

Risk Management for Hedge Funds with Position Information

Philippe Jorion

Journal of Portfolio Management (2007)

Philippe Jorion is Professor at the School of Business at the University of California at Irvine, CA, and managing director at Pacific Alternative Asset Management. pjorion@uci.edu

The author wishes to thank Jane Buchan for comments, and Gaiyan Zhang and Zach Nye for excellent research assistance.

Risk Management for Hedge Funds with Position Information

Abstract

Risk management is a challenge for hedge funds because traditional risk measurement methods based on return data are unreliable with dynamic trading strategies. This paper illustrates how Value at Risk (VAR) methods can be used to measure and control the market risk of hedge funds. VAR methods have two key features: (1) they are based on current position information, and (2) they focus on a lower quantile of the distribution of losses or some other risk metric. For rapidly changing positions, VAR should be measured at frequent interval, as is done for banks' proprietary trading portfolios. This paper demonstrates the usefulness of dynamic risk measures for a hypothetical hedge fund with short option positions, which are equivalent to dynamic trading. Imposing daily ex ante VAR limits using position information can be very successful at controlling realized risk.

The first hedge fund was started by A.W. Jones in 1949. Unlike the typical equity mutual fund, the fund took long and short positions in equities. Since then, the hedge fund industry has undergone exponential growth. Hedge funds now have more than \$1,500 billion in equity capital, up from \$35 billion only in 1991.¹

The rapid growth of hedge funds has led to concerns from several fronts. Regulators worry about the potential for systemic risk. Indeed the spectacular failure of the hedge fund Long-Term Capital Management (LTCM) in 1998 is said to have endangered the world financial system. This has led to a general improvement in counterparty risk management practices.² Yet, we are currently in the midst of a renewed debate on the regulation of this industry. Some regulators advocate increased oversight of hedge funds. Others believe instead that the primary mechanism for regulating risk is the discipline provided by creditors, counterparties, and investors.³ This requires, however, effective tools for managing risk. Conversely, from the viewpoint of investors, the concern is that risk may not be properly measured nor managed. The management of dynamic market risk for hedge funds is the focus of this paper.

Hedge fund strategies can be broadly classified into two groups: infrequent and frequent traders. Some strategies invest in inherently illiquid assets, such as distressed debt, that do not trade frequently. For this first category of hedge funds, the foremost issue is asset valuation, due to insufficient market transactions. This creates attendant problems for risk measurement. Stale prices induce artificial smoothing of returns,

¹ According to estimates provided by Hedge Fund Intelligence [2006]. Because of their leverage, hedge funds control assets far in excess of this number.

² The Counterparty Risk Management Policy Group [2005] has produced two reports that provide sound advice for managing counterparty risk.

³ See the recent discussion by Chairman Bernanke [2006].

biasing volatility and systematic risk measures downward.⁴ Stress tests are needed to evaluate the risk of such positions.

The second group of funds trade frequently, most likely in liquid assets. As a result, their risk profile may change rapidly, creating a different type of challenge for risk measurement. This issue is the subject of this paper. The question is whether modern risk management techniques such as Value at Risk (VAR) can be applied to measure, control, and manage such dynamic hedge fund risk. VAR is a measure of downside risk, taken as the quantile of the distribution of losses at some prespecified confidence level over a prespecified horizon. VAR originated from the proprietary trading desks of commercial banks, which needed a risk measure to control active traders.

Indeed many hedge funds implement dynamic trading strategies, as shown in an early paper by Fung and Hsieh [1997]. An interesting example is given by Lo [2001], who considers a hypothetical hedge fund, appropriately called Capital Decimation Partners (CDP). The CDP strategy is initially judged on the basis of the distribution of its realized returns. The fund has much higher average returns than the benchmark, taken as the S&P 500 index. At the same time, its volatility is only slightly higher than the index. As a result, its Sharpe ratio is much higher than the index. Hence, superficially, this looks like a hedge fund with a winning track record.

