Value at Risk—New Approaches to Risk Management

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Managing risk has always been an integral part of banking. Recently, however, "risk management" has become a popular buzzword—the phrase appeared in the *American Banker* 72 times in 1990 and 325 times in 1995.[1] At the center of the recent interest is an approach to risk management called "Value at Risk." In the past two years it has been accepted by both practitioners and regulators as the "right" way to measure risk, becoming a de facto industry standard. Yet, the danger is that overreliance on value at risk can give risk managers a false sense of security or lull them into complacency. After all, value at risk is only one of many tools for managing risk, and it is based on a number of unrealistic assumptions. Moreover, there is no generally accepted way to calculate value at risk, and various methods can yield widely different results.

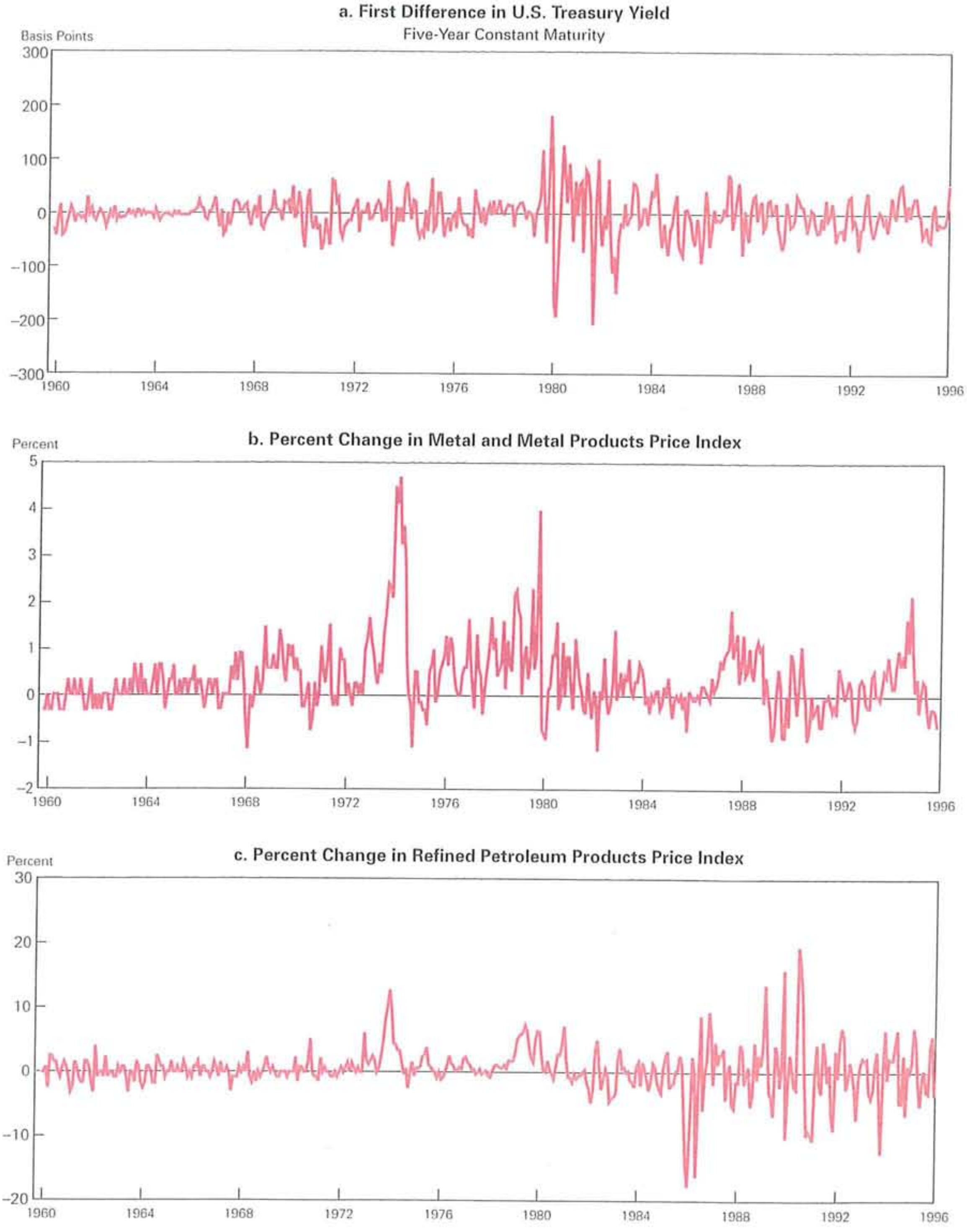
This article will review briefly the reasons for the new approaches and describe the Basle Market Risk Standard, which proposes the use of banks' internal value-at-risk models to set appropriate capital levels to cover market risk in bank trading operations. The article will describe several common methods for calculating value at risk (VAR) and highlight important assumptions and methodological issues. These issues will be illustrated by two step-by-step examples of calculating VAR for a single instrument. The article concludes with a brief discussion of strengths and weaknesses of VAR.

