CHAPTER 2

DO MARKET RISK MANAGEMENT TECHNIQUES AMPLIFY SYSTEMIC RISKS?

This chapter assesses how market risk management techniques may have contributed to the benign financial environment of recent years, and whether seemingly prudent behavior by individual firms, reacting to similar market risk systems, could serve to amplify market volatility in periods of stress beyond what would otherwise have occurred. Based on simulations and observed risk management practice, there are grounds for believing that this could be the case. Results of the simulations suggest that, in a period of stress, having a variety of risk models is more stabilizing than uniformity. Perhaps more important, however, is the presence of a variety of types of financial institutions with differing investment horizons and risk appetites, as well as the scope to take offsetting positions when prices overshoot and "fire sales" occur.

From 2002 to early 2007, the decline in volatility in the global economy and financial markets was reflected in lower measures of market risk, which encouraged firms to increase their risk-taking, thereby enhancing market liquidity and resulting in even lower levels of volatility (Figure 2.1). Conversely, shocks in an environment of heightened risk-taking could result in a rapid deterioration of such a benign environment, as reductions in risky positions lead to rising volatility and asset correlations, a reduction in market liquidity, and a further retrenchment in risk-taking.[1] As similar market risk measurement techniques spread across more institutions, the question arises as to whether the potential for reinforcing behavior has increased, given that past and current episodes of stress indicate that many financial institutions react by following the basic tenets of their risk management systems by selling risky assets, calling in higher-quality collateral, and increasing margin requirements.[2]

Certainly, over the last decade, the risk management techniques of financial institutions have greatly improved, been used more broadly, and may, along with specialized instruments, have contributed to the lower volatility and less pronounced disruptions of markets. Over time, financial institutions have taken a more holistic view of their risks and have instituted better risk management practices. These have included improved internal and external reporting of various types and measures of risk, better decision-making structures, and greater involvement of boards of directors in setting the risk appetite of the firm and overseeing risk management policies. Moreover, the use of more rigorous risk modeling has made firms more sensitive to, and aware of, their risks—the first defense against systemic problems.

Value-at-risk (VaR) methods are now used almost universally by banks, as well as by many hedge funds, to measure market risk. Put simply,

Note: This chapter was written by John Kiff, Laura Kodres, Ulrich Klueh, and Paul Mills, with the aid of Jon Danielsson on risk modeling. Yoon Sook Kim provided research support.

[1]See Persaud (2000 and 2003) for early expressions of this possibility.

[2]This chapter focuses primarily on market risk in the trading books of large investment and commercial banks. Trading book positions are held with the intention of profiting from transaction fees or short-term changes in valuations. Banks hold credit and interest rate risk (a component of market risk) in their banking books, where the intention is to hold the position for more than one year. For many commercial banks this can be where their greatest risks lie. Aggregation problems across risk categories are discussed later in this chapter.

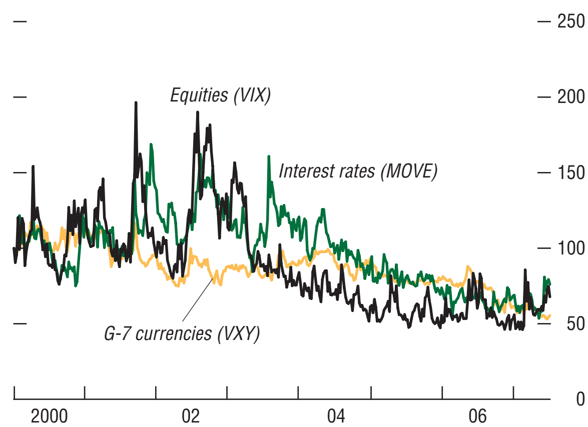
VaR is an estimate of the expected loss that an institution is unlikely to exceed in a given period with a particular degree of confidence. VaR is usually supplemented with other tools, and risk managers say that they do not (and will not) react to the signals from any one of their risk models mechanistically. Nonetheless, most market participants maintain position limits, some of which are connected to the measures discussed in this chapter, and these and similar risk mitigation techniques may reinforce the natural inclination for firms to close positions during periods of price pressures and liquidity strains.