It turns out that the investment strategy of this hedge fund is fairly simple. It consists of rolling over short positions in out-of-the-money put options on the S&P index, with leverage dictated by margin requirements implemented at monthly intervals. For such strategy, a static, ex post, monthly standard deviation measure is insufficient to

⁴ When this is the case, improved measures of systematic risk can be obtained by regressing on leads and lags, as shown by Dimson [1979]. Getmansky et al. [2004] discuss the effect of illiquidity on hedge fund returns.

capture its dynamic risk. Applying VAR to the realized monthly return distribution is not very informative either. As a result, one might be tempted to discard VAR as a risk measure. Yet banks' proprietary trading desks are making extensive use of VAR methods. So, these methods can't be all that bad.

This paper discusses whether VAR-type methods can be used to measure and control risk effectively in such situations. It starts with a review of the literature on VAR. The analysis separates two key features of VAR, which are usually not well delineated. The first is the use of the lower quantile as a single measure of risk. This allows users to report risk as a potential dollar loss, which is more intuitive than the standard deviation. The second is that, in practice, VAR should be based on current positions, which creates a forward-looking, ex ante, measure of risk. With dynamic trading strategies, VAR can thus be recomputed as frequently as needed, providing a useful tool to control risk. Recent theoretical literature indeed indicates that dynamic trading with VAR limits can be very effective in controlling risk. The key point is the use of position information; other summary risk measures, however, such as Expected Tail Loss (ETL) could be used as well.

The present paper illustrates this point with the hypothetical CDP hedge fund. It shows that daily ex ante VAR measures for the CDP fund experience wide swings that are not captured by monthly risk measures. In addition, the paper demonstrates that realized, ex-post, risk can be controlled effectively using daily, ex-ante, VAR limits.

APPROACHES TO RISK MEASUREMENT

Traditional measures of risk are based on the distribution of ex post, or realized returns. The standard deviation is a typical measure of dispersion. Notably, it is used to compute the Sharpe ratio, a risk-adjusted performance measure. In the presence of asymmetric or long-tailed distributions, however, the standard deviation is an insufficient measure of risk.

Recently, financial institutions have turned to VAR as a standard method to measure risk.⁵ VAR has two major features, which unfortunately are often entangled. First, it specifically measures downside risk by focusing on a quantile representing the left tail of the distribution of profits and losses at a high confidence level. This could be applied to the ex post return series, providing more information on the extent of possible losses than a simple measure of the spread such as the standard deviation. Gupta and Liang [2005], for example, measure the risk of hedge funds based on return information. They use extreme value theory to smooth out the left tail, and derive VAR measures for various groups of hedge funds. Reporting a dollar quantile is intuitive but only adds more information when the distribution is non-normal.

The other major feature of VAR is the use of current instead of historical positions. This is crucial when positions change frequently. Because this creates a forward-looking measure of risk, it can be used to control risk.

In practice, VAR has become the preferred method for reporting financial risk. The Bank for International Settlements (BIS) provides regular surveys of disclosures by global commercial banks and securities houses. In 1993, barely 5% of the surveyed

⁵ See Jorion [2006] for an exposition of VAR.

institutions provided VAR-type disclosures of their market risk. In contrast, in 2002, 98% of the surveyed institutions disclosed their VAR. For example, at year-end 2005, JPM Chase reported a 1-day trading VAR of \$103 million at the 99 percent confidence level.

While VAR has become a universally accepted benchmark for measuring financial risk, it does have drawbacks. VAR provides a measure of downside risk but fails to provide information on the magnitude of losses worse than VAR. This could be a problem for instruments that have option-like payoffs. In the JPM Chase example, we should expect to observe a loss greater than \$103 million every day out of a hundred, on average. The question is whether the average loss beyond VAR is \$150 million or \$150,000 million. The first number is reasonable. The second is not: Such loss would wipe out the firm's equity.

Recently, some academic research has emphasized the shortcomings of quantile-type risk measures. Artzner et al. [1999] argue that the expectation of loss beyond VAR, also called Conditional VAR (CVAR), or Expected Tail Loss (ETL), has better theoretical properties than VAR. For instance, the CVAR of a portfolio is less than the sum of CVARs, which is not necessarily the case with the quantile.⁶ On the other hand, Christoffersen and Goncalves [2005] show that the estimation error in CVAR is substantially larger than that in VAR, so CVAR has other practical drawbacks.⁷

⁶ Indeed, this property is satisfied with the volatility, as the volatility of a portfolio is less than the sum of volatilities. However, VAR also satisfies this property with elliptical distributions, which are symmetric and unimodal. These include the Student t and normal distributions.

