West t -statistic	1.43	Newey-West t -statistic	1.09

Panel B: Dead Funds

<i>Non-Lockup Funds (dlock=0)</i>			<i>Lockup Funds (dlock=1)</i>		
Decile	CF VaR	Return	Decile	CF VaR	Return
Low CF VaR	-0.54%	0.80%	Low CF VaR	-1.25%	0.88%
2	1.17%	0.67%	2	0.98%	0.88%
3	2.01%	0.60%	3	2.13%	0.84%
4	2.86%	0.77%	4	3.38%	0.92%
5	3.81%	0.60%	5	4.47%	0.68%
6	4.86%	0.69%	6	5.82%	0.59%
7	6.01%	0.65%	7	7.36%	0.73%
8	7.39%	0.57%	8	8.61%	1.14%
9	9.64%	0.52%	9	10.90%	1.26%
High CF VaR	16.71%	-0.11%	High CF VaR	16.82%	1.04%

<i>Non-Lockup Funds (dlock=0)</i>		<i>Lockup Funds (dlock=1)</i>	
High CF VaR - Low CF VaR	-0.91%	High CF VaR - Low CF VaR	0.16%
standard <i>t</i> -statistic	-1.96*	standard <i>t</i> -statistic	0.23
Newey-West <i>t</i> -statistic	-1.95*	Newey-West <i>t</i> -statistic	0.24

Figure 1. Historical Return and 95% VaR for Live and Defunct Funds in the Last 24-Month History