This chapter focuses particularly on VaR not only because it has become the most widely used measure for market risk management among banks, but also because it is an archetype of other risk management techniques—the factors that influence VaR also drive other risk measures. In addition, VaR forms the basis for a number of risk controls (e.g., position limits and margin requirements) as well as for regulatory market risk capital, and shares many of the same traits as banks' economic risk capital (ERC) models.[3] Showing what happens to VaR measures in benign and stressful periods should illustrate the signals other risk management measures are giving to banks and hedge funds. For instance, the characteristics of standardized VaR techniques—their backward-looking nature and treatment of tail events—are shared by other approaches that, if used instead, could also lead to the amplification of volatility.

The first part of this chapter reports the results of VaR simulations to demonstrate that, even when calculated with differing sets of parameters, VaR measures react similarly in periods of both low volatility and stress. This sug-

[3]ERC models measure the amount of capital required to absorb losses from extremely unlikely events over long time horizons. For example, typical ERC models use confidence intervals of up to 99.97 percent (versus 95 to 99 percent for VaR models) and horizons of up to one year (versus one to 10 days for VaR models). ERC calculations account not just for market risk, but also for credit and operational risks, and may make provision for liquidity, legal, and reputational risks.

Figure 2.1. Implied Volatility Indices
(January 2000 = 100)



Source: Bloomberg L.P.
Note: VIX is the Chicago Board Options Exchanges S&P Volatility Index. MOVE is the Merrill Lynch Option Volatility Estimate Index. The JPMorgan VXY index measures volatility in a basket of G-7 currencies.

gests that risk management systems *could* lead to similar reactions by market participants. A new type of exercise is then described in which a set of firms adjust their asset holdings in response to risk perceptions based on VaR estimates. The *collective* impact of their reactions demonstrates that market price dynamics can be amplified by the models during stressful times.

The second part of the chapter investigates the extent to which market risk measures may be adhered to during stressful periods and how they could amplify market stresses. Given that the simulation results are only suggestive, the connections between market risk models and firms' behavior are critical to understanding the potential for amplification of volatility and herding behavior.[4] It is comforting that most risk managers say they understand the shortcomings of their models and believe that they have the latitude to make an independent assessment of their risk-taking during a period of stress. However, some firms have less well-developed risk management systems and may be prone to interpret their models more rigidly.

To circumvent the potential for a mechanistic reaction to risk model signals to amplify shocks, rather than just a diversity of risk models, it seems more important to have a range of underlying positions being taken by financial institutions, or other market participants who are able to step in, with sufficient capital, to take risky positions during such periods. Hedge funds are one such set of institutions where market risk models are used more flexibly and position limits tend to be less binding. While not the focus of this chapter, other institutions—such as pension funds and insurance companies—also have different investment horizons and strategies, which may allow them to ride out a stressful period without adding to dislocations (IMF, 2004).

Three important policy implications flow from this chapter's examination of market risk management techniques and models:

- While continuing to raise the overall quality of market risk management, supervisors and other policymakers need to acknowledge and encourage risk management approaches that reflect firms' particular business and risk profiles and that can be tested with relevant stress scenarios.
- Financial institutions could be more transparent and disclose to investors and counterparties how their market risk management systems would react and could be managed in a stressed environment, rather than simply reporting aspects of a single risk metric, such as VaR.
- Policymakers should recognize that a diversity of market participants with differing investment strategies and horizons, and with different risk management systems, is more likely to be conducive to market stability.

To help mitigate the collective action problems potentially caused by the similarity of responses to market risk models (or risk limits) in periods of systemic stress, more financial institutions need to become aware beforehand that such events can take place and make provision for such circumstances, allowing them to react more flexibly at such moments.