⁷ Estimation error is the natural sampling variability of the estimate due to limited sample size. In practice, different samples, e.g., moving the window by one day, create different estimates of the risk statistics. Estimation error depends on the sample size and on the statistic to be estimated. The mean, for example is estimated more precisely than the 99% quantile. Similarly, CVAR has more sampling variability than VAR because of the small number and dispersion of data in the left tail.

Another strand of literature focuses on the behavioral effect of VAR systems. Basak and Shapiro [2001] study the dynamic optimization problem of an investor subject to a VAR limit on the target horizon. They show that this investor could modify the distribution of payoffs so as to satisfy the VAR limit at the expense of incurring a very large loss beyond VAR. This is a worrisome result, because it implies that VAR limits may actually make institutions less safe, by inducing them to take exposure to risk that are rare but catastrophic.

This literature, however, fails to recognize the other feature of VAR, which is the use of current positions and the possibility to recompute VAR as frequently as needed.⁸ Indeed, any risk measure starts by assuming that current positions are maintained over the horizon. The more frequent the trading, however, the worst the approximation. In practice, this issue is typically handled by using a shorter horizon for actively traded portfolios and recomputing VAR frequently. Bank proprietary trading desks, whose trading strategies are similar to many hedge funds, do compute VAR on a daily if not intraday frequency.

Recent theoretical work confirms this line of reasoning. Cuoco et al. [2001] formulate a dynamically consistent model of optimal portfolio choice subject to VAR limits and show that the conclusions of earlier papers are incorrect if, consistently with common practice, VAR is reevaluated dynamically, making use of available conditioning information. They show that the risk exposure of a trader subject to a VAR limit is always lower than that of an unconstrained trader and that the probability of extreme

⁸ Another benefit of using current positions is that a long enough trading record may not be available to evaluate risk. The risk of current positions, however, can be measured using the history of the risk factors.

losses is also lower. In addition, limits based on CVAR are dynamically equivalent to VAR limits.

Thus, it seems that hedge funds, even with dynamic trading strategies, should be able to manage effectively their risk based on position information. This is examined in the following sections.

A HEDGE FUND STRATEGY

We now apply these ideas to the risk management of a hypothetical hedge fund. Exhibit 1 compares the performance of the Capital Decimation Partners fund with the S&P 500 index over the 1992-2002 period, based on monthly return data. The fund's annual average return was 33%, compared to 10% for the index, with only slightly higher volatility. As a result, the Sharpe ratio is 1.51, which is 4 times higher than that of the index. Superficially, this looks like a great investment.

In fact, this strategy follows the example given in Lo [2001]. The fund's strategy consists of rolling over out-of-the-money S&P 500 (SPX) put options. At the close of each month t , the fund shorts a put option that is approximately 7 percent out of the money and expires in the middle of month $t+2$. The position is left unchanged for a month. At time $t+1$, the option is liquidated and a new one opened.

The position starts with \$10 million in equity. The initial size of the option position is determined by the Chicago Board Options Exchange (CBOE) margin requirements, plus an additional 66 percent of the margin in collateral. Defining S and K as the spot and exercise prices, the margin per contract is currently set at the paid option premium plus the highest of $[15\% \times S - \text{Max}(S-K, 0)]$ and $[10\% \times K]$, all multiplied by the

contract size of 100. On December 1991, for instance, the maximum margin is \$10,000,000 divided by 1.66, or \$6,024,096. With $S=479.63$, we pick an out-of-the-money strike of $K=440$. Because the second term is binding, the margin per contract is $100 \times [10\% \times K] = \$4,400$. This gives a maximum number of contracts of $\$6,024,096 / \$4,400$, or 1369. Rounding down, the fund initially shorts 1360 contracts. As in Lo [2001], margin calls during the month are ignored.