I. Why a New Approach?

Increased volatility in the financial markets since the 1970s has spurred new emphasis on risk management. Increased volatility first became apparent in the currency markets after the collapse of the Bretton Woods Agreement, followed, in short order, by interest rates and

Figure 1

Examples of Volatility Patterns



commodity prices. Figures 1a, 1b, and 1c depict examples of these volatility patterns.

Rapid advances in information technology have increased proprietary trading activity and heightened the emphasis on money management performance. At the same time, the growing complexity of financial products, particularly derivatives, has made it more difficult to evaluate and measure the risks taken by financial institutions, as accounting and disclosure rules have failed to keep pace with financial innovation. The use of derivatives has also increased linkages between markets. For example, a shock in the equity futures market of one country can be transmitted rapidly to the market for the underlying equities and perhaps to currency and equity markets of other countries as well.

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The sharp rise in transaction volume in derivatives markets, coupled with several well-publicized trading losses, has led to a new interest in an "objective" way of gauging the adequacy of capital. In their search, financial institutions turned in part to analytical tools introduced in derivatives markets, and VAR emerged as the favored method for measuring risk. The 1993 study by the Group of Thirty, *Derivatives: Practices and Principles*, strongly recommends VAR analysis; that study's recommendations have been broadly accepted by the industry as the standard of "best practices."

Currently, derivatives techniques have spread to many instruments and their structures have become increasingly complex. More than 1,000 banks, nonfinancial corporations, insurance companies, mutual funds, and other asset managers use them to manage their risks. The availability of data on derivatives prices from the past decade gives a better empirical foundation to VAR analysis. The Bank for International Settlements (BIS) has allowed banks to use their own internal models of risk in setting capital requirements for market risk. The acceptable models must rely on VAR methodologies.

VAR has an intuitive appeal because it summarizes the risk of the entire portfolio in a single number. Moreover, it expresses in dollar terms the major concern of risk management—the potential loss to portfolio value. VAR can be applied to many different instruments and can calculate and aggregate risk across instruments and types of assets.

VAR is applied primarily to market risk, though applications have recently been expanded to incorporate credit risk. (See the box for definitions of the main types of risks in banking.) VAR holds promise of combining all quantifiable risks across the business lines of an institution, yielding one firm-wide measure of risk.

II. What Is Value at Risk?

Essentially, VAR poses the question: "How much money might we lose over the next period of time?" Rephrasing it more precisely, "Over a given period of time with a given probability, how much could the value of the portfolio decline?" For example, if the given time is one week, the given probability 1 percent, and the value at risk $20 million, then we estimate that the odds that this portfolio will decline in value by more than $20 million within the next week are 1 in a 100.

To calculate VAR, one needs to choose a common measurement unit, a time horizon, and a probability. The common unit can be U.S. dollars, German marks, or whatever currency the organization primarily uses to do business. The chosen probability of loss usually ranges between 1 and 5 percent. The time horizon can be of any length, but it is assumed that the portfolio composition does not change during the holding period. The most common holding periods used are one day, one week, or two weeks. The choice of the holding period depends on the liquidity of the assets in the portfolio and how frequently they are traded. Relatively less liquid assets call for a longer holding period.

[1] See "New Risk Tests Win Fans—But Will They Work?" *American Banker*, 2/7/96.

Banking—What Are the Risks?

The risks of banking can be divided into five categories: credit, liquidity, operational, legal, and market (Figure 2).

Credit risk is the possibility of loss as a result of default, such as when a customer defaults on a loan, or more generally, any type of financial contract.

Liquidity risk is the possibility that a firm will be unable to fund its illiquid assets.

Operational risk is the possibility of loss resulting from errors in instructing payments or settling transactions.

Legal risk is the possibility of loss when a contract cannot be enforced—for example, because the customer had no authority to enter into the contract or the contract turns out to be unenforceable in a bankruptcy.

Market risk is the possibility of loss over a given period of time related to uncertain movements in market risk factors, such as *interest rates, currencies, equities, and commodities.* The market risk of a financial instrument can be caused by more than one factor. For example, holding a bond denominated in a foreign currency exposes one to currency risk and to interest rate risk. Similarly, entering into a domestic equity swap exposes one to equity risk and interest rate risk.

Banks may be exposed to some equity and commodity risk through swap positions and many large banks have currency risk through their currency trading, but by far the largest market risk of the banking industry is *interest rate risk.* A principal source of earnings for banks is net interest income, the difference between interest received and interest paid. The main source of interest rate risk is the volatility of those interest rates and the mismatch in the timing when the rates on assets and liabilities are reset.

Interest rate risk, in turn, can be divided into three types—*yield curve level risk, yield curve shape risk,* and *basis risk,* depending on the type of interest rate change that can cause losses.

Yield curve level risk refers to an equal change in rates across all maturities: for example, if all Treasury yields, from 3-month T-bills to 30-year long bonds, move up or down uniformly by 1 percent.

