For all its cachet, value at risk is no cookie-cutter solution to the risk-management problems facing financial institutions. Implementation is hampered by the need to make simplifying assumptions. Differences in VAR methodology and the many assumptions required mean that risk managers should have a clear understanding of the components of their VAR measures and must combine VAR with other risk tools.

Report Card on Value at Risk: High Potential but Slow Starter

Tanya Styblo Beder

While value at risk (VAR) shows increasing promise as a risk-measurement tool, there are more questions than answers after three years of use. Despite this, the concept is widely endorsed by regulators such as the Bank for International Settlements, the Federal Reserve, the Office of the Comptroller of the Currency, and the Securities and Exchange Commission. It is mandated for many under generally accepted accounting principles, is part of the rating process by agencies, and is encouraged by key industry groups such as the Group of Thirty, the Derivatives Policy Group, and the International Swaps and Derivatives Association. But implementation of VAR is harder than grasping the simplicity of its concept. *First*, not all VARs are equal. *Second*, vast quantities of data and significant modeling or systems efforts may be required. *Third*, firms must design and implement risk-management add-ons to address VAR's limitations and weaknesses. While dealers typically are further along with VAR implementation than end users, few if any are finished with the process. This article surveys the current realities of VAR and what we have learned to date.

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Three Main Types of VAR

VAR is the great equalizer. It translates the risk of any financial instrument into its potential loss under specific assumptions.[1] There are three main types of VAR: variance/covariance VAR, historical VAR, and simulation VAR.

Variance/covariance VAR

Under this method, sometimes called "analytic VAR," financial instruments are decomposed (or "mapped") into delta equivalents[2] consisting of basic financial building blocks, or market factors. Once historical or other distributions for these market factors are specified, VAR and other measures are computed using standard statistical techniques. In most cases, historical data is used to build the variance/covariance matrix for the market factors, making this aspect of the calculation dependent upon the time period selected. Over the past two years, data sets that provide distributions for many common market factors (for example RiskMetrics[3]) have become available, as have commercial software packages that perform VAR computations.

Historical VAR

Under this method, financial instruments are analyzed over the number of days in the historical observation period (for example, 100 days), and the actual change that was experienced in the value of each financial instrument is calculated using the desired time horizon (for example, overnight). Note that while most users analyze financial instruments specifically, some translate their financial instruments into "equivalent" building blocks or market factors and calculate the changes on these. Once the changes in value are calculated, each change is added to today's value for the financial instrument or its "equivalent" to produce an array of observations. As this replicates historical behavior, the risk view depends upon the time period selected. To complete the calculation, the array is analyzed statistically. For example, if there are 100 observations, the 5th lowest observation value would be the one-day 95% confidence interval VAR.

Simulation VAR

Under this methodology, the theoretical probability distribution of changes in value for each financial instrument or its "equivalent" is calculated for the desired time horizon (for example, over two weeks) as per the distribution parameters specified in the simulation. Typically, correlations and lognormal or other distributions are incorporated. The theoretical changes in values are then added to today's value for the financial instrument or its "equivalent" and arrayed as in the case of historical VAR to produce the desired confidence interval VAR. The process is often completed under varying sets of parameters.

Each type of VAR has its strengths and weaknesses. Variance/covariance VAR is the least computationally intensive and free data is available. However, it is based on normal or lognormal distributions so it misses fat-tailed behavior[4] and does not properly incorporate options or other nonlinear instruments. Historical VAR is the easiest to implement from a systems perspective and may be the easiest to explain to the nonmathematically inclined. However, its output depends heavily on the time period selected (simply stated, history must repeat itself). Simulation VAR can incorporate any joint distribution for the market factors, so offers the greatest flexibility for sensitivity analyses regarding market plus model issues, and fully captures nonlinear instruments. However, it has the greatest systems, programming, and data needs.

Seven Lessons about VAR

Beginning in 1994, dealers focused on implementing at least *some* VAR measure and devoted their resources to data, systems, and programming challenges. Risk-management software vendors took a similar approach, focusing primarily on the need to expand their systems to include at least *one* VAR alternative. At first, most implemented variance/covariance or historical VAR calculations. Larger corporations implemented VAR as well, with the goal of comparing the treasury area's performance versus an established internal benchmark. Some institutional investors and investment managers (particularly insurance companies, mutual funds, and "manager of managers") began to implement VAR over the past 6 to 12 months, with the goal of calculating risk adjusted portfolio performance. Many smaller corporations, as well as pension funds, public funds, foundations, and endowments, have started to address VAR more recently.

To date and in general, the theoretical discussions of VAR far exceeded firms' actual practices.[5] This is due to the many practical issues that complicate and surround its implementation. However, valuable lessons have been learned, and these are being addressed as VAR approaches its third year of use in risk management. Seven lessons follow.

Lesson One: For instruments with nonlinear price functions, variance/covariance VAR understates risk

The variance/covariance approach significantly understates risk for portfolios with options or financial instruments with nonlinear price functions,[6] particularly during periods of large volatility or with large changes in the price of the underlying. Most dealers with significant nonlinear exposures have implemented or are switching over to simulation-based VAR calculations for at least the nonlinear books within their businesses. This presents aggregation issues regarding VARs calculated with different methods over different time horizons. Research is under way regarding risk-management add-ons to a variance/covariance approach that better reflect nonlinear risks.