All positions are valued using the Black-Scholes model. Initially, we assume an implied volatility of 23 percent for pricing purposes. This is higher than the realized volatility of 17 percent per annum, however, based on daily volatility of 1 percent per day.⁹ The CDP fund is priced daily, including the 1-month LIBOR return on the investment. This is compared to the total return on the S&P index, including dividends.

Using only ex post, return information, the volatility of this strategy appears reasonable, albeit slightly higher than the index. From Exhibit 1, there is some indication that the tail risk is higher, with a 99 percent VAR of 19.5%, versus 10.3% for the index. The skewness is also very high, and negative. Without information about the positions, however, it is difficult to assess and control the true risk of this strategy.

RISK MANAGEMENT WITH POSITION INFORMATION

This short position in a put option is equivalent to a dynamically changing position in the underlying asset. The delta is positive and increases as S decreases. The

⁹ This was calibrated so that the strategy provides the same average return as in Lo [2001] over the 1992 to 1999 period in the previous paper. This can be rationalized by the fact that implied volatilities for at-the-money options are typically higher than realized volatilities, and that this even more so for out-of-the-money options.

strategy therefore can be interpreted as active trading in the underlying asset during the month, which can create wide swings in the daily risk profile.

We now extend the previous analysis by measuring the daily VAR of the option position, using full valuation based on the current position. This is achieved by first drawing the worst down move in S using the physical distribution, with daily volatility of 1%, and second repricing the option on the next day.

Exhibit 2 plots the daily ex ante VAR of the CDP fund, as a percent of the investment. With information about the daily positions, it is now immediately apparent that the CDP fund experiences wide swings in its ex ante risk profile. For instance, on the first day, VAR is 2.8%. During the first month, VAR drifts down to a value close to zero, reflecting an appreciating index and time decay. In other months, in contrast, VAR spikes up, reflecting a drop in the value of the index, often more than 10% (later, we will add the effect of implied volatility). Thus the risk profile of the fund is highly irregular. An investor monitoring the risk of this fund using position information would discover this very quickly.

Note that we used information about the option positions to compute VAR, by repricing the option one day ahead at the worst move in the index. This approach can be extended to a situation where the fund implements dynamic hedging to replicate the option position. With daily information, the risk manager can still compute VAR using the option delta and a linear approximation. This assumes that the risk manager only observes the position in the underlying asset without knowing about the dynamic replication. On the first day, for example, the linear VAR is 2.4%, which is close to the

full-valuation VAR of 2.8%.¹⁰ Because the linear VAR ignores the increase in risk due to gamma, there is a slight underestimation of risk over short horizons.

The bottom panel in Exhibit 1 records the average daily VAR. For the index, this is 2.50%. For the CDP fund, the average VAR with is 2.42% with full valuation and 2.05% with linear valuation. These averages, however, mask wide swings in VAR values, which range from 0% to 13%.

The ETL is 2.92%, which is 21 percent higher than the VAR of the CDP fund. . For a normal distribution, this difference should be 15 percent only. For the S&P index, the ETL is 34 percent higher than VAR. Thus, these distributions have much fatter tails than the normal distribution.

How can this fund use this information to manage risk better? Now that risk is measured based on position information, it can be controlled. Assume that, consistently with bank trading practices, a daily VAR limit is enforced, based on full valuation. As in the original CDP strategy, positions are reset at the end of the month, but during the month the position is cut down if the daily VAR exceeds a limit. This limit is taken as the average of the month-end VARs over the entire period, which is 3%.

Exhibit 3 plots the daily ex ante VAR for this new fund, which we could call Risk Control Partners (RCP). VAR can still drift down, following a limited dynamic strategy, but is now capped at the limit within the month.

Of course, there is no guarantee that the actual, ex post loss will stay within this limit. In fact, it should exceed the limit with a frequency equal to $100\% - 99\% = 1\%$. The interesting and non-obvious issue, however, is whether the systematic application of such

¹⁰ The starting option delta is 0.148. We multiply by the number of options and S to get the dollar delta value, which is \$9,681,000. With a daily volatility of 1.07%, the index VAR is 2.5%. Multiplying, this gives a dollar VAR of \$242,000, or 2.4% of the initial value of \$10 million.