VaR and Other Risk Management Techniques

While typical market risk management frameworks use a complex set of different techniques, the VaR measure is at the heart of current practice in most financial institutions. VaR was first used by major financial institutions in the late 1980s. JPMorgan's release of its VaR methodology as RiskMetrics™ in 1994 brought it into mainstream practice. Since then it has become the primary quantitative measure of market risk within most financial institutions—especially for fixed-income, equity, and foreign exchange positions—and is the cornerstone of the 1996 market risk amendment to the Basel Accord (BIS, 1996). VaR is a useful standardized yardstick across portfolios within a firm over time, and its basic concepts have been extended to more recent ERC measures (Box 2.1).

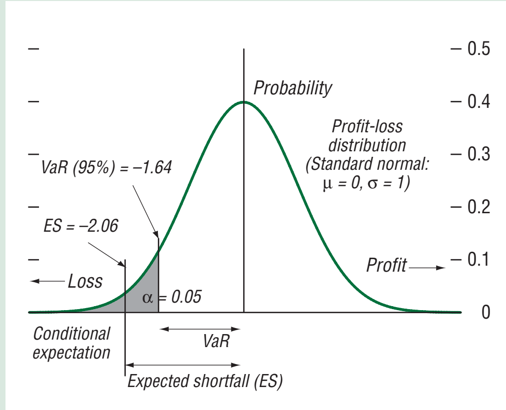
[4]"Herding" arises in financial markets when market participants' investment decisions are made on the basis of the short-term actions of others, rather than on fundamental characteristics.

Box 2.1. Criticism of VaR-Based Risk Management Models and Alternatives

While VaR constitutes the cornerstone of most market risk management systems, it has been criticized for saying nothing about the size of potential large gains or losses in the tail of the profit and loss (P&L) distribution. This has prompted a number of efforts to examine the more extreme possible outcomes.

Expected shortfall (ES), which measures the expected loss if losses exceed the VaR, has been suggested as an alternative that overcomes this criticism (Artzner and others, 1999). Whereas VaR at a given confidence level, α, is defined as the maximum loss expected to occur with probability, $p = (1–\alpha)$, ES is the conditional expectation of loss given that the loss is beyond the VaR level. Liang and Park (2007) find that hedge fund returns are better explained by ES because they are more likely to be exposed to the tails of P&L distributions.[1]

VaR may also not be appropriate for P&L distributions with "fat" and "super fat" tails—portfolios containing assets that change very little in price most of the time but occasionally jump, such as loans that rarely default and some option positions (Danielsson and others, 2006). Much of the academic literature has therefore focused on improving VaR through the use of more appropriate distributional assumptions and extreme value theory. Bams, Lehnert, and Wolff (2005) evaluate a number of these approaches against more standard techniques.



However, their findings suggest that more sophisticated tail modeling often leads to VaR being estimated with a higher degree of uncertainty because there are too few underlying tail observations for precise estimates.[2]

Generally, these other measurement techniques have not been widely applied in financial institutions. Many firms recognize that VaR does not adequately capture episodes of extreme volatility and market illiquidity, but the alternatives are typically data intensive, difficult to verify through backtesting, and hard to explain to senior management. Thus, financial institutions tend to complement VaR measures with more straightforward stress tests to assess the impact of tail events.

[1]See Lo (2001) for a list of other reasons why VaR may not be an appropriate hedge fund risk measure.

[2]See ECB (2007) for a more detailed review of alternatives to VaR, and Bervas (2006) for a summary of recent work on VaR measures that incorporate liquidity risk ("L-VaRs").

