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Bank Risk Management: Theory

David H. Pyle

Booth Professor of Banking and Finance
Haas School of Business, University of California, Berkeley

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ABSTRACT

This paper discusses why risk management is needed. It outlines some of the theoretical underpinnings of contemporary bank risk management, with an emphasis on market and credit risks.

keywords: risk management, scenario analysis, value at risk analysis

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David H. Pyle
Booth Professor of Banking & Finance (Emeritus)
Haas School of Business
University of California, Berkeley

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INTRODUCTION¹

Not too many years ago, the then Chairman of the U.S. House Banking Committee told me it was out of the question to require banks and savings and loans to mark their assets to market. Would anyone responsible for financial regulatory oversight have the temerity to be similarly dismissive today? I suspect the answer is yes. However, the increased attention formal, scientific appraisal of bank risks has received since then is gratifying to me and, I imagine, to most financial economists. The fact that contemporary bank risk management employs many of the important theoretical and methodological advances in our field is a source of collective pride. My role on this program is to outline some of the theoretical underpinnings of contemporary bank risk management. I shall begin with a discussion of why bank risk management is needed. Then I shall provide some of the theoretical bases for bank risk management with an emphasis on market and credit risks.

WHY IS RISK MANAGEMENT NEEDED?

Recent financial disasters in financial and non-financial firms and in governmental agencies point up the need for various forms of risk management. Financial misadventures are hardly a new phenomenon, but the rapidity with which economic entities can get into trouble is. The savings and loan (S&L) crisis in the United States took two decades plus serious regulatory ineptness and legislative cupidity to develop into the debacle it became. The manager of the Orange County Investment Pool (OCIP) took less than three years to increase that quasi-bank's potential one-month loss from a significant but perhaps manageable 1.8% to a disastrous 5% of its investors'

¹ In writing this paper, I have benefited from a set of notes on risk management by Hayne Leland.

deposit-like claims². Anyone who is aware of the leverage inherent in various interest rate derivatives knows he could have done this faster and even more ruinously had he set his mind to it. To their credit, most regulatory authorities appear to recognize that the core of the problem is not derivatives per se but inadequate risk management.

Banks and similar financial institutions need to meet forthcoming regulatory requirements for risk measurement and capital.³ However, it is a serious error to think that meeting regulatory requirements is the sole or even the most important reason for establishing a sound, scientific risk management system. Managers need reliable risk measures to direct capital to activities with the best risk/reward ratios. They need estimates of the size of potential losses to stay within limits imposed by readily available liquidity, by creditors, customers, and regulators. They need mechanisms to monitor positions and create incentives for prudent risk-taking by divisions and individuals.

Risk management is the process by which managers satisfy these needs by identifying key risks, obtaining consistent, understandable, operational risk measures, choosing which risks to reduce and which to increase and by what means, and establishing procedures to monitor the resulting risk position.

² Potential one-month losses estimated at a 5% probability of occurrence. See Jorion (1995) for a thorough and entertaining discussion of the Orange County fiasco.

³ Regulatory capital requirements result from the need to control the moral hazard inherent in the bank/depositor relationship when there are governmental deposit guarantees (explicit or implicit). Merton (1977) provided the classic theoretical demonstration of this moral hazard and its determinants.

WHAT ARE THE KEY RISKS?

Risk, in this context, may be defined as reductions in firm value due to changes in the business environment. Typically, the major sources of value loss are identified as:

Market risk is the change in net asset value due to changes in underlying economic factors such as interest rates, exchange rates, and equity and commodity prices.

Credit risk is the change in net asset value due to changes the perceived ability of counter-parties to meet their contractual obligations.

Operational risk results from costs incurred through mistakes made in carrying out transactions such as settlement failures, failures to meet regulatory requirements, and untimely collections.

Performance risk encompasses losses resulting from the failure to properly monitor employees or to use appropriate methods (including "model risk").