Yield curve shape risk refers to changes in the relative rates for instruments of different maturities. For example, the yield curve could "bulge," so that yields rise for intermediate maturities, such as 3- to 5-year Treasury notes, while rates for bills and long-term bonds remain unchanged.

Basis risk refers to the risk of changes in rates for instruments with the same maturity but pegged to a different index. For example, suppose a bank funds itself by borrowing at a 6-month Libor (London Interbank Offer Rate), a commonly used rate for interbank borrowing, and invests in an instrument whose rate is tied to the 6-month Treasury rate. If the Libor rises relative to the Treasury rate, the bank will lose money.

Of course, in reality all interest rates continuously change, exposing the bank to all three types of interest rate risk. However, it is useful to distinguish among them conceptually to pinpoint the areas of particular vulnerability.

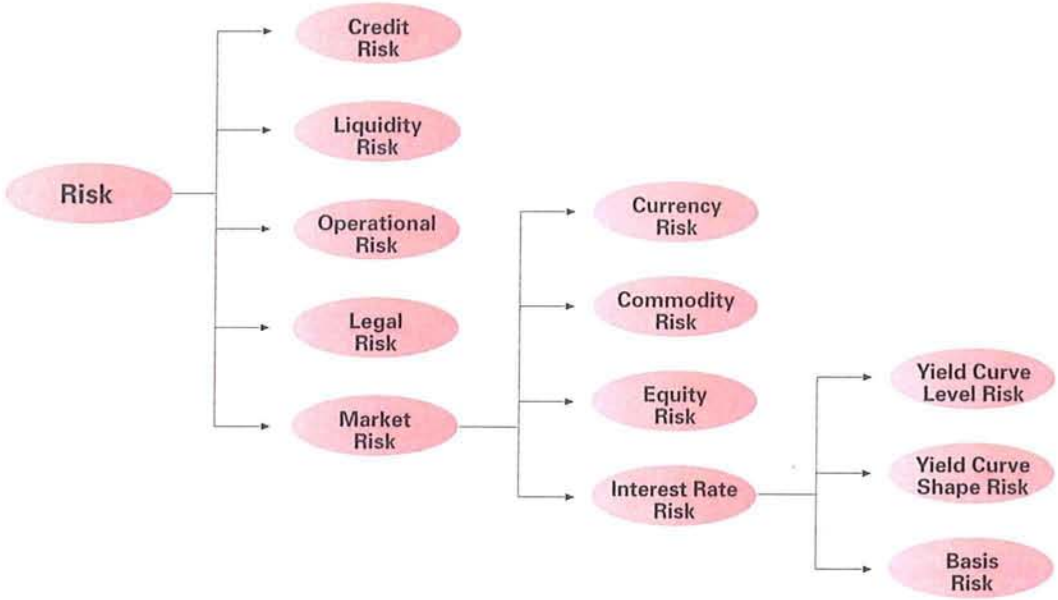
III. VAR and Capital Requirements for Market Risk

VAR models have been accepted by both practitioners and bank regulators as the state of the art in quantitative risk measurement. In its recent risk-based capital proposal, the Basle Committee on Banking Supervision endorsed the use of banks' VAR models to allocate capital for market risk. The Basle standard covers internationally active banks and applies only to their trading account. The proposal offers two alternatives: "standardized" and "internal models." U.S. bank regulators favor the internal models approach, whereby the bank's own VAR model is used to set aside capital for market risk. The proposal has an implementation period of two years and will take effect in January 1998.

To be acceptable to regulators for the purposes of allocating capital, banks' internal models must meet certain qualitative and quantitative standards. In essence, qualitative standards relate to the institution's risk management function as a whole. They call for independent validation of the models by the bank or a third party; strong controls over inputs, data, and model changes; independence of the risk management function from business lines; full integration of the

Figure 2

Types of Risk



model into risk management; and, most important, director and senior management oversight of the risk management process.

Quantitative standards relate to specific features of the VAR model. They call for the use of a 1 percent probability level and a two-week holding period. In addition, the VAR thus found is to be multiplied by a factor of three. The multiplication factor is designed to allow for potential weaknesses in the modeling process and other nonquantifiable factors, such as incorrect assumptions about distributions, unstable volatilities, and extreme market movements.

Many practitioners, however, consider these standards too restrictive. They note that a holding period of two weeks is too long for many instruments, as traders get in and out of positions many times during a typical day. Moreover, a two-week holding period combined with a 1 percent probability safeguards against events that can be expected to occur only once in four years. This makes it difficult to validate the model within a reasonable period of time.

It should be noted that a few features of the proposal have been modified as a result of industry criticism. In particular, an earlier version of the proposal allowed the models to account for correlations of asset returns within, but not among, asset classes, such as equities, currencies, and bonds. Now, all correlations are allowed.