Lesson Two: Historical VAR and simulation VAR can differ drastically

The historical VAR and simulation VAR

approaches may produce vastly different results, especially when the historical period comprises a heavily trending market. This is due to the fact that the key variables in simulation VAR are computed according to the user's expectations or may be computed randomly and often differ substantially from those for the recent historical period. There are many types of simulation, each determined by the user's preferences and parameters. Monte Carlo simulations are the most common type of random simulations. To the degree random or user-specified expectations vary from trending market expectations, differences between the two approaches will be magnified. Note that the choice of simulation parameters is itself an important determinant of the VAR result, so some dealers and end users are beginning to stress-test the sensitivity of the VAR result to alternate sets of parameters. Appropriate stress tests vary and depend upon factors such as portfolio composition, holding period, risk appetite, systems capabilities, etc.

The choice of simulation parameters is itself an important determinant of the VAR result.

Lesson Three: Mapping can impair VAR calculations

For large dealers and end users, historical VAR and simulation VAR[7] require vast quantities of data plus numerous pricing models. To enable calculation of VAR as models and databases are built or to reduce the total amount required, most VAR users have resorted to some degree of mapping financial instruments into equivalents and/or matrix pricing. This often results in significant differences between the risk/reward profile of the actual financial instrument and its mapped equivalent. Research is under way to learn the degree to which this impacts the VAR result, particularly in the case of nondiversified portfolios, heavily engineered instruments, exotic instruments, etc. I have reviewed several cases in which the VAR calculation was performed correctly, but the accuracy lost through mapping or matrix pricing produced misleading results for the actual portfolio.

Lesson Four: Poor assumptions about diversification can lead to flawed results

The variance/covariance approach requires mapping financial instruments into market factors that are contained in the matrix. To facilitate this process, entire instrument classes are often mapped into market indices. For example, all domestic stocks may be mapped into the S&P 500 or all corporate bonds into a swap index. For several portfolios we have reviewed, mapping an undiversified portfolio into an assumed diversified portfolio produced misleading results. Research is under way to analyze the relationship between the quality of the VAR result after such mapping and varying degrees of diversification.

Lesson Five: Combining adjusted VARs from different time periods can be misleading

Many VAR users employ different time horizons for different trading areas or asset classes. For example, an overnight horizon is used for the forward foreign exchange positions, while a longer time horizon is used for real estate or illiquid/exotic financial instruments. To obtain a firmwide VAR statistic for a comparable time period, adjustments are made using statistical approximations such as the square root of time. To the degree that markets do not follow linear price behavior and normal distributions (most markets do not) and to the degree that drift should be considered, misleading results will be produced by such approximations.

Lesson Six: VARs may be less comparable than they appear

Performance measurement and capital allocation are common goals of VAR users. The desire is to allocate capital to areas that have the greatest performance with the least amount of risk. However, many financial instruments and markets are inefficient and have risk profiles that change over time. Thus, the VAR for highly liquid, diversified portfolios may be compared to the VAR for highly illiquid, undiversified portfolios, and results are often not comparable. Furthermore, two portfolios or business areas with equivalent VAR and return may have different risk tails, thus producing different expectations of loss outside of the confidence bands. Research is under way to see what can be learned from analyzing the changes in VAR over time (that is, the first derivative with respect to time). Other research is studying the relationship between downside risk and the degree of diversification to determine how these risk dimensions should be incorporated into performance measurement and the capital allocation decision.

Lesson Seven: Accounting and economic measures may not mix

Many corporations use VAR in conjunction with a benchmark in the treasury area. For many, the goal is to manage the volatility of earnings. Two common problems arise with this approach. *First*, accounting realities may differ significantly from economic realities. To the degree that the benchmark is accounting based and the VAR calculation is economic based, this problem will be exacerbated. *Second*, earnings occur continuously and involve all business activities of the company, while VAR typically is based on a snapshot of selected activities of the corporation at a point in time. Both require adjustments in how VAR is employed.

Which VAR Should You Use?

VAR research to date primarily has involved portfolios of simple, highly liquid financial instruments such as Treasury strips, equity index options, and forward foreign exchange contracts. Our review of dozens of dealers' and end users' risk-management techniques revealed vast differences not only in the type of VAR calculation but also in the VAR statistics produced. Variances in the VAR statistic ranged by as much as 14 times for the same portfolio, depending on the type of VAR calculation and the time horizon.[8] Large variances in VAR have been corroborated by others' research, particularly for portfolios that contain options.[9] Yet other research suggests that variances in VAR may be less significant for portfolios that do not contain options or other instruments with nonlinear price behavior, especially over one-day holding periods,[10] and that the length of sampling periods plays an important role.[11]

Typically, dealers and end users with complex portfolios set a goal of implementing a consistent, firmwide VAR that reflects their outlook preferences and the complexity of the portfolio.