With the exception of model risk, financial theory does not have a lot to say about the latter two types of risk, though as the managers of various firms have discovered to their regret they can be highly important.⁴ Consequently, in what follows, I focus on the theoretical underpinnings of market risk management with a few comments on credit risk.

MEASURING MARKET RISK

There are significant differences in the internal and external views of what is a satisfactory market risk measure. Internally, bank managers need a measure that allows active, efficient management of the bank's risk position. Bank regulators want to be sure a bank's potential for catastrophic net worth loss is accurately measured and that the bank's capital is sufficient to survive such a loss. Consider the differences in desired risk measure characteristics that these two views engender.

⁴ Perhaps, conventional wisdom is more relevant than theory for many of these risks. For example, Barings might have benefited from an intelligent application of the adage "Don't put the fox in charge of the hen house."

Timeliness and Scope

Both managers and regulators want up-to-date measures of risk. For banks active in trading, this may mean selective intraday risk measurement as well as a daily measurement of the total risk of the bank. Note, however, that the intraday measures that are relevant for asset allocation and hedging decisions are measures of the marginal effect of a trade on total bank risk and not the stand-alone riskiness of the trade. Regulators, on the other hand, are concerned with the overall riskiness of a bank and have less concern with the risk of individual portfolio components.

Nonetheless, given the ability of a sophisticated manager to "window dress" a bank's position on short notice, regulators might also like to monitor the intraday total risk. As a practical matter, they probably must be satisfied with a daily measure of total bank risk.

The need for a total risk measure implies that risk measurement cannot be decentralized. For parametric measures of risk, such as standard deviation, this follows from the theory of portfolio selection (Markowitz (1952)) and the well-known fact that the risk of a portfolio is not, in general, the sum of the component risks. More generally, imperfect correlation among portfolio components implies that simulations of portfolio risk must be driven by the portfolio return distribution, which will not be invariant to changes in portfolio composition. Finally, given costly regulatory capital requirements, choices among alternative assets require managers to consider risk/return or risk/cost trade-offs where risk is measured as the change in portfolio risk resulting from a given change in portfolio composition. The appropriate risk scaling measure depends on the type of change being made. For example, the pertinent choice criterion for pure hedging transactions might be to maximize the marginal risk reduction to transaction cost ratio over the

available instruments while the choice among proprietary transactions would involve minimizing marginal risk per unit of excess return.

Efficiency

Risk measurement is costly and time consuming. Consequently, bank managers compromise between measurement precision on the one hand and the cost and timeliness of reporting on the other.⁵ This trade-off will have a profound effect on the risk measurement method a bank will adopt. Bank regulators have their own problem with the cost of accurate risk measurement which is probably one reason they have chosen to monitor and stress test bank risk measurement systems rather than undertaking their own risk measurements.

Information Content

Bank regulators have a singular risk measurement goal. They want to know, to a high degree of precision, the maximum loss a bank is likely to experience over a given horizon. They then can set the bank's required capital (i.e. its economic net worth) to be greater than the estimated maximum loss and be almost sure that the bank will not fail over that horizon. In other words, regulators should focus on the extreme tail of the bank's return distribution and on the size of that tail in adverse circumstances. Bank managers have a more complex set of risk information needs. In addition to shared concerns over sustainable losses, they must consider risk/return trade-offs. That calls for a different risk measure than the "tail" statistic, a different horizon, and a focus on more usual market conditions. Furthermore, even when concerned with the level of sustainable losses, the bank manager may want to monitor on the basis of a probability of loss that can be

⁵ See Pritsker (1996).

observed with some frequency (e.g. over a month rather than over a year). This allows managers to use the risk measurement model to answer questions such as:

Is the model currently valid? For example, if the loss probability is set at 5%, do we observe a violation once every 20 days on average?

Are traders correctly motivated to manage and not just avoid risk? How often does Trader 1's position violate his risk limit relative to the likelihood of that event?