Technically, VaR is an estimated portfolio loss that a firm or portfolio is unlikely to exceed, over a given time horizon, at a given probability level. It is expressed in the monetary units of the firm's accounts or the portfolio's value. For instance, if a firm's one-day estimated VaR is \$10 million, at a confidence level of 95 percent, this implies that a loss of \$10 million or greater is expected on five trading days out of 100. The time horizon chosen usually ranges from one to 10 days, depending on how long it is estimated it would take to liquidate or hedge a position or portfolio. The level of statistical confidence is usually set at between 95 and 99 percent—the higher the confidence level, the more cautious the measure. The Basel II Accord stipulates that, for the purpose of establishing bank regulatory market risk capital, a 99 percent (one-tailed) confidence interval be used over a 10-day horizon.[5]

To calculate a VaR, one needs two elements—a set of positions in financial instruments (the portfolio) and their prospective returns (or price changes). Typically, the positions are taken as fixed for the time horizon under consideration (e.g., for one or 10 days), and so the critical assumption concerns the distribution of expected price changes. Different assumptions give rise to alternative measurements of VaR (see Box 2.2 for the two measures used below).

VaR is best suited to quantify portfolio risks under typical market conditions. And, as is true of most statistical models, VaR assumptions about future price changes are derived from actual changes in the recent past, suffering similar weaknesses as other models (Box 2.1). Stress tests are a way to assess potential portfolio impacts of atypical events (BIS, 2005) and entail either scenario or sensitivity analysis.[6]

[5]The accord also stipulates that the probability calculation's statistical inputs (market value volatilities and correlations) be based on at least one year of profit and loss data—if calculated over shorter horizons, banks must scale them up to a 10-day horizon by the "square root of time rule." For example, a $100 million one-day VaR is scaled up to a $316 million 10-day VaR by multiplying by the square root of 10 (3.16). See Danielsson and Zigrand (2006) for a critique of this scaling rule.

[6]When the IMF conducts a Financial Sector Assessment Program (FSAP) of a member country's financial system, country authorities and IMF staff jointly conduct "stress tests." These, however, differ from banks' usual scenario or sensitivity analyses in that they test a *(cont.)* country's vulnerability over the medium term to a macroeconomic or system-wide shock, rather than a short-term extreme movement in market prices.

Box 2.2. The Basics for Constructing VaR Measures

In the simulation exercises reported, two alternative ways of constructing VaR are considered: exponentially weighted moving average and historical simulation. In each method, the proportions of the assets in the portfolio are considered fixed and the price changes (return) variances and their covariances across the assets take on different assumptions.

Exponentially weighted moving average: This method assumes that each asset's price change (or return) can be characterized by a variance that changes over time. The variance is updated each day using a weighted average of yesterday's estimated variance and yesterday's squared return of the asset:

$$h_t = \lambda\, h_{t-1} + (1 - \lambda)\, r_{t-1}^2,$$

where h_t is the variance of the asset at time t and r_{t-1} is the return at time t–1. An initial variance, h_0, is constructed using an early part of the sample, say, the first 30 days. The weight (λ), usually between 0.86 and 0.98, is chosen to put more weight on the most recently estimated variances. A similar method weights the covariance between every two assets in the portfolio. These variances and covariances, along with the portfolio proportions, are used to construct a portfolio value and variance. This conditional variance, along with an assumption of normality, is used to construct the VaR estimate for the next day. Typically a 95th or a 99th percentile of a normal distribution is used.

Historical simulation: The second approach assumes that the history of price changes for the assets in the portfolio over some past period (say the last 300 days) is a good guide to what the price changes will be tomorrow. These price changes are then applied to the portfolio's positions to produce a range (or distribution) of possible portfolio outcomes. From that distribution, the 95th or the 99th percentile defines the VaR obtained by taking the 15th smallest observations from the historical sample (in the case of the 95th percentile VaR with a sample size of 300 days). The historical data "window" moves through time so the most recent days are used. A long enough window is needed so that the 95th (or other percentile) corresponds to an integer data observation with at least a few other tail observations to reduce statistical uncertainty.

Scenario analysis usually draws from historically stressful events such as the October 1987 stock market crash, the 1997 Asian crisis, or the bursting of the technology stock bubble and estimates the current portfolio's maximum loss and/or VaR if similar circumstances were to be repeated. Sensitivity analysis quantifies the impact of standardized large movements in the relevant financial instruments, so that vulnerabilities to hypothetical extreme events can be identified.