VAR limit based on position information can control the actual, ex post risk of the trading strategy.

The performance of this risk-controlled fund is reported in Exhibit 4. Initially, VAR is cut on the same day as observed. Call this strategy RCP(t). Later, we will allow implementation with a 1-day lag, which is called RCP(t+1). For RCP(t), the average of the ex-ante daily VAR is 1.87% per day, which is much less than the index, at 2.50%. It is also much lower than the 2.42% average daily VAR for the CDP fund, as expected.

The question is whether such strategy can control risk out of sample. Relative to the CDP fund, the monthly mean is lower, at 2.28% instead of 2.79%. The ex post monthly volatility is also lower, however, at 3.84% instead of 5.46%. As a result, the Sharpe ratio is higher than before, at 1.70 versus 1.52. The ex post VAR is now at 11.5%, which is close to that of the index. Thus, this strategy is successful at controlling risk. Even when the VAR limit is enforced with a 1-day lag, Exhibit 4 shows that this RCP(t+1) strategy is not very different from the original one.

Overall, the RCP strategy looks like a winning investment. On a risk-adjusted basis, the RCP fund dominates both the index and the CDP fund. This demonstrates the benefit of risk management with position information, with limits enforced at frequent intervals.

Such results, of course, should raise suspicion. What is driving the performance of the CDP and RCP funds? Both funds sell options priced using a constant implied volatility of 23%, against a realized volatility of 17% only. Such strategies capture the richness of the option premiums. The actual implied volatility, however, changes over time, and is correlated with movements in the index. To be more realistic, Exhibit 5

repeats the analysis using instead the actual CBOE implied volatility (VIX). Over this period, the average implied was 19.9%, which is lower than before. As a result, the performance of the two funds decreases considerably, as expected.¹¹ Even so, the RCP fund displays much safer risk characteristics than the CDP fund. The ex post, monthly VAR is 14.94% instead of 21.53% for the CDP fund. This demonstrates that ex ante risk controls based on position information are very effective in limiting risk.

CONCLUSIONS

Many hedge funds employ active trading strategies, often involving options or dynamic trading. An issue sometimes raised is whether VAR methods can be effective in managing this type of market risk. In practice, however, such methods are widely used on the proprietary trading desks of commercial and investment banks, which also involve similar trading activities. Therefore, it seems that there is no practical reason to reject the use of VAR for managing the risk of hedge funds. The key to the proper management of risk is access to the underlying positions and frequent measurement of risk. Dynamic trading strategies require dynamic risk measures based on position information.

The paper illustrated this point using the example of a hypothetical hedge fund with a trading strategy involving short options positions. Measuring risk from monthly return data indeed fails to capture the risk of the strategy. On the other hand, this paper has shown that implementing daily risk controls based on current positions can provide an effective tool for managing realized risk.

¹¹ These results are very conservative, however. First, the traditional VIX numbers represent implied volatilities for at-the-money options derived from the Black-Scholes model. Out-of-the-money options have higher volatility due to the volatility skew. Second, these simulations are based on the new VIX numbers, which are derived from a model-free estimate and are lower than the older VIX numbers, on average.

The key point of modern VAR methods is that they are based on current positions. Because risk management is a large-scale aggregation problem, this requires simplifications such as mapping positions on the chosen set of risk factors. Once this database has been constructed, it is straightforward to build the entire distribution of profits and losses. This can be summarized by the quantile, VAR, or the expected tail loss, for example. This apparatus can also be used to implement stress tests.

Daily reporting of VAR or some other risk metric has other advantages. Hedge fund managers are very reluctant to reveal their positions. At the same time, investors are especially worried about tail events. This leads to a dilemma that can be resolved by disclosing risk measures. Position information leads to VAR numbers but not vice versa. As a result, both sides could be satisfied if hedge fund managers revealed their VAR or ETL on a frequent basis. This would protect the confidentiality of positions while providing useful information about tail events.