Market Risk Measurement Alternatives

There are two principle approaches to risk measurement, scenario analysis and value-at-risk analysis.

Scenario analysis: In scenario analysis, the analyst postulates changes in the underlying determinants of portfolio value (e.g. interest rates, exchange rates, equity prices, and commodity prices) and revalues the portfolio given those changes. The resulting change in value is the loss estimate. A typical procedure, often called stress testing, is to use a scenario based on an historically adverse market move. This approach has the advantage of not requiring a distributional assumption for the risk calculation. On the other hand, it is subjective and incorporates a strong assumption that future financial upsets will strongly resemble those of the past. Given the earlier discussion, it should be clear that stress testing can provide regulators with the desired lower tail estimates, but is of limited utility in day-to-day risk management.⁶ It should also be clear that meaningful scenario analysis is dependent on having valuation models that are accurate over a wide range of input parameters, a characteristic that is shared to a considerable extent by value-at-risk models. Pioneering research on capital asset pricing (Sharpe

⁶ Even for the regulators, reliance on a given scenario carries the risk of establishing a "Maginot line" defense against catastrophe.

(1964)), option pricing (Black and Scholes (1973), Merton (1973)), and term structure modeling (Vasicek (1977)) has provided the basis for reliable valuation models, models that have become increasingly accurate and applicable with subsequent modification and extension by other researchers.

Value-at-Risk (VaR) analyses use asset return distributions and predicted return parameters to estimate potential portfolio losses. The specific measure used is the loss in value over X days that will not be exceeded more than Y% of the time. The Basle Committee on Banking Supervision's rule sets Y equal to 1% and X equal to 10 days. In contrast, the standard in RiskMetrics™ (the J.P. Morgan/Reuters VaR method) is 5% over a horizon sufficiently long for the position to be unwound which, in many cases, is 1 day. The difference in probability levels reflects the differences in informational objectives discussed above. The differences in horizon might appear to reflect differences in the uses to which the risk measure is put, in particular the desire of regulators to set capital rules that provide protection from failure over a longer period. This conclusion may be correct, but it is somewhat contradicted by the arbitrary multiplication of the resulting VaR figure by 3 to get regulatory required capital. The Basle Committee could have gotten about the same result using a 1-day horizon and multiplying by 9.5. Perhaps order of magnitude arbitrariness is less palatable than single digit arbitrariness.

There are two principle methods for estimating VaR ... the analytical method and Monte Carlo simulation ... each with advantages and disadvantages.⁷ There are implementation problems common to both methods, namely choosing appropriate return distributions for the instruments in the portfolio and obtaining good forecasts of their parameters. The literature on volatility estimation is large and seemingly subject to unending growth, especially in acronyms (Arch, Grach, Egarch, et.al.). Since I am not an expert on forecasting, it will be safest and perhaps sufficient to make two comments on forecasting for VaR analysis. Firstly, the risk manager with a large book to manage needs daily and, in some cases, intraday forecasts of the relevant parameters. This puts a premium on using a forecasting method that can be quickly and economically updated. Secondly, forecasting models that incorporate sound economic theory, including market microstructure factors, are likely to outperform purely mechanical models.⁸

Modeling portfolio returns as a multivariate normal distribution has many advantages in terms of computational efficiency and tractability. Unfortunately, there is evidence going back to Mandelbrot (1963) and beyond that some asset returns display non-normal characteristic. The fact that they display "fat" tails...more extreme values than would be predicted for a normal variate...is particularly disturbing when one is trying to estimate potential value loss. To some degree, these fat tails in unconditional return distributions reflect the inconstancy of return volatility and the problem can be mitigated by modeling individual returns as a function of volatility as in the RiskMetrics™ model:

⁷ It is also possible to use the Cox-Ross-Rubinstein (1979) tree-based methods to generate a VaR estimate, but the use of this method is limited to a small number of risk sources and thus it is an unlikely candidate for use in bank risk management.