Which VAR methodology to select depends on several factors. Typically, dealers and end users with complex portfolios set a goal of implementing a consistent, firmwide VAR that reflects their outlook preferences and the complexity of the portfolio. For portfolios with options or significant nonlinear price behavior, the historical VAR and simulation VAR produce superior results to the variance/covariance VAR. However, the systems, model, data, personnel, educational, and time requirements of the historical and simulation VARs often result in the use of variance/covariance VARs or multiple VAR methodologies on an interim basis. The choice between historical and simulation VAR resides largely with the user's outlook preferences and the desire to perform sensitivity analyses. Historical VAR is based on actual, past market experience whereas simulation VAR is based on the user's outlook and expectations. Full sensitivity analyses can be performed only on the latter.

Once the outlook preferences and the complexity of the portfolio are analyzed and one or more VARs are selected, users must make decisions about several important dimensions of the calculation:

- the length of the VAR horizon (overnight, two weeks, longer),
- database,
- correlation assumptions,
- mathematical engine and quantitative approach,
- percentage of outcomes to be considered,
- other risk-management and risk-measurement tools combined with VAR.

The length of the VAR horizon (overnight, two weeks, longer)

VAR requires the firm to select a time horizon for analyzing risk in the context of expected losses. For example, dealers often select overnight time horizons, while pension funds and corporations often select longer horizons.

One challenge in the selection of the time horizon is that while a model may produce adequate views of capital at risk on an overnight or weekly basis, it may produce inadequate risk views over time horizons of several months, a year, or longer. For example, the calculation of one-day or overnight VAR may be misleading for customized or exotic products that cannot be analyzed, action decided upon, and liquidated in such a time frame. The 1995 Basle Amendment suggests that firms employ a single time horizon of two weeks (10 business days) for VAR calculations. This may be short relative to the life of many asset classes and other exposures and potentially too long for highly liquid instruments.

A second challenge is that while longer time horizons may be preferred for instruments such as illiquid, path-dependent options, some mathematical functions are inaccurate beyond small market moves. For example, many mathematical models are incapable of handling discontinuities such as market gapping or require linearity to produce accurate information, yet these are used in pricing models that are part of the VAR calculation. Over the past two years, dozens of dealers and end users announced losses due to differences between estimated short-term profits and actual experience over longer time horizons. This suggests that firms should test the sensitivity of the VAR calculation to alternate assumptions regarding pricing models (see "Mathematical engine and quantitative approach," below) and time horizon.

While a model may produce adequate views of capital at risk on an overnight or weekly basis, it may produce inadequate risk views over several months, a year, or longer

For some firms, a third challenge is to compare and combine VARs calculated over alternate time frames and under different methods. As discussed above, the translation of long-horizon VARs into short-horizon VARs (and vice versa) typically assumes linearity, joint normal relationships (that is, that the square root of time is sufficient), or static relationships (that is, no drift), which may produce misleading results.

Database

VAR requires data covering all relevant market factors and variables on which to perform the calculations. Vastly different risk views may be produced by alternate data sets. For example, during a recent 24-hour period, the 10year U.S. Treasury traded at as high a price as 103 for three hours but only at par for one hour. Thus, time of day (or intraday data versus end-of-day data) can produce contrary risk views via VAR. Different risk views can also be created by the use of historical versus market-implied data. Note that historical end-of-day data is most often employed to calculate VAR, but the historical period selected varies significantly from firm to firm. Some firms employ the most recent 90day time horizon while others use the past year at a minimum. Other firms expand the time horizon to capture periods of stressful market moves such as market crashes or dislocations. The proposed Basle Amendment suggests that firms employ a one-year minimum data set for VAR calculations.

Length of time is not the sole criterion to establish and test regarding the data set. As discussed, mapping procedures are a critical part of most VAR processes. Furthermore, sampling frequency and independence of data also can affect VAR significantly. For example, a one-year database comprised of 12 end-of-month data points may be no more relevant than a data set of 12 points selected through random chance. Alternately, theoretical mark-to-model prices for customized or illiquid instruments may be far from market prices at the time of transactions. Such data issues can cause unpleasant surprises, as experienced in 1994 by many mutual funds, pension funds, and municipalities that monitored engineered mortgage securities and/or inverse floaters at month-end based on theoretical values.[12]

Another decision regarding the data is whether to exclude certain data points. For example, should the data set include outlier events caused by onetime events, market gapping, or other dislocations? Such occurrences are often characterized as extreme but low probability events. Recent examples are the devaluation of the Mexican peso, the 1987 stock market crashes, and commodity volatility during the Gulf War. Note that two databases, distinguished by inclusion of outlier events, are likely to produce different VAR calculations.

Yet another challenge is to determine whether an outlier event is an indication of structural change in the market. For example, fundamental change in the prepayment patterns for mortgage-based securities in the United States occurred over the past few years, driven by mortgage broker activity and education of the home owner. Before the change, conventional wisdom dictated that a drop in interest rates had to prevail for two to three months before refinancing occurred. Subsequently, this refinancing lag shortened from months to weeks, and the mortgage market demonstrated new prepayment patterns during the rally that ended with the Federal Reserve's interest-rate hike in February 1994. Thus, use of historical prepayment data was misleading in predicting the expected life (and therefore return) of many mortgage securities.