Assessing Amplification Effects in a Stylized Market Risk Management Framework[7]

Analytical Framework

The objectives of this section are twofold: first, to analyze the behavior and performance of VaR measures for different portfolios in two types of environments—the recent period of falling volatility and a hypothetical stressful period; and second, to examine whether VaR-based risk management procedures have the potential to destabilize price dynamics. To set such cycles in motion, linkages between VaR-type measures and trading behavior would need to function, at least partly, in a mechanistic way, through trading limits based on VaR, margin requirements and capital regulation, or behavioral channels. In addition, risk measures across institutions would need to become sufficiently similar, resulting in more correlated behavior than otherwise. Finally, the VaR measures would then need to react to the market dynamics resulting from the correlated behavior to produce a feedback mechanism.

The first exercise gauges the sensitivity of VaR measures to changes in the volatility of the market environment by examining two distinct scenarios:[8]

- *The decline in volatility of many financial assets over the past several years.* To what extent has falling volatility resulted in declining VaR measures on unchanged portfolios? Are different portfolios characterized by similar adjustment paths, and how does the choice of alternative VaR techniques affect the results?
- *An episode of financial market distress, when volatilities and correlations strongly increase in an abrupt fashion.* What are the adjustment paths and liquidation pressures that unfold during extended periods of distress, and how are these dynamics influenced by the choice of sample period and other assumptions?

The exercise is conducted with three portfolios that resemble stylized positions that may be taken by an investment bank's proprietary trading desk:[9]

- A broad portfolio with wide-ranging asset classes, including long positions in mature market stocks from several countries, emerging market stocks, 10-year fixed-income securities, exposures to commodity price fluctuations, and long foreign currency and two-year interest rate swap positions;
- A portfolio with greater exposure to emerging market risks, with a geographic focus on Asia and Latin America;[10] and
- A portfolio with greater exposure to riskier mature market instruments, particularly equities and high-yield debt instruments.

The VaR of a portfolio reflects daily profit and loss (P&L) (reported here in U.S. dollars), meaning that currencies have to be added as an additional asset for each nondollar asset. The value of each portfolio is fixed at $1,000. The two choices of VaR methodology were guided by actual industry practice and the need for sufficiently distinct approaches to generate meaningful comparisons (Box 2.2):

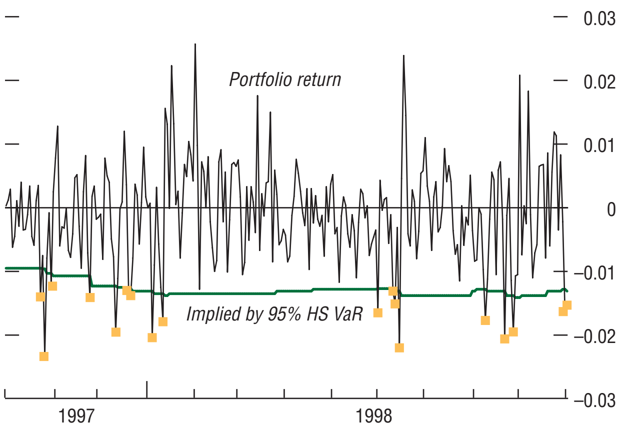
[7]This discussion summarizes the methodology and results of a VaR simulation exercise. A fuller description and analysis is provided in Danielsson, Klueh, and Zigrand (forthcoming).

[8]This first exercise builds on the approach taken in Bank of England (2007).

[9]None of the portfolios involve options or other positions with nonlinear payoffs.

