Using Probability and Monte Carlo Simulations

Part One: Managing Discretionary Trading Risk

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Experienced hedgers often find themselves in situations where it would be optimal to lift the hedge and perhaps reset it at a different level. This is a practice called **discretionary hedging**. As risk management advisors, we are often called upon to set volumetric limits for our clients so that the risk of these discretionary trading activities may be properly controlled and limited.

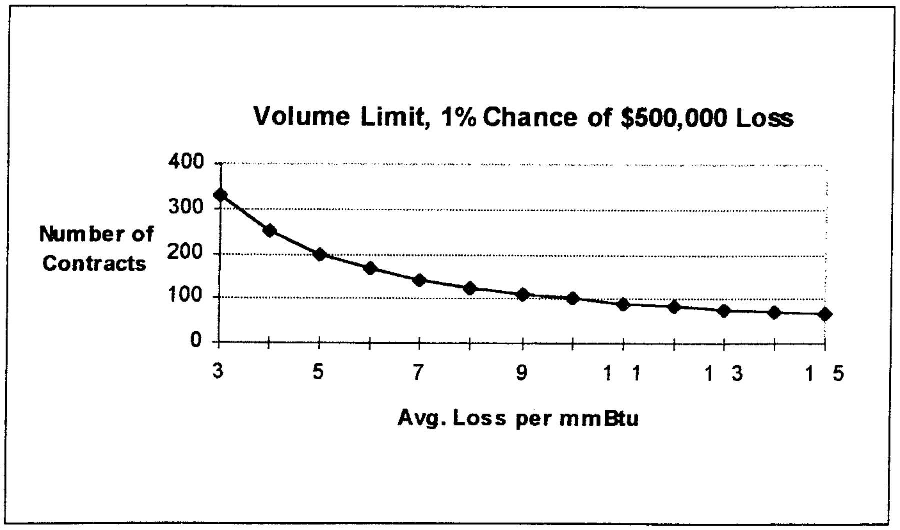
This article addresses the use of probability theory and Monte Carlo simulations in setting trading limits and assessing the probable outcome of discretionary hedging activities. A Monte Carlo simulation is simply an experiment or test where random tests may be run many times and empirical results may be achieved. Monte Carlo simulations have numerous applications. While this article evaluates trading result probabilities, Part Two will use such simulations to evaluate the probability of various market price scenarios.

A decision to reset a hedge carries the risk that the reset will be at a worse price rather than a better one, due to the probability that the market is not entirely predictable and no one has perfect judgment at all times. Therefore, all situations where the odds of resetting a better price are less than 100 percent carry some risk of losing some money relative to a passive hedge case. Figuring out the number of contracts to use in a discretionary hedging program without risking more money than management is comfortable with can be solved using a subset of probability theory called stochastic processes.

Let's look at a simple example, by playing a game whereby each time we toss a coin, we face a 5 cent per MMBtu loss. We are willing to take a 25% chance of reducing our cumulative capital by $10,000. Given a 1/2 chance of a loss, 2 losses in a row has a probability equal to the square of 1/2, or 1/4, or 25%, meaning the probability of two losses in a row of $5,000 results in 25% probability of a cumulative drawdown of $10,000. At 10 contracts we face a $5,000 loss per trade. Thus we play this game with 10 contracts.

Now let's evaluate a more realistic example: We have a group of traders who have a record of winning trades, or positive resets 70 percent of the time. The traders' average losses vary from 3 to 15 cents per MMBtu, and improvements on hedge price run twice the amount of worse hedges. Management will allow a discretionary trading program which carries a 1% risk of drawing down the cumulative positive hedge result by no more than $500,000 at any given time. Using probability theory to solve this problem yields a result as shown on Chart 1 below.

Chart 1



Thus the higher the average loss, the larger each individual loss on a per contract basis. So the trader with the higher average loss gets to trade fewer contracts in order to stay within the risk parameters of his firm.