Some firms employ data sets based on implied market information to reduce dependence on historical data. Whatever the data set, firms should stress-test the sensitivity of the VAR calculation not only to exclude any data points but also for sampling error and the use of specific historical periods and/or mark-to-model dependence. The goal is to determine whether alternate data sets drive large differences in the value of VAR for the same portfolio or exposures.

Correlation assumptions

VAR requires that the user decide which exposures are allowed to offset each other and by how much. For example, is the Japanese yen correlated to movements in the Italian lira or the Mexican peso? Is the price of Saudi Light correlated to movements in the price of natural gas? If so, by how much? VAR requires that the user determine correlations not only *within* markets (for example, U.S. dollar [USD] currency underlyings vs. USD commodity underlyings) but also *across* markets (for example, how do changes in the bond market in the United States relate to changes-in the equity market in Australia?). Note that mapping procedures have additional embedded correlation assumptions. For example, mapping individual stocks into the S&P 500 or fixed income securities into the swap curve translate into the assumption that individual financial instruments move as the market overall. While this may be a reasonable assumption for well-diversified portfolios, it may not be reasonable for undiversified or illiquid portfolios.

Dealers, end users, regulators, and financial theorists espouse wildly different views on the topic of correlation relationships both within and across markets.

Dealers, end users, regulators, and financial theorists espouse wildly different views on the topic of correlation relationships both within and across markets. For instance, pension funds have tackled correlation issues for decades in analyzing strategic versus tactical allocation of assets. Pension funds with a *lack* of diversification across asset classes (for example, stocks versus bonds) or capital markets (for example, domestic versus foreign) may well be considered to be in violation of the prudent man standard of the Employee Retirement Income Security Act of 1974 (ERISA). Financial theory[13] demonstrated the value of diversification, both within and across markets, decades ago. While cross-border *legal* and netting risks may exist, these risks typically are managed and reserves are taken separately from *market* risks. Despite the use of separate reserves and risk calculations, the 1995 Basle Amendment allows only the extreme position of correlation *within* asset classes. For calculating VAR, the amendment assumes a correlation of 1 between long positions and a correlation of -1 between long and short positions. While this may be of little consequence for some relationships (for example, the correlation between strong currencies and interest rates in European Community countries), it is of huge consequence for others (for example, the correlation between the price of a restaurant stock in Sri Lanka and a Yankee bond issued by the Canadian telephone company). Not surprisingly, the rigid correlation methodology in the 1995 Basle Amendment raises VAR significantly relative to more common correlation assumptions.[14]

Additional challenges exist. What happens if a market breaks through its historical or implied trading pattern and violates the correlation assumption in place? A recent example is provided by the many currencies that previously displayed little or no historical correlation to the Mexican peso but made sympathy moves during the peso's devaluation. What happens if some temporary phenomenon alters correlations significantly? For example, barrier options on spreads (also known as knockout or knockin options) have been blamed for unexpected, high correlations during periods that market levels approach strike levels, with both the writers and the buyers of the barriers suspected of large trading volume to influence the outcome in their favor.

In CMRA's review of different approaches to VAR, some firms assumed that all cash flows were correlated across all markets, while others assumed a lower degree of correlation. Sophisticated mean-variance models, for example the one used to compute the RiskMetrics data set, allow correlation for all instruments across all markets that are covered. At the other extreme are models such as the 1995 Basle Amendment, which require correlation of 1 or - 1, depending on what is least favorable to the VAR calculation.

Mathematical engine and quantitative approach

All VAR calculations require the use of mathematical models to value individual instruments (or their components or assumed equivalents) as well as to value the aggregate portfolio. Valuation variances produced by widely accepted models (termed "mark-to-model" risk) are well documented and the subject of numerous articles.[15] For example, the Black-Scholes versus

Hull and White options models can produce differences of 5% or more in pricing, even when all input data and curve construction (that is, crossover from futures to cash, interpolation, extrapolation, etc.) are identical. In addition, the selection of probability distribution(s)[16] in one model versus another varies from firm to firm and is a topic of great debate among theoreticians and practitioners alike.

While many dealers and end users are well versed in testing the behavior of an individual position or portfolio given market moves (for example, what happens if interest rates rise or fall by 1 basis point or by 200 basis points?), they have only recently commenced testing the behavior of individual positions or portfolios for changes in *model* assumptions. Given the increased pace of losses due to model risk (the risk that the market price will be different than that calculated theoretically by a model), firms should test the sensitivity of the VAR calculation to alternate mapping and model assumptions. The goal is to determine how much the risk picture changes if one changes either the underlying mathematical model or one or more assumptions regarding the data source, time of collection, curve creation, probability distribution, mathematical process, or other factors to reflect the VAR approaches described in the 1995 Basle Amendment, the RiskMetrics Technical Document, or other common VAR models. To the degree that other common models indicate an aggressive stance by the firm, an adjustment to the VAR calculation may be appropriate or a higher VAR factor may be appropriate to protect the firm's capital from a market-risk perspective. Such model-risk adjustments should be taken in addition to those for credit risk, market risk, liquidity risk, operations risk, or other standard risk reserves.