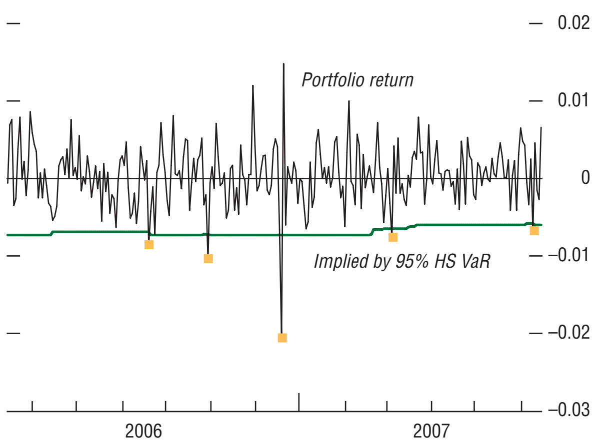
[10]These regions were chosen to represent emerging markets where investment banks and hedge funds had greatest exposures over the data period, which includes the Asian and Long-Term Capital Management crises.

Figure 2.2. Backtesting Results: Broad Portfolio, October 1997 to October 1998



Sources: Bloomberg L.P.; and IMF staff estimates.
Note: HS VaR = historical simulation of value-at-risk. Yellow squares indicate VaR violations.

Figure 2.3. Backtesting Results: Broad Portfolio, June 2006 to June 2007



Sources: Bloomberg L.P.; and IMF staff estimates.
Note: HS VaR = historical simulation of value-at-risk. Yellow squares indicate VaR violations.

- The historical simulation (HS) methodology assumes that recent price changes will be representative of changes in the future. It uses actual P&L observations over the previous 400 days to estimate the theoretical quantiles of the P&L distribution one day into the future.
- The exponentially weighted moving average (EWMA) methodology applies exponentially declining weights to the underlying variances and covariances of the asset returns. A higher value for the weighting parameter, λ, implies a more persistent reaction to a given shock. Here, λ is set to 0.94—a standard market practice inspired by RiskMetrics™ (JPMorgan, 1993). The covariance matrix, combined with an assumption of conditional normality, is then used to calculate a VaR forecast one day into the future.

A number of validation exercises (referred to as "backtesting") confirm that the number of loss exceptions to the estimated VaR is generally in line with the model's intended construction. For example, at a confidence level of 95 percent, losses exceeding the one-day VaR should occur on around five days out of 100.

VaR at the Firm Level in a Period of Declining Volatility

While the decline in volatility over recent years is well established for many asset classes, it is interesting to see how it translates into lower VaR estimates, and how the observed adjustment paths of VaR depend on the actual estimation approach. The backtesting exercises show how the decline in historical asset volatilities affects the number of VaR exceptions. Using the HS method and constant proportions of assets in the broad portfolio, there is a clustering of exceptions during the turbulent 1997–98 episode (Figure 2.2) and a paucity of violations during the recent calmer period (Figure 2.3).

For all portfolios, both HS (upper panel of Figure 2.4) and EWMA (lower panel of Figure 2.4) methods yield a decrease in the VaR. It is also noteworthy that the VaR of the emerging market portfolio is now similar to the level of the mature market portfolio in the late 1990s. The fact that major trends in VaR are replicated in similar ways and that recent years have seen a pronounced convergence of estimates, despite the fact that the portfolios and methods differ markedly, reflects the convergence of volatility across a number of asset classes, due in part to lower economic, or fundamental, volatility.[11]

Nonetheless, it is interesting to see how the backward-looking nature of VaR can lead to markedly different results with respect to turning points. Figure 2.5 illustrates that HS's equally weighted historical daily prices can lead to higher VaRs over a prolonged period of volatility declines. At the same time, HS occasionally produces stepwise or very abrupt changes.