IV. Parametric VAR

No consensus has been reached on the best way to implement VAR analysis. Most methodological issues revolve around estimation of the statistical distributions of asset returns. The main approaches are known as parametric (also known as the analytical or correlation method), historical, historical simulation, and stochastic simulation (also known as Monte Carlo).

Parametric VAR is based on the estimate of the variance–covariance matrix of asset returns, using historical time series of asset returns to calculate their standard deviations and correlations. The main assumption of the parametric VAR is that the distributions of asset returns are normal. This means that the variance–covariance matrix completely describes the distribution.[2]

[2] While a number of distributions other than normal can be completely described by their parameters, in VAR analysis the parametric approach usually refers to a normal distribution.

The parametric approach can be summarized by the equation:

$$\sigma_p^2 = \sum(a_i \cdot \sigma_i)^2 + \sum_{i \neq j} \sum_{i \neq j} a_i \cdot a_j \cdot \rho_{ij} \cdot \sigma_i \cdot \sigma_j,$$

where:

σ_p^2 = the volatility of portfolio returns,
a_i = the dollar amount of the portfolio share of the ith instrument,
σ_i^2 = the volatility of the ith instrument, and
ρ_{ij} = the correlation between the returns of the ith and jth instruments.

The equation shows that portfolio risk, as expressed by its variance, is a function of the variance of the return on each instrument in the portfolio, as well as on the correlations between each pair of returns. This means that unless the returns in the portfolio are perfectly correlated (all $\rho_{ij} = 1$), the variance of the portfolio does not equal the simple sum of the variances of the individual positions. When the risk that any investment contributes to the portfolio is less than the risk of that investment alone because of diversification, the risk of the portfolio is less than the sum of the risks of its parts.

The best-known parametric VAR model is J.P. Morgan's RiskMetrics. J.P. Morgan has done much to advance the public understanding and acceptance of VAR analysis by making both the methodology and the data sets of volatility and correlation estimates for RiskMetrics publicly available on the Internet.

To illustrate the parametric approach we will calculate the VAR for one instrument—a Treasury bond futures contract.[3] In this example, we will estimate the VAR of a position consisting solely of a June 1996 Treasury bond futures contract purchased on May 24, 1996. The closing futures price for that day was 110. Since each Treasury bond futures contract is for the delivery of $100,000 in face value of bonds, each $1 change in the futures price results in a $1,000 change in the value of the position. VAR is usually estimated in terms of returns, rather than prices.

The return is calculated as:

$$R_t = \frac{P_t - P_{t-1}}{P_{t-1}} \cdot 100,$$

Table 1
Daily Returns on a Bond Futures Contract

Date	Futures Price	Daily Return (%)
May 24, 1996 (Today)	110.00	
May 23, 1996	109.4063	.542702
May 22, 1996	110.1563	−.68085
May 21, 1996	109.5625	.541928
May 20, 1996	109.7813	−.171086
***	***	***
May 31, 1995	111.25	.674157
May 30, 1995	111.125	.112486

where R is the daily return and P is the price of the instrument. The daily returns on the bond futures contract are shown in Table 1.

To calculate the one-day VAR of this position, we need to estimate the mean of the daily returns, and the volatility, as measured by the standard deviation. (Since the portfolio consists of only one instrument, we need not be concerned about correlations.) If these returns are governed by the normal distribution, then 95 percent of all returns will fall within 1.96 standard deviations of the mean return. Moreover, 98 percent of all returns will fall within 2.33 standard deviations of the mean return. The mean and the standard deviation in our case of Treasury future returns were found to be -0.00224 percent and 0.605074 percent, respectively. This means that 98 percent of all returns would fall between -1.41 percent and 1.41 percent and only 1 percent of returns will be lower than -1.41 percent (Figure 3).

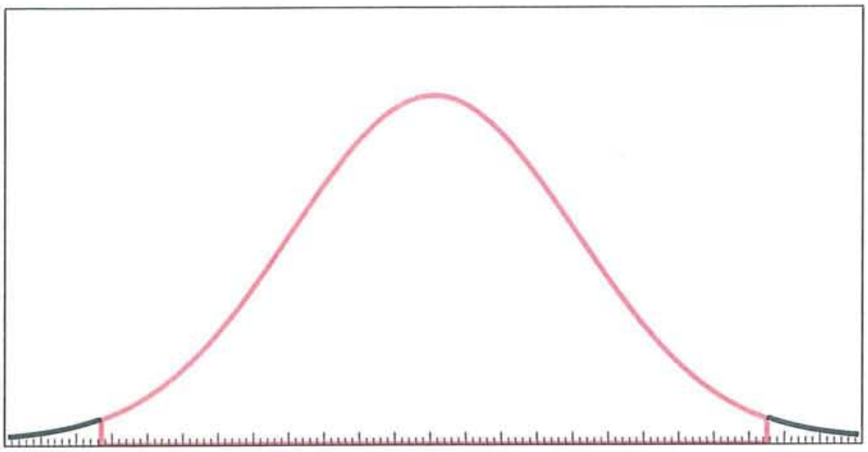
To convert the negative return of 1.41 percent to a dollar amount, we recall that the futures price on May 24, the day for which we are calculating the VAR, was 110. From this we calculate a one-day VAR at the 1 percent probability level to be $1.41\%/100 \times 110 \times$ \$1,000 or \$1,551.00. If the VAR estimate is correct, the daily loss on this position will exceed $1,551.00 no more than one day out of a hundred.