Percentage of outcomes to be considered

The VAR methodology requires the firm to select the percentage of outcomes that will be used to determine the expectation of loss. For example, some firms calculate VAR under the requirement that the outcome or a worse outcome is expected approximately 1% of the time (often called a "99% confidence interval"). Others pose a lower requirement of expecting the outcome approximately 10% or 5% of the time. Perhaps due to the "confidence interval" terminology, some firms make the mistake of equating their VAR expectation to a *certainty* that the firm will not lose more than the stated amount. This is incorrect.

A 95% "confidence" interval dictates that losses are expected to exceed the VAR limit at least once every three weeks.

An important challenge in selecting the percentage of outcomes is to address the firm's need for an absolute loss limit. For example, a 95% "confidence" interval dictates that losses *are expected* to exceed the VAR limit at least once every three weeks. Users should address how large these losses may become through stress-testing and establish limits accordingly. Furthermore, users may wish to address the potential for cumulative losses, none of which exceed the VAR limit individually, to be greater than the risk appetite of the firm. What if the amount of the VAR limit is lost continuously over contiguous time horizons (for example, daily for an entire month)?

Other risk-management and risk-measurement tools combined with VAR

Most users combine VAR with stress-testing to address questions such as "How much do I expect to lose the other 1% of the time?" As with VAR, the quality of the answer depends on the inputs, including the financial engineer's ability to select appropriate scenarios. Both the European currency crisis and the Gulf War demonstrated that predicting factors such as "maximum" volatility is difficult and that correlation relationships can change substantially during extreme market moves. The increasing complexity and optionality of many derivatives and engineered securities make relevant scenario selection even harder. Given such challenges, firms often resort to designing stress tests that analyze large historical market moves.

Portfolios do not necessarily produce their greatest losses during extreme market moves.

In CMRA's experience, portfolios do not necessarily produce their greatest losses during extreme market moves. Whether asset based or asset plus liability based, portfolios often possess Achilles' heels that require only small moves or changes between instruments or markets to produce significant losses. Stress-testing extreme market moves does little to reveal the greatest risk of loss for such portfolios. Furthermore, a review of a portfolio's expected behavior over time may reveal that the same stress test that indicates a *small* impact today indicates embedded land mines with a *large* impact during future periods. This is particularly true of options-based portfolios that change characteristics due to time, rather than due to changes in the components of the portfolio. For this reason, it is paramount to employ stress-testing to reveal the following:

- For market variables or model assumptions that have a high likelihood of change, what is the impact of small and large changes on VAR?
- For variables or exposures considered to offset each other, how do alternate correlation assumptions affect VAR?
- How wide is the variance of results produced by other common VAR approaches compared to yours?

The Mexican peso devaluation in December 1994 illustrates the difficulty in using stress-testing to analyze crises. The devaluation and subsequent market dislocation caused a 30% drop in the value of holdings in five days, with average losses ranging between 15% and 50%. More than 400 funds and most emerging market derivatives portfolios held TELMEX stock, so they experienced significant, unexpected losses. How should such dramatic market moves be captured by the VAR calculation or other tests? In virtually all cases, the VAR calculation considered the likelihood of occurrence minuscule (far less than a 1% expectation) when analyzing either historical or expected movements of the peso. In virtually all cases, firms' stress tests considered far less dramatic market moves. Today, firms remain divided about including such a low-probability event in future calculations. Firms are divided as well on the inclusion of the December 1994 peso move in historical data sets. In other words, the peso move is considered to be an outlier, so some firms remove it from their historical data sets when calculating VAR. Regardless of whether such moves are included, a valuable post mortem is to *assume* such an event occurred and to determine whether losses expected under VAR equal those incurred. Back-testing a firm's qualitative and quantitative risk-management approach for actual, extreme events (whether market dislocations or the actions of a rogue trader) often reveals the need to adjust reserves, increase the VAR factor, adopt additional policies/limits/controls/procedures, or expand risk calculations plus reporting.

The Mexican peso crisis was not a stand-alone event in terms of magnitude, suggesting the importance of such back-testing. *At least one* major market (not an emerging market) makes a 10 or more standard deviation move every year. For example, there have been nine Hong Kong market declines greater than 20% and two more than 50% in the past 15 years. The devaluation of the Italian lira, the stock market crashes of 1987, and the oil shocks in the 1970s are further examples of market moves far beyond the 2- to 3 standard-deviation assumption used in most VAR calculations. In the case of the 1982-87 U.S. bull market followed by stock market crash (508 point plunge on October 19, 1987), within six months the markets stabilized and in less than 2 years the markets returned to pre-crash levels.

Many risk variables such as political -risk, personnel risk, regulatory risk, phantom liquidity risk, and others are difficult or impossible to capture through quantitative techniques.