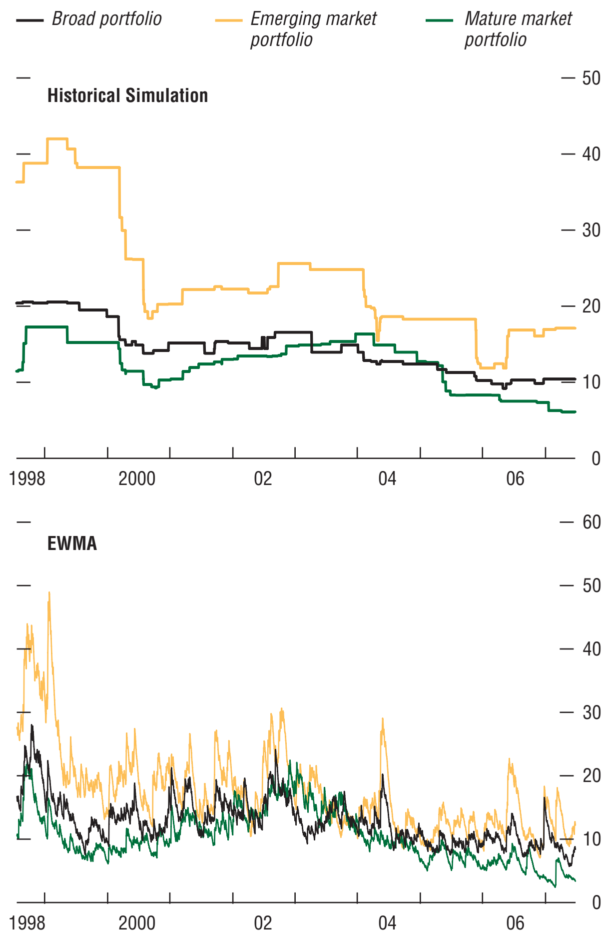
VaR Measures at the Firm Level During Stressful Periods

The aim of the exercise reported here is to demonstrate the behavior of VaR measures during episodes of financial turmoil. To stress the VaR estimates, two alternative approaches are employed. The first is based on estimates of the return distribution during a particular stress event, and assumes the returns follow either a normal or a fatter-tailed *t*-distribution. The other analyzes the impact of the stressful episode on VaR by separating out the effects of volatility and asset correlations.

Figure 2.6 presents the results of stressing the VaR estimates for the emerging market portfolio, using data from the 1997 Asian crisis. It compares the VaR during the baseline period (January 1999 to June 2007) with the VaR derived from the stressful period (October to December 1997), using alternative assumptions about the underlying distribution of P&Ls. The results indicate a high degree of sensitivity to

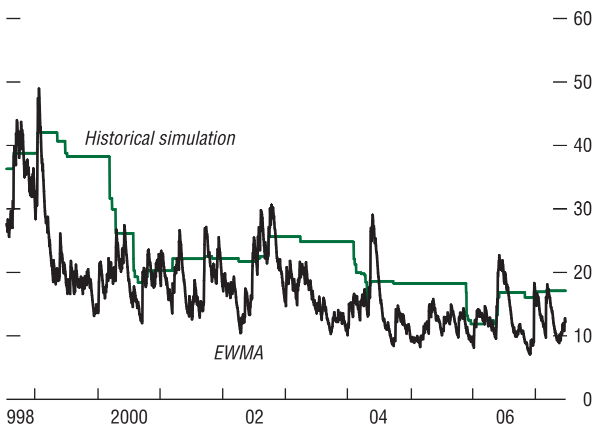
[11]In this context, the analysis assumes constant position sizes. Declining VaR measures for an actual portfolio or institution could reflect decreasing volatility, lower exposures, and/or greater diversification.

Figure 2.4. VaR in an Era of Declining Volatilities
(In U.S. dollars; July 17, 1998 to June 21, 2007)