Suppose that the risk manager decides that a one-day holding period is too short, and that a one-week holding period is more appropriate. If, in addition to normality, we assume that returns are serially independent, meaning that a return on one day does not affect the return on any other day, then the standard deviation increases proportionately with the square root of time. Thus, if the one-day standard deviation of returns is 0.605074 percent, the standard

[3] A futures contract is an agreement to buy or sell an asset at a certain time in the future for a certain price. A Treasury bond futures contract is traded on the Chicago Board of Trade and is the most popular long-term interest rate derivative.

Figure 3

VAR for Normally Distributed Futures Returns



For example, had we used only the last two months of returns, rather than a full year, we would have found the standard deviation to be 0.6513, rather than 0.605074, resulting in a VAR of \$1,669.22, rather than \$1,551.00. Clearly, the result would have been different still, had we used one month, six months, or five years of historical data on returns.

One popular way to estimate volatility is through exponential weighting of observations. This approach emphasizes more recent observations at the expense of the more distant ones because the weights assigned to past observations decline with time. The volatilities and correlations are updated every day in accordance with the most recent data, as the earliest observation is dropped from the historical series and the newest one is added.

The formula for the standard deviation (σ) of the daily return (R) and mean return μ with exponential weights based on a historical period of N days is:

$$\sigma = \sqrt{(1 - \lambda)\sum_{i=1}^{N} \lambda^i (R_{N-i} - \mu)^2}.$$

The parameter λ is known as the decay factor; it determines how fast the weight on past observations decays. The higher the λ, the slower is the rate of decay and the more weight is given to the more distant observations.[4] One study (Hendricks 1996) estimated volatilities for a number of decay factors and historical periods of different length for 1,000 simulated foreign exchange portfolios and found significant differences in the resulting volatilities.

deviation for one week consisting of five trading days is $\sqrt{5} \times 0.605074$, or 1.3530 percent. This gives us a one-week VAR of \$3,467.70 with a 1 percent probability level, which means that if we held the position for a week, we should not expect to lose more than \$3,467.70 more often than in one week out of a hundred.

The two assumptions about the distribution of returns that underlie the parametric method—normality and serial independence—allow us to be very parsimonious in the use of data. Since volatilities and correlations are all we need to calculate the VAR at any confidence level for any holding period, it is unnecessary to have the historical returns themselves, which are used in the historical approach, as shown in Section VI.

V. Does Volatility Change over Time?

In the preceding example, by calculating the volatility of the daily returns from a year of data, we implicitly assumed that the volatility of returns was constant throughout the year. However, volatility can change over time, sometimes quite abruptly, and it may make sense to pay more attention to the most recent observations in forecasting future volatility.

[4] See J.P. Morgan, RiskMetrics Technical Document, 3rd ed. Chapter 2, Section 3 for details on the choice of decay factors. RiskMetrics currently uses a decay factor of 0.94 for all daily volatilities of the series it maintains (Peter Zangari, J.P. Morgan, personal communication).

Table 2
Estimates of VAR Using Different Decay Factors

λ = .94 (rapid decay)		λ = .97 (slower decay)		λ = .99 (slowest decay)	
δ	VAR	δ	VAR	δ	VAR
.5829	$1,494.04	.5503	$1,410.48	.4011	$1,028.44

To check if our VAR estimate is sensitive to a choice of decay factors, we estimate the 1 percent probability level VAR for our bond futures returns using three different decay factors for a period of 50 days. Table 2 shows these estimates.

In the time period chosen for our example, the volatility of the return on the Treasury bond futures was increasing over time. Thus, the lower the weight placed on the more distant observations, the higher the estimate of volatility.