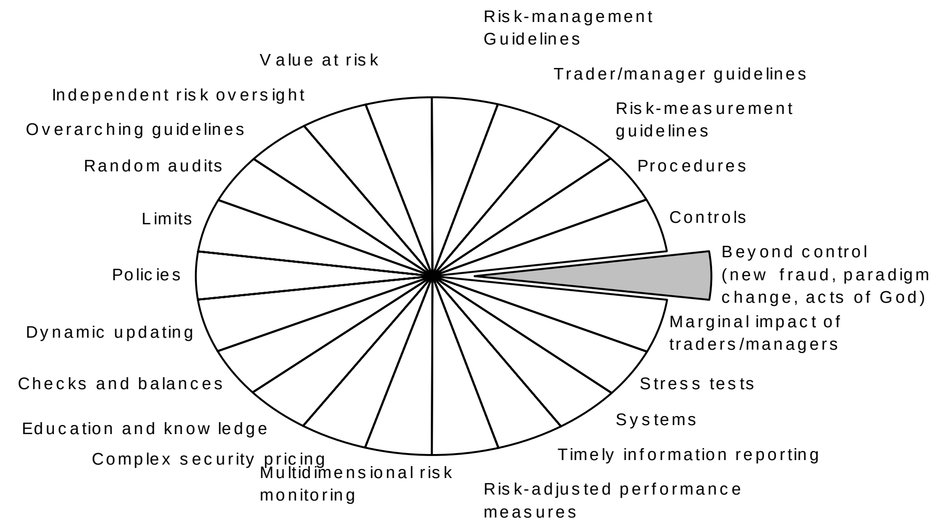
Many risk variables such as political risk, personnel risk, regulatory risk, phantom liquidity risk, and others are difficult or impossible to capture through quantitative techniques. Yet as demonstrated by recent, well-publicized losses, such variables can cause significant risk. For this reason, VAR must be supplemented not only with stress-testing but also with prudent checks and balances, procedures, policies, controls, limits, random audits, appropriate reserves, and other risk measures *(Exhibit 1).*

VAR in Practice

Comparing five different variance/covariance, historical, and simulation VARs for a hypothetical portfolio consisting of Treasury strips plus S&P 500 equity index contracts and options shows some of the vagaries of VAR. *Exhibit 2* sets forth the portfolio as of May 25, 1995, comprised of long positions in 2-year and 30-year U.S. Treasury strips[17] and a long position in the S&P 500 equity index contract plus long and short options on the same index. The net investment in the portfolio is $2 million.

Exhibit I

Risk-Management Framework



Variance/covariance VAR is calculated once, using the JP Morgan RiskMetrics data set. Historical VAR is calculated twice, using 250-day and 100-day prior historical periods. Simulation VAR is calculated twice, using correlations and volatilities from the RiskMetrics data set (Simulation A) and from the 10 years prior (Simulation B). The results of the calculations appear in *Exhibits 3,* 4, and 5.

The actual VAR statistics are set forth in *Exhibit 3* and may be interpreted as follows: under the *assumptions specific to the particular VAR calculation,* there is a 1% (or 5%) expectation that the portfolio will suffer a loss greater than or equal to the statistic shown. Thus, *under the assumptions made* to perform historical VAR over a 250-day period and assuming a two-week holding period, there is a 1% expectation of loss equal to or exceeding 1.08% of the $2 million investment in the portfolio (that is, a loss greater than or equal to $21,600).

The distributions for the VAR calcula-

Exhibit 2

The Strip and Equity Index Portfolio

Portfolio Composition

Instrument	**2-Year Strip**	**30-Year Strip**	**Total Portfolio**
Yield	5.91%	6.85%	
Price	89.12	14.94	
Face amount	$779,778	$2,041,424	
Purchase amount	$694,964	$305,036	$1,000,000

Instrument	**Jun 520**	**Jun 545**	**Sep 530**	**Dec 540**	**S&P 500**	
Type	Put	Call	Call	Put	Long	
Strike vs. market	+20	+45	+30	+40	0	
Price	1.95	0.60	14.90	18.45	528.59	
Number	4,157.4	-28,723.8	19,784.8	1l,617.0	945.9	
Purchase Amount	$8,107	($17,234)	$294,793	$214,335	$499,999	$1,000,000
Total Portfolio						**$2,000,000**

tions are set forth in *Exhibits 4* and 5. For both the 1% and 5% expectation of loss results, the alternate methods produce quite different results. Several observations may be made:

- In all cases, Simulation B produces much higher expected loss levels. This is due to the fact that all four other VAR calculations depend significantly upon a more recent historical period, whereas Simulation B is based upon correlations and volatilities drawn from a 10-year prior period.

- The 100-day and 250-day historical VAR calculations produce quite different downside and upside risk expectations. For example, the 1% expectation of loss for VAR in the case of the 100-day historical simulations is a *single* data point, consisting of the largest loss over a *single* overnight and over a *single* 10-day trading period. Furthermore, there is high autocorrelation in the data set. In other words, not only does a 1% probability consist of only 1 of the 100 observations, but there are only 10 distinct 10-day periods. During the 100-day and 250-day periods included in the historical VAR calculations, the value of Treasury strips largely appreciated. Had a period of rising interest rates been selected, the opposite result would have been produced. The danger in basing VAR estimates on direct historical observations, and over short data periods, is apparent-history must repeat itself for this method to provide an accurate expectation of future loss.
- The loss of the fat tails due to the non-

Exhibit 3
VAR Results

1-Day VAR for the Portfolio

	1%	5%
Variance/covariance	0.80%	0.57%
Simulation A	0.77%	0.57%
Simulation B	1.14%	0.89%
Historical-250 days	1.08%	0.74%
Historical-100 days	0.73%	0.48%