⁸ See Figleski (1997) for evidence on the relative accuracy of various volatility forecasting methods.

$$r_{i,t} = \sigma_{i,t} \varepsilon_{i,t} \quad \text{where } \varepsilon_{i,t} \text{ is } N(0,1) .$$

Another alternative is to assume that returns follow a non-normal distribution with fat tails (e.g. the Student's t distribution), but only if one is prepared to accept the concomitant portfolio return computation problems. Danielson and deVries (1997) have proposed a method for explicit modeling of the tails of financial returns. Since VaR analysis is intended to describe the behavior of portfolio returns in the lower tail, this is obviously an intriguing approach. Furthermore, the authors show that the tail behavior of data from almost any distribution follows a single limit law, which adds to the attractiveness of the method. However, estimating tail densities is not a trivial matter so, while promising, there are computational issues to be resolved if this is to become a mainstream VaR method.

Analytical VaR: The analytical method for VaR uses standard portfolio theory. The portfolio in question is described in terms of a position vector containing cash flow present values representing all components of the portfolio. The return distribution is described in terms of a matrix of variance and covariance forecasts (covariance matrix) representing the risk attributes of the portfolio over the chosen horizon. The standard deviation of portfolio value (v) is obtained by pre- and post-multiplying the covariance matrix (Q) by the position vector (p) and taking the square root of the resulting scalar:⁹

$$v = \sqrt{p'Qp} .$$

⁹ To keep this method manageable in terms of parameter estimation and speed of calculation, the size of the covariance matrix can be constrained and the portfolio position vector described in terms of a subset of the actual risks being faced. For example, in the RiskMetrics data base, equity risk appears as the variances and covariances of 32 equity indices and a given equity position is made to correspond to this description by scaling its present values by the equity's "beta".

This standard deviation is then scaled to find the desired centile of portfolio value that is the predicted maximum loss for the portfolio or VaR:

$$VaR = v f(Y)$$

where: $f(Y)$ is the scale factor for centile Y .

For example, for a multivariate normal return distribution, $f(Y) = 1.65$ for $Y = 5\%$ or 2.33 for $Y = 1\%$.

Analytical VaR is attractive in that it is fast and not terribly demanding of computational resources. As the following algebra demonstrates, analytical VaR also lends itself readily to the calculation of the marginal risk of candidate trades:¹⁰

$$\Delta v_i = \frac{p'Q}{v} a_i \quad \text{where } a_i \text{ is a given candidate trade and } \Delta v_i \text{ is its marginal risk.}$$

Given trade cashflow descriptions, the information needed to calculate the marginal risk of any candidate trade can be accumulated during a single calculation of v .

Analytical VaR has a number of weaknesses. In its simplest form, options and other non-linear instruments are delta-approximated which is to say the representative cash flow vector is a linear approximation of position that is inherently non-linear. In some cases, this approximation can be improved by including a second-order term in the cash flow representation.¹¹ However, this does not always improve the risk estimate and can only be done with the sacrifice of some of the computational efficiency that recommends analytical VaR to bank managers.

¹⁰ Incremental VaR, as defined here, is a first order approximation of the change in risk due to a candidate trade and is applicable when the cashflows for such trades are small relative to the aggregate cash flow of the existing portfolio. See Garman (1996).

¹¹ See Fallon (1996) and JP Morgan (1996).

Monte Carlo Simulation: Monte Carlo simulation of VaR begins with a random draw on all the distributions describing price and rate movements taking into account the correlations among these variates. Mark-to-model and maturation values for all portfolio components at the VaR horizon are determined based on that price/rate path. This process is repeated enough times to achieve significance in the resulting end-of-horizon portfolio values. Then the differences between the initial portfolio value and these end-of-horizon values are ranked and the loss level at the Yth centile is reported as the VaR of the portfolio.