VI. The Historical Approach

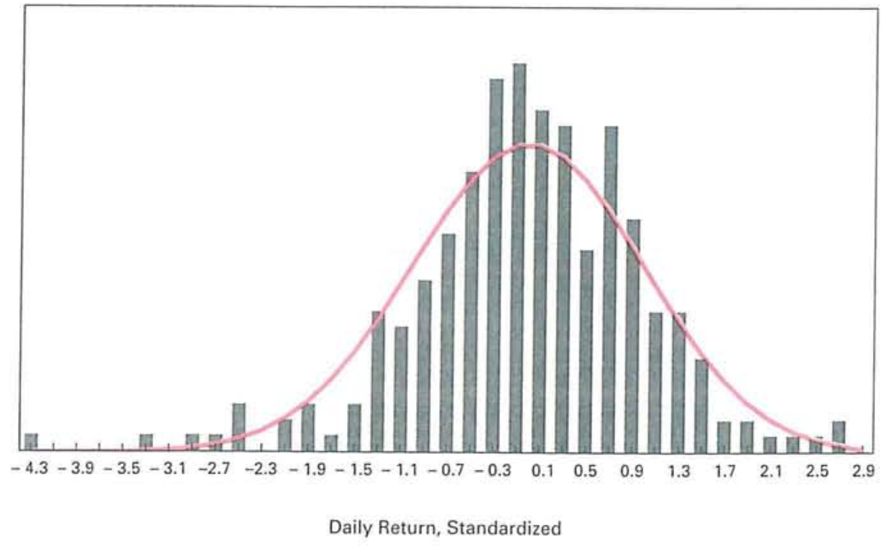
The simplicity and convenience of the normal distribution are powerful inducements for its use in VAR analysis, but this does not necessarily make its use appropriate. Since the early work of Mandelbrot (1963) and Fama (1965), most empirical research into the statistical properties of asset returns has found systematic deviations from normality. In particular, many studies have found that distributions of asset returns tend to exhibit kurtosis; namely, they are more peaked around the mean and have fatter tails than the normal distribution. Moreover, some, though not all, asset returns tend to be skewed to the left; that is, more unusually large negative returns are present than would have been expected if returns were normal.

To see if these observations apply to our chosen example of the bond futures contract, we construct a frequency distribution of the daily returns between May 1995 and May 1996. The resulting histogram is shown in Figure 4, with a normal distribution superimposed for comparison. The returns exhibit the typical pattern found in many asset returns: "fat tails" and left-skewness.

Fortunately, it is possible to calculate VAR without resorting to the assumption of normality, by using a simple historical method. This entails finding the lowest returns in the real historical data. To calculate VAR at the 1 percent probability level, we ranked the daily returns and identified the lowest 1 percent of returns. The first percentile return is 1.73 percent, giving us the daily VAR of 1.73%/100 × 110 × $1,000= $1,903.00, almost 23 percent greater

Figure 4

Daily Returns on a U.S. Treasury Bond Future



than the \$1,551.00 calculated with the parametric approach.

If we want to recalculate the VAR for a different holding period without making the assumption of serial independence, we cannot simply multiply the daily VAR by the square root of time. Instead, we must recalculate all the returns for the new holding period, construct the new frequency distribution, and identify the appropriate percentiles.

The historical method has a number of advantages over the parametric method. First, it makes no explicit assumptions about the volatilities of returns and the covariances between them. Second, it makes no assumptions about the shape of the distributions themselves. In particular, it makes no assumption of normality. On the other hand, the historical approach lacks flexibility. Unlike the parametric method, it does not allow one to try different values for volatilities and correlations to test the sensitivity of VAR to these assumptions. In addition, it requires investors to obtain and maintain large amounts of actual, historical data. Long historical data series relevant for one's portfolio can be expensive or may not even exist. In contrast, the parametric approach requires just the parameters of distributions, if one is willing to delegate the estimation of those parameters to a third party.

The historical method makes no explicit assumptions about the volatilities of returns and the covariances between them, or about the shape of the distributions themselves. On the other hand, it lacks flexibility and requires large amounts of actual, historical data.

VII. Simulation Approaches—From Risk Factors to VAR

Often, it is not appropriate to calculate VAR directly by estimating the probability distribution of returns on the instrument itself, as was done in the last example. If an institution has a large or complicated portfolio, it may be impossible or impractical to maintain historical data on all the instruments involved. Moreover, historical data do not exist for many instruments, particularly those that are customized. In those cases, the historical data set used to calculate the VAR will consist of returns not on the instruments themselves, but on their "risk factors," that is, other instruments or factors that influence their values. For example, for a domestic bond, the risk factor is the interest rate. For a bond denominated in foreign currency, the risk factors are the foreign interest rate and the exchange rate. For many equity derivatives, the main risk factor is the value of the S&P 500 index. For an S&P 500 option, the relevant risk factors are the value of the S&P 500 index, its volatility, the dividend yield on the index, and the risk-free interest rate.

In these cases, we can improve on the pure historical approach by using "historical simulation." Instead of looking at the volatility of the actual portfolio returns in the past, we will "simulate" the past portfolio returns by using the actual values of the risk factors and the *current* portfolio composition. Then, we can construct the empirical frequency distribution of the simulated portfolio returns by ranking them into percentiles and determining the VAR at the chosen confidence level.

Stochastic Simulation in Six Easy Steps

Historical simulation shares one disadvantage with the simple historical approach: a lack of flexibility to investigate different assumptions. However, instead of using the past values of the risk factors, we can model these factors explicitly by specifying the underlying distributions and their parameters. Using these distributions and parameters, we can generate thousands of hypothetical scenarios for the risk factors and determine the portfolio value for each scenario. As in the historical simulation, the resulting portfolio returns can then be used to construct the empirical frequency distribution and determine the VAR at the desired confidence level. This is the approach generally known as the Monte Carlo, or "stochastic simulation."