10-Day VAR for the Combined Portfofio

	1%	5%
Variance/covariance	2.54%	1.80%
Simulation A	3.00%	2.51%
Simulation B	8.91%	3.21%
Historical-250 days	2.89%	2.56%
Historical-100 days	1.71%	1.24%

Exhibit 4
Distribution of One-Day Returns

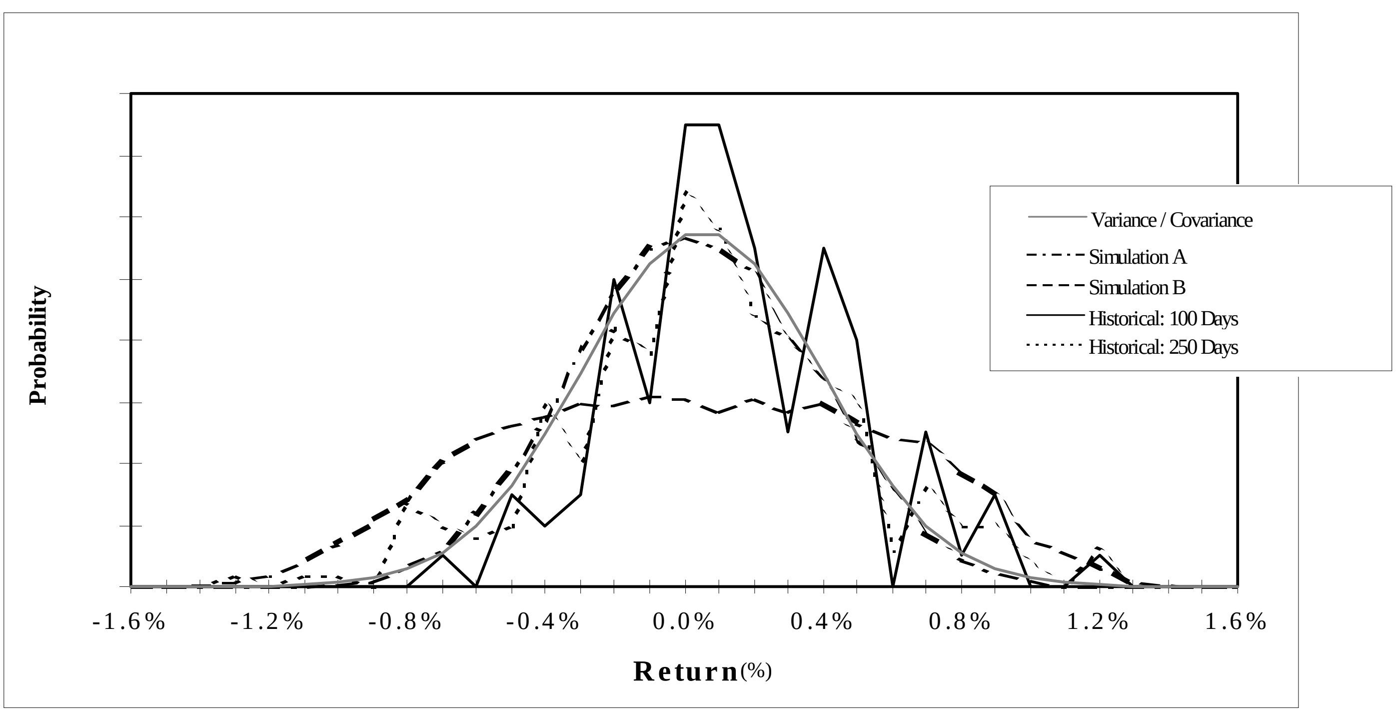
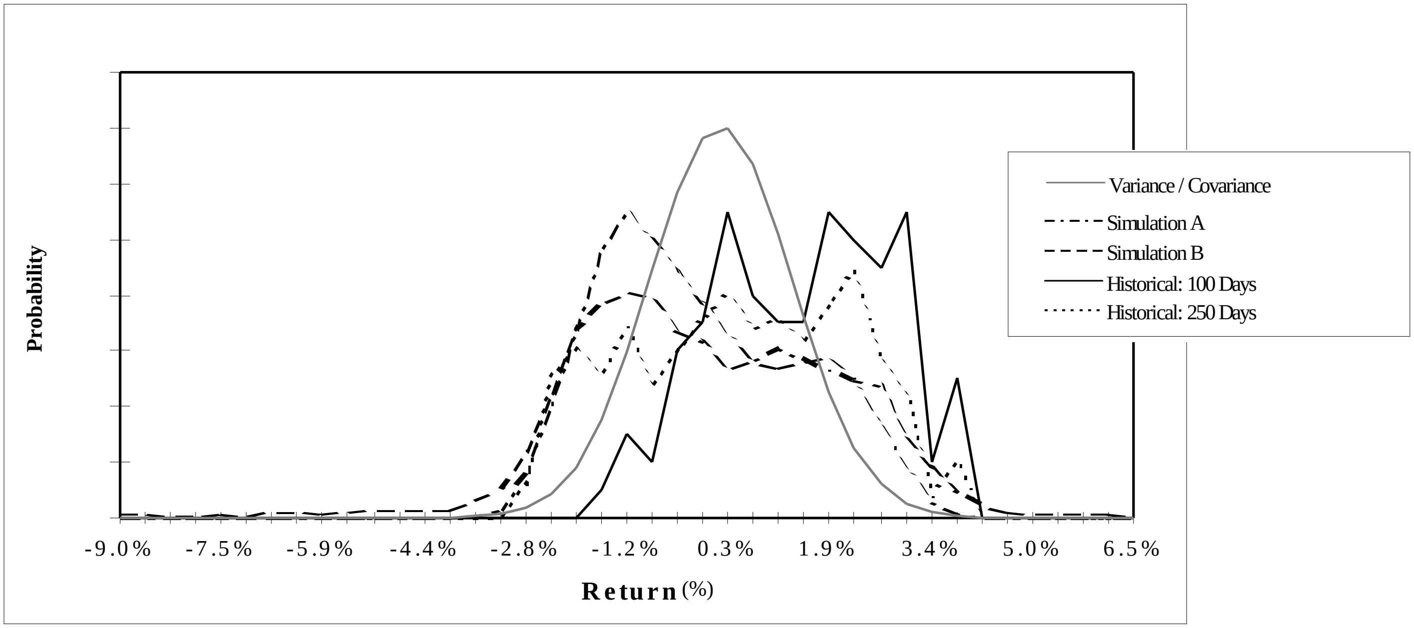