To avoid bias in this calculation, the analyst must use risk-neutral equivalent distributions and, if the horizon is sufficiently long, be concerned with bias introduced by the return on capital. If model error is not significant, the use of Monte Carlo simulation solves the problem of non-linearity though there are some technical difficulties such as how to deal with time-varying parameters and how to generate maturation values for instruments that mature before the VaR horizon. From the risk manager's viewpoint, the main problem is the cost of this method and the time it takes to get reliable estimates.

MEASURING CREDIT RISK

To be consistent with market risk measurement, credit risks are defined as changes in portfolio value due to the failure of counter-parties to meet their obligations or due to changes in the market's perception of their ability to continue to do so. Ideally, a bank risk management system would integrate this source of risk with the market risks discussed above to produce an overall measure of the bank's loss potential. Traditionally, banks have used a number of methods...credit

scoring, ratings, credit committees...to assess the creditworthiness of counter-parties. At first glance, these approaches do not appear to be compatible with the market risk methods. However, some banks are aware of the need for parallel treatment of all measurable risks and are doing something about it¹². Unfortunately, current bank regulations treat these two sources of risk quite differently subjecting credit risk to arbitrary capital requirements that have no scientific validity. There is danger in this since it can lead to capital misallocation and imprudent risk-taking.

If banks can "score" loans, they can determine how loan values change as scores change. If codified, these changes would produce over time a probability distribution of value changes due to credit risk. With such a distribution, the time series of credit risk changes could be related to the market risk and we would be able to integrating market risk and credit risk into a single estimate of value change over a given horizon.

This is not a "pipe dream". Considerable research on the credit risk of derivatives, including a paper at this conference, is available. Obviously, banks themselves are in the best position to produce the data series necessary for broader application of this approach. If it is reasonable to require banks to produce and justify market risk measurement systems, why can't they be required to do the same for credit risk and to integrate the two? The House Banking Committee Chairman I mentioned at the start of this talk would have rejected this idea out of hand. I hope today's regulatory authorities won't.

¹² See J.P. Morgan (1997).

REFERENCES

- Black, F. and M. Scholes (1973). The pricing of options and corporate liabilities. *J. Political Economy* 81, 637-59.
- Cox, J.C., S.A. Ross, and M. Rubinstein (1979). Option pricing: a simplified approach. *J. Financial Economics* 7, 229-63.
- Danielson, J. and C.G. de Vries (1997). Extreme returns, tail estimation, and value-at-risk. Working Paper, University of Iceland (<http://www.hag.hi.is/~jond/research>)
- Fallon, W. (1996). Calculating value-at-risk. Working Paper, Columbia University (bfallon@groucho.gsb.columbia.edu).
- Figlewski, S. (1997). Forecasting Volatility. *Financial Markets, Institutions & Instruments* 6, No.1.
- Garman, M.B. (1996). Improving on VaR. *Risk* 9, No. 5
- Jorion, P. (1995). *Big bets gone bad*. Academic Press, San Diego, CA.
- JP Morgan (1996). *RiskMetricsTM-technical document*, 4th ed.
- JP Morgan (1997). *CreditMetricsTM-technical document*.
- Mandelbrot, B. (1963). The variation of certain speculative prices. *J. Business* 36, 394-419.
- Markowitz, H. (1952). Portfolio selection. *J. Finance* 7, 77-91.
- Merton, R.C. (1973). Theory of rational option pricing. *Bell Journal of Economics and Management Science* 4, 141-83.
- _____. (1977). An analytical derivation of the cost of deposit insurance and loan guarantees: an application of modern option pricing theory. *J. of Banking & Finance* 1, 3-11.
- Pritsker, M. (1996). Evaluating value at risk methodologies: accuracy versus computational time, unpublished working paper, Board of Governors of the Federal Reserve System (mpritsker@frb.gov).
- Sharpe, W. (1964). Capital asset prices: a theory of market equilibrium under conditions of risk. *J. Finance* 19, 425-42.
- Vasicek, O.A. (1977). An equilibrium characterization of the term structure. *J. Financial Economics* 5, 177-88.