REFERENCES

- Artzner, Philippe, Freddy Delbaen, Jean-Marc Eber, and David Heath. "Coherent Measures of Risk." *Mathematical Finance* 9 (1999), pp. 203--228.
- Basak, Suleyman and Alex Shapiro. "Value-at-Risk Based Risk Management: Optimal Policies and Asset Prices." *Review of Financial Studies* 14 (2001), pp. 371--405.
- Bernanke, Ben. "Hedge Funds and Systemic Risk." Remarks at the Federal Reserve Bank of Atlanta's May 16, 2006 Financial Markets Conference, Board of the Governors of the Federal Reserve System, Washington, 2006.

- Christoffersen, Peter and Silvia Goncalves. "Estimation Risk in Financial Risk Management." *Journal of Risk* 7 (Spring 2005), pp. 1--27.
- Counterparty Risk Management Policy Group. "Toward Greater Financial Stability: A Private Sector Perspective." CRMPG, New York, 2005.
- Cuoco, Domenico, Hue He, and Sergey Isaenko. "Optimal Dynamic Trading Strategies with Risk Limits." Working paper, University of Pennsylvania, 2002.
- Dimson, Elroy. "Risk Measurement When Shares are Subject to Infrequent Trading." *Journal of Financial Economics* 7 (1979), pp. 197--226.
- Financial Services Authority. "Hedge funds: A discussion of risk and regulatory engagement." FSA: London, 2005.
- Fung, William and David. Hsieh. "Empirical characteristics of dynamic trading strategies: The case of hedge funds." *Review of Financial Studies* 10 (Summer 1997), pp. 275--302.
- Getmansky, Mila, Andrew Lo, and Igor Makarov. "An econometric model of serial correlation and illiquidity in hedge fund returns." *Journal of Financial Economics* 74 (December 2004), pp. 529-609.
- Gupta, Anurag and Bing Liang. "Do hedge funds have enough capital? A value-at-risk approach." *Journal of Financial Economics* 77 (July 2005), pp. 219-253.
- Jorion, Philippe. "Value at Risk: The New Benchmark to Manage Financial Risk." McGrawHill, 2006.
- Lo, Andrew. "Risk Management for Hedge Funds: Introduction and Overview." *Financial Analysts Journal* (November 2001), pp 16-33.

EXHIBIT 1

Performance of Capital Decimation Partners Fund (CDP), 1992-2002

This table compares the performance of a hypothetical hedge fund strategy (CDP) with that of the S&P 500 index over the period January 1992 to December 2002. The annual Sharpe ratio is obtained from the annualized average return minus the risk-free rate divided by the annualized volatility. Options are priced with an implied volatility of 23%.

| Statistic | CDP | S&P 500 |
|-----------------------------------|------------|--------------------|
| Based on return data | | |
| Monthly mean (%) | 2.79 | 0.83 |
| Monthly standard deviation (%) | 5.46 | 4.31 |
| Annualized mean (%) | 33.43 | 9.94 |
| Annualized standard deviation (%) | 18.90 | 14.94 |
| Annual Sharpe ratio | 1.52 | 0.35 |
| Total return (%) | 2886.43 | 162.95 |
| Monthly 99% VAR (%) | 19.51 | 10.33 |
| Skewness | -5.06 | -0.60 |
| Minimum month (%) | -40.25 | -14.46 |
| Maximum month (%) | 6.19 | 9.78 |
| Correlation with S&P | 0.76 | 1.00 |
| Based on position data | | |
| Daily VAR average (%) | | |
| Linear valuation | 2.05 | 2.50 |
| Full valuation | 2.42 | 2.50 |
| Expected Tail Loss | 2.92 | 3.35 |