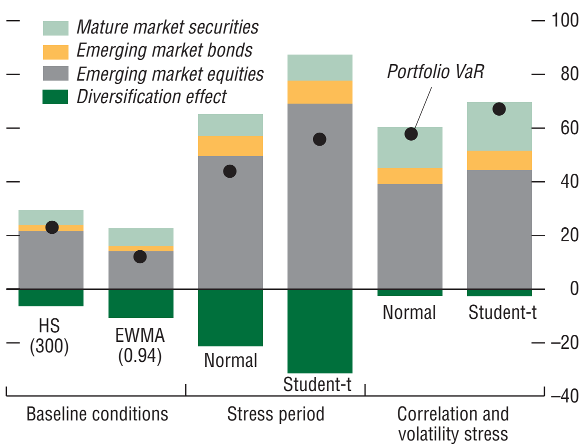
Sources: Bloomberg L.P.; and IMF staff estimates.
Note: VaR = value-at-risk; EWMA = exponentially weighted moving average. The window size for historical simulation is 400 days and the smoothing constant for EWMA is 0.94. The figure shows the VaR for a portfolio value of $1,000.

Figure 2.5. VaR Measures: Historical Simulation versus EWMA
(In U.S. dollars; July 17, 1998 to June 21, 2007)



Sources: Bloomberg L.P.; and IMF staff estimates.
Note: VaR = value-at-risk; EWMA = exponentially weighted moving average. The window size for historical simulation is 400 days and the smoothing constant for EWMA is 0.94. The figure shows the VaR for a portfolio value of $1,000.

Figure 2.6. Asian Crisis: Stressed VaR Estimates at the 99 Percent Confidence Level
(In U.S. dollars)



Sources: Bloomberg L.P.; and IMF staff estimates.
Note: VaR = value-at-risk; HS = historical simulation; EWMA = exponentially weighted moving average. Baseline conditions refer to the period from January 1, 1999 to June 21, 2007 and the stress period ranges from October 1, 1997 to January 1, 1998. The figure shows the VaR for a portfolio value of $1,000. The right-hand bars show the VaRs when the correlations between asset classes are increased by 78 percent and the volatilities by 76 percent compared with the baseline scenario.

the stress event, with the portfolio's VaR at least doubling. To gauge the sensitivity of VaR to more extreme changes in correlations, we calculated the portfolio's VaR during a hypothetical scenario in which a pronounced increase in volatility (75 percent) is combined with an extreme rise in asset correlations (78 percent).[12] Again, the portfolio's VaR more than doubles, as the diversification effect falls away with the rise in correlations.

Figure 2.7 shows estimates of the VaR for the Russian crisis of 1998 with correlations increasing to extreme levels. The experiment is applied to a broad range of asset classes and over a more sustained period of time. In this case, the amplification effect of such a scenario is severe, leading to nearly a fourfold increase of the VaR relative to the baseline scenario for the *t*-distribution.

A disadvantage of this exercise is that the VaRs for stress and nonstress periods are based on different estimation strategies. Specifically, the baseline periods use HS and EWMA, while the other two exercises estimate normal and *t*-distributions from the P&L data during the stressful episode and calculate VaRs at the 99th percentile of the lower tail. In a final step, we add data from the stress period to the end of the nonstress data set. For example, one might be interested in how today's VaR would behave if the Russian crisis were to recur now. This allows an examination of the dynamic response of different risk measures when moving into an extreme shock.

Figure 2.8 shows the effect of a sustained increase in volatility and correlations at a more recent point in time, thus taking into account that the volatilities embodied in current VaRs have been exceedingly low. The figure shows

[12]One advantage of VaR is its ability to take account of correlations across the portfolio's assets that lower risk (a "diversification effect"). Formally, this effect is measured as the sum of the individual component VaRs less the VaR for the portfolio. Note that in Figures 2.6 and 2.7, the observed diversification effect remains substantial in the stressed VaR due to the portfolios' very diverse sets of asset classes.

that the EWMA picks up the increasingly unstable environment at the outset, while the HS remains constant over most of the episode. However, when more extreme movements occur toward the end of the observation period, the HS-VaR increases abruptly, and by a similar magnitude to the EWMA-VaR. The fact that both measures, though based on different estimation strategies, produce a jump that occurs simultaneously, suggests that the use of different VaR estimation techniques would not necessarily prevent a common result arising from market stress.

When a Number of Firms Use VaR Measures