As an illustration of this approach, we will calculate the one-day VAR for a position consisting of one call option, which gives the holder the right, but not the obligation, to buy an asset for a certain price. In this example, we will calculate the VAR for a call option on the S&P 500 index—a popular equity derivative traded on the Chicago Board of Trade. This particular option was bought on May 28, 1996 for \$20.90 (the closing price for the contract on that day). The option expires on July 20, 1996 and gives the holder the right to buy the S&P 500 index for \$670. (The actual value of the S&P 500 on May 28. 1996 was \$674.9606.)

Finding the one-day VAR on May 28, 1996 involves the following six steps:

1. Calculate the daily returns on the S&P 500 and find the parameters of the normal distribution of returns.
2. Simulate returns on the S&P 500 for one day by generating random numbers from a normal distribution with the calculated parameters.
3. Use the simulated S&P 500 returns as input to calculate the simulated S&P 500 prices.
4. Use an option-pricing model to calculate the value of the call option at each simulated value of the S&P 500 index.
5. Calculate the one-day returns on holding the call option from the simulated call option prices.
6. Find the parameters of the distribution of call option returns and calculate the VAR.

The crucial part of this process is the transformation from the distribution of the S&P 500 to the distribution of the option values. In this example, the option was valued using the standard Black-Scholes model modified to value a stock index.[5] The formula is as follows:

$$c = Se^{-q(T-t)}N(d_1) - Xe^{-r(T-t)}N(d_2),$$

where d_1 and d_2 are given by:

$$d_1 = \frac{\ln(S/X) + (r - q + \sigma^2/2)(T - t)}{\sigma\sqrt{T - t}}$$

$$d_2 = d_1 - \sigma\sqrt{T - t}.$$

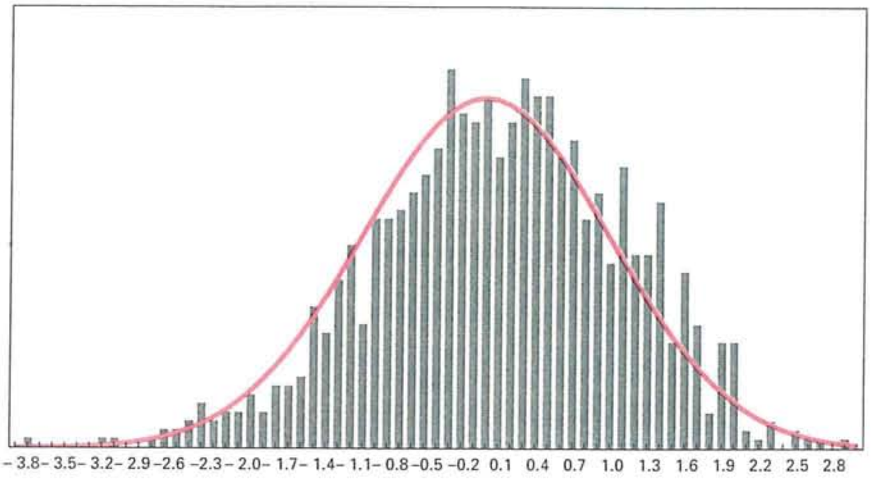
The notation is as follows:

- *c:* the value of the call option;
- *S:* the price of the S&P 500 index;
- *T − t:* the time left until the expiration of the option (in this case, 53 days);
- *q:* the dividend yield of the S&P 500 (estimated to be 2 percent per year);
- *X:* the strike price of the option (in this case, \$670);
- *N(x):* the cumulative probability distribution for a standardized normal variable (that is, the probability that such a variable will be less than *x*);
- *r:* risk-free rate of interest, in this case, the federal funds rate, or 5.5 percent per year;
- *σ:* volatility of the S&P 500 index.

The distribution of the resulting simulated returns is depicted in Figure 5. To calculate VAR, we rank the returns into percentiles and identify the 1 percentile return. This happens to be −0.3560. The price of the call option on May 28, 1996 was 20.90.

Figure 5

Daily Returns on Simulated S&P 500 Call Premiums



[5] The model for valuing options for non-dividend-paying stocks was developed by Black and Scholes (1973). The formula for valuing options on stock indexes paying dividends was derived by Merton (1973).

Every option contract on the S&P 500 is for \$100 of the index. Thus, the dollar value of VAR for one contract is $0.3560 \times 20.90 \times \$100 = \$744.04$. This means that the chance is 1 in 100 that we will lose more than \$744.04 on the call option contract in one day.

It should be noted that, in this example, volatility was calculated from one year of data with all observations weighted equally. Of course, a longer or shorter historical period could be used along with various exponential weighting schemes to generate a different estimate of volatility of the S&P 500 index, which would result in a different VAR for the call option.