EXHIBIT 2. CDP Fund: Daily VAR

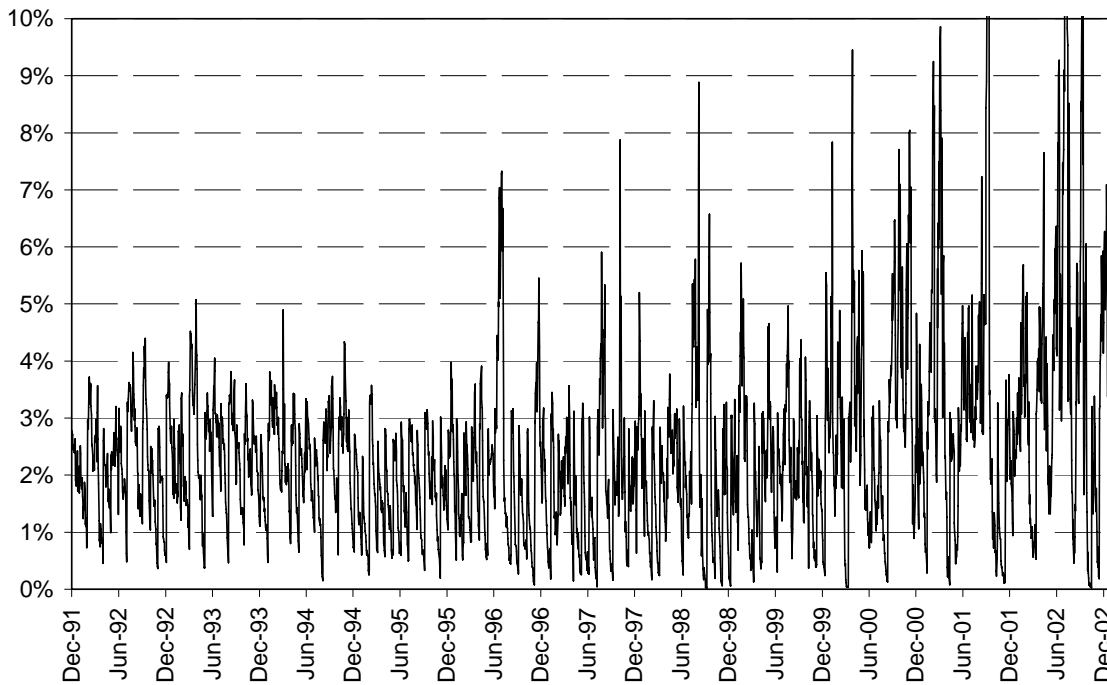


EXHIBIT 3. RCP Fund: Daily VAR

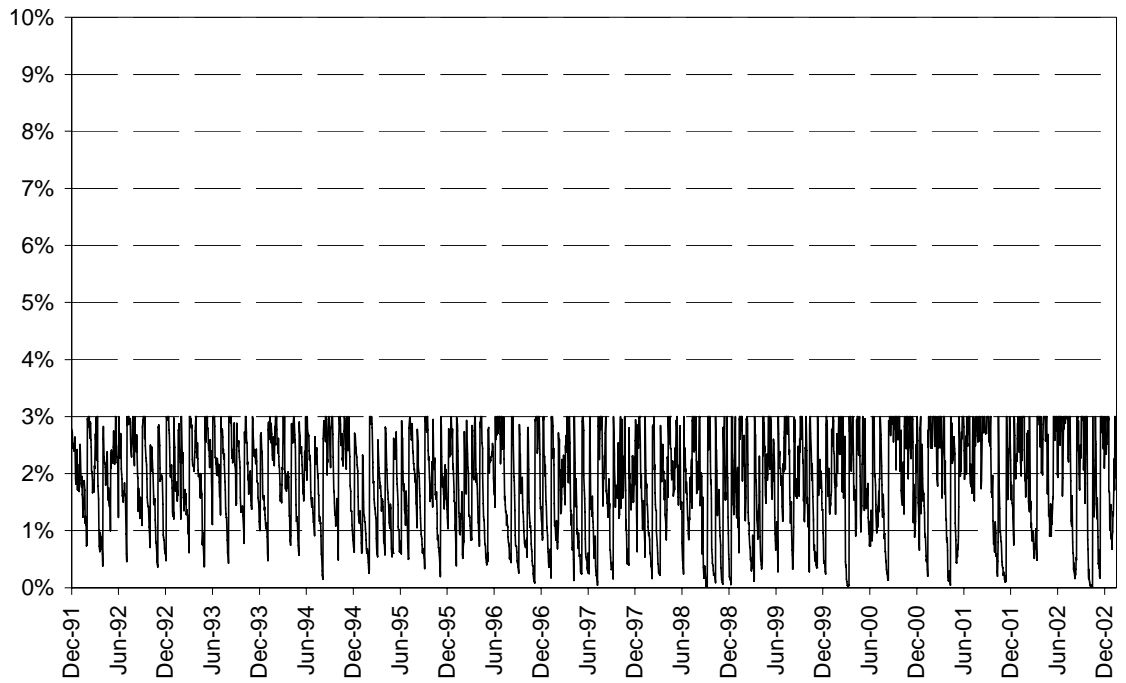


EXHIBIT 4

Performance of Risk-Controlled Partners Fund (RCP), 1992-2002

This table compares the performance of a hypothetical risk-controlled hedge fund with that of the S&P 500 index over the period January 1992 to December 2002. The strategy is similar to CDP; VAR is computed daily and positions are cut the same day (for RCP(t)) and the following day (for RCP(t+1)) if the VAR limit of 3% is exceeded. Options are priced with an implied volatility of 23%.

| Statistic | RCP(t) | RCP(t+1) | S&P 500 |
|-----------------------------------|---------------|-----------------|--------------------|
| Based on return data | | | |
| Monthly mean (%) | 2.28 | 2.38 | 0.83 |
| Monthly standard deviation (%) | 3.84 | 3.94 | 4.31 |
| Annualized mean (%) | 27.35 | 28.61 | 9.94 |
| Annualized standard deviation (%) | 13.31 | 13.64 | 14.94 |
| Annual Sharpe ratio | 1.70 | 1.75 | 0.35 |
| Total return (%) | 1674.01 | 1919.99 | 162.95 |
| Monthly 99% VAR (%) | 11.52 | 11.84 | 10.33 |
| Skewness | -2.35 | -2.67 | -0.60 |
| Minimum month (%) | -17.18 | -19.29 | -14.46 |
| Maximum month (%) | 5.49 | 5.54 | 9.78 |
| Correlation with S&P | 0.82 | 0.80 | 1.00 |
| Based on position data | | | |
| Daily VAR average (%) | | | |