Once the downside or probability of a poorer result has been defined, the question is often raised as to what positive results may be expected. The way we approach this question is to run a Monte Carlo simulation.

We could for example, toss a coin, with a 50/50 probability of coming up heads or tails, heads paying $1.00 and tails receiving $1.00 and evaluate the probability of losing $5.00 after 100 tosses. We might have the computer toss the coin 100 times in 1000 tests and plot the results.

Here we will evaluate trading scenarios containing 100 trades each, assuming a trader with a 70 percent accuracy, an average loss of 8 cents per MMBtu, and an average gain of 16 cents per MMBtu. We also assume a fairly wide variation around the average losses and gains with the loss standard deviation greater on a

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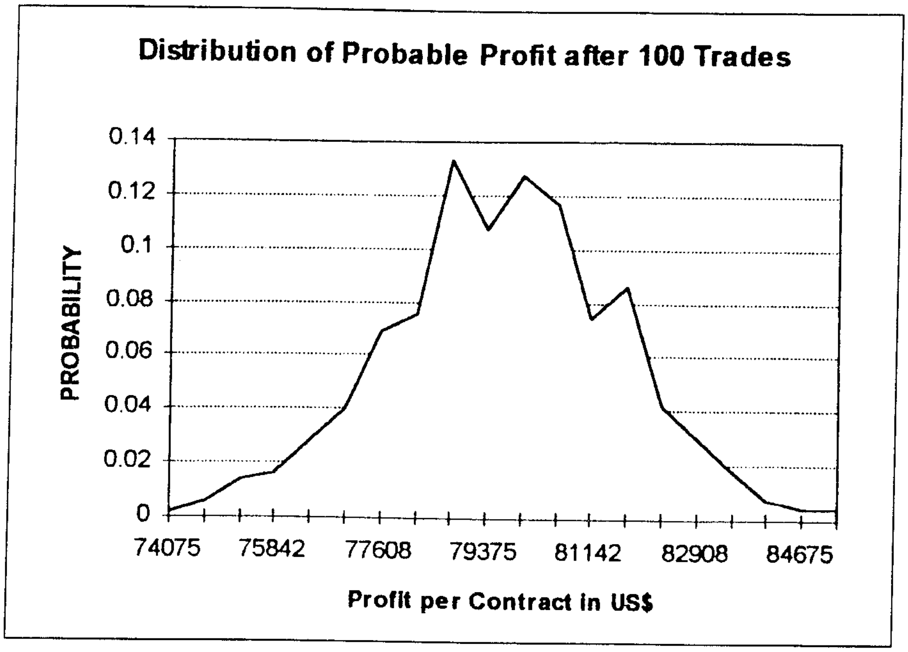
Chart 2



percentage basis. Finally we assume wins are more or less normally distributed, and that losses are skewed such that larger losses are experienced from time to time than one would expect assuming a normal distribution. Our Monte Carlo iterations were run 1000 times; that is, we ran 1000 sets of 100 trades.

Chart 2 shows the probability distribution of profit after these 100 trades.

As one would expect, the mean expectation is less than the $88,000 per contract we would expect with no variation in the average wins and losses given our bias toward higher variation in losses than in wins.

Going back to the volume limit chart, a trader with an average 8 cent loss may trade 124 contracts. So this trader with exceptional performance will improve the company's hedge results by between 9.5 and 10.3 million dollars after 100 trades.

The final Monte Carlo simulation we will review is a simulation of the expected results after each trade. Chart 3 shows the expected band of results for the first 6 trades. With such an approach, should the trader's performance be below the 5th percentile of that based on the assumed performance parameters, the company can take action to reduce his trader allowance and thus adjust the number of contracts to reflect the actual, lower performance.

Thus we can see that probability theory may be used both to assure management that the volumes being traded are such that the firms risk parameters are adhered to, to assess what trading results are probable given acceptable trader performance, and finally whether trading results are as expected on an ongoing basis.

Chart 3