VIII. Conclusion

In many financial circles, the reputation of value at risk stands as high as that of motherhood and apple pie. But, as with motherhood and apple pie, a good concept is not enough—good implementation is equally important. Value-at-risk analysis is a general framework that covers models with a wide variety of assumptions and methods of calculation, and, inevitably, it produces a wide variety of results. Our examples demonstrate that varying assumptions about distributions and methods of calculating volatilities produced quite different estimates.

Value at risk is a useful tool for risk management but it is not a panacea. One limitation is that it focuses on a single arbitrary point on the distribution of profits and losses, while it would be more useful to have a representation of the whole distribution. A second limitation of value at risk is that it tells us little about how risks are to be measured in extreme market conditions. During market crises, correlations between asset prices break down, liquidity disappears, and price data may not be available at all. Modeling risk under such conditions would require some sense of the concentration of ownership of different securities, information that most market participants would be reluctant to disclose, for competitive reasons.

Value at risk is often put forward as the way to aggregate risks across the whole institution. While integrating disparate risks is the ultimate purpose of global risk management, the use of value at risk for this purpose is problematic. Value-at-risk analysis works best for frequently traded instruments for which market values are easily available. Value at risk first took hold at the derivatives desks in the trading rooms of a few large banks, because they had both the expertise and the need to estimate and aggregate the market risks of many dissimilar instruments. From derivatives desks it spread to other trading desks, such as those for bonds and currency, and it is now beginning to be applied beyond trading to the broader arena of asset–liability management. However, many bank assets and liabilities, in particular deposits and loans, have long-term horizons and are not actively traded. Thus, they have poor or nonexistent price data and marking them to market on a day-to-day basis would be both impractical and misleading. Value at risk has the same limitations for life insurance companies, because these institutions have long-term, non-traded liabilities. Other methods may prove superior to value at risk as a global measure of risk. One alternative is a measure of how much one is willing to pay to eliminate risk, or the price of purchasing a guarantee to avoid a loss of a certain magnitude. Value at risk, which focuses on the distribution of possible losses, is only one element in the valuation of such a guarantee.

Overall, value at risk constitutes a useful though limited family of techniques for measuring risk. It is most useful in measuring short-term risk of traded instruments in normal market conditions. An additional benefit is that its use has created a common language for discussions about risk, and it has prompted more dialogue about risk issues. However, successful risk management is a much broader task, which depends crucially on appropriate incentives and internal controls.

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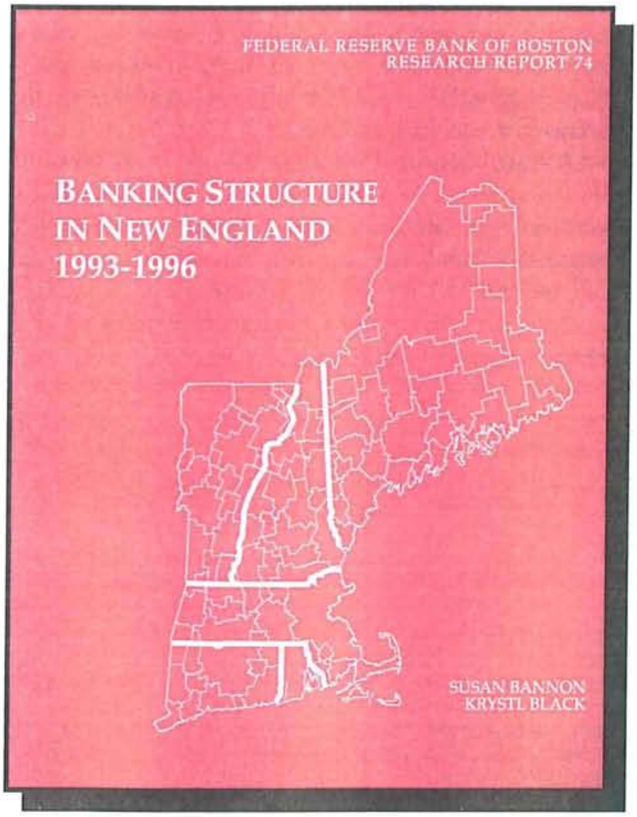
Research Report



Research Report No. 74 has just been issued. *Banking Structure in New England 1993-1996*, by Susan Bannon and Krystl Black, summarizes structural changes in New England's banking industry that occurred between June 30, 1993, and April 30, 1996, including mergers and acquisitions, bank holding company formations, bank openings and closings, and name changes. An update of Research Report No. 73, the new report uses 1995 data to rank New England commercial banking and thrift organizations by total consolidated New England deposits. Rankings are presented for all of New England, for each state, and within local banking markets. For each local banking market, Herfindahl-Hirschman Indexes and three-firm concentration ratios are provided. The report begins with a discussion of relevant antitrust issues.

Research Report No. 74 is available without charge. Requests should be sent to Research Library - D, Federal Reserve Bank of Boston, P.O. Box 2076, Boston, MA 02106-2076. The fax number is (617) 973-4292, and the e-mail address is boston.library@bos.frb.org.