Exhibit 5
Distribution of Two-Week Returns



linearity of both the options and the Treasury positions is clear when the variance/covariance VAR distribution is compared to all other results.

VAR: Only One Aspect of Risk Management

While firms typically select a single VAR measure, it is important to determine the degree to which the answer changes under different methods. Several important dimensions of VAR are now being researched and may provide insights into adjustments that may be practicable for various methods:

- the impact of time horizon;
- the impact of nonlinearity;
- the degree of price opacity (reverse engineering complexity, illiquid underlyings, illiquid instruments, lack of historical data, etc.);
- the degree of residual error (differences between the actual and the mapped port folio, equivalents, etc.);
- the impact of diversification (whether it magnifies, dampens, or does not affect differences across VAR calculations);
- the impact of sampling issues (sufficiency of sample period, size, and breadth).

VAR, while an important advance in risk measurement, is *only one* aspect of an overall risk-management program. Different VAR methodologies and selection of the key decision factors for VAR are appropriate for different firms and depend upon many factors. These include the types of exposures, other qualitative and quantitative risk-management techniques employed, and the firm's risk appetite relative to its capital base. However, combined with the appropriate additional risk-management and risk measurement tools, VAR gets high marks.

Notes

[1]Mathematically, VAR quantifies the amount of expected loss based on the probability of certain market events occurring during a stated time period.

[2]A delta equivalent is a linear estimate of a security's value based on its first derivative with respect to a specific factor or factors.

[3]RiskMetrics is perhaps the most widely used of available data and assumes normal distributions.

[4]Fat-tailed behavior, also known as leptocurtosis, refers to distributions in which there is a broad range of values at the tails (for example, 1% of the time).

[5]Charles Smithson of CIBC Wood Gundy summed it up very well in a recent discussion regarding VAR: "The talk to action ratio is very high."

[6]Nonlinear price functions exist not only for options, derivatives with exponential functions, and leveraged instruments but also when yields are mapped into prices (for example, basic bonds). For an example of how these affect VAR, see Tanya Styblo Beder, "VAR: Seductive but Dangerous," *Financial Analysts journal,* September-October 1995.

[7]1t is possible to run a simulation VAR that uses variance/covariance data, such as RiskMetrics. This technique is illustrated in the section, "VAR in Practice" (page 21).

[8]See, for example, Tanya Styblo Beder, "VAR: Seductive but Dangerous."

[9]See, for example, J. V. Jordan and R. J. Mackay, "Assessing Value at Risk for Equity Portfolios: Implementing Alternative Techniques," *Handbook of Finnwide Risk Management,* Beckstrom, Campbell, and Fabozzi, editors, forthcoming 1996, as reported in *Risk Magazine,* January 1996. Differences of more than 10 times are set forth in this data.

[10]See, for example, Darryll Hendricks, "Evaluation of Value-at-Risk Models Using Historical Data," *FRBNY Economic Policy Review,* April 1996.

[11]See, for example, Philippe Jorion, "Risk2: Measuring the Risk in Value at Risk," *Financial Analysts journal,* forthcoming

[12]Learning from these mistakes, firms often limit the portion of their portfolio or overall exposure that is based on theoretical mark-to-model values or erratic/infrequent data points. In addition, firms often impose the requirement that risk management, audit, IRO, or custodian obtain outside pricing from a different dealer than the dealer from whom the customized or illiquid securities were purchased.

[13]The seminal work by Markowitz.

[14] See, for example, Tanya Styblo Beder, "VAR: Seductive but Dangerous."

[15]See, for example, Tanya Styblo Beder, "Derivatives: The Realities of Marking to Model," *Bank Accounting & Finance,* Summer 1994, 4.

[16]An assumption of anticipated or experienced market behavior.

[17]The market yield for each strip as of May 25, 1995, is stated on an actual/365 basis with semiannual compounding. The price of each strip is stated as a percentage of face amount.