| Linear valuation | 1.57 | 1.61 | 2.50 |
| Full valuation | 1.87 | 1.91 | 2.50 |
| Expected Tail Loss | 2.26 | 2.32 | 3.35 |

EXHIBIT 5**Performance of Funds with Implied Volatility Set at VIX, 1992-2002**

This tables compares the performance of two hypothetical hedge fund strategies, Capital Decimation Partners (CDP) and Risk-Controlled Partners (RCP), with the S&P 500 index over the period January 1992 to December 2002. Options are now priced with an implied volatility equal to the daily level of the CBOE Volatility Index (VIX).

| Statistic | CDP | RCP | S&P 500 |
|-----------------------------------|------------|------------|--------------------|
| Based on return data | | | |
| Monthly mean (%) | 1.68 | 0.91 | 0.83 |
| Monthly standard deviation (%) | 6.94 | 4.74 | 4.31 |
| Annualized mean (%) | 20.16 | 10.97 | 9.94 |
| Annualized standard deviation (%) | 24.04 | 16.42 | 14.94 |
| Annual Sharpe ratio | 0.64 | 0.38 | 0.35 |
| Total return (%) | 525.84 | 184.97 | 162.95 |
| Monthly 99% VAR (%) | 21.53 | 14.94 | 10.33 |
| Skewness | -2.80 | -1.80 | -0.60 |
| Minimum month (%) | -46.00 | -23.72 | -14.46 |
| Maximum month (%) | 19.84 | 12.79 | 9.78 |
| Correlation with S&P | 0.76 | 0.82 | 1.00 |
| Based on position data | | | |
| Daily VAR average (%) | | | |
| Linear valuation | 1.56 | 1.10 | 2.50 |
| Full valuation | 1.87 | 1.36 | 2.50 |
| Expected Tail Loss | 2.27 | 1.66 | 3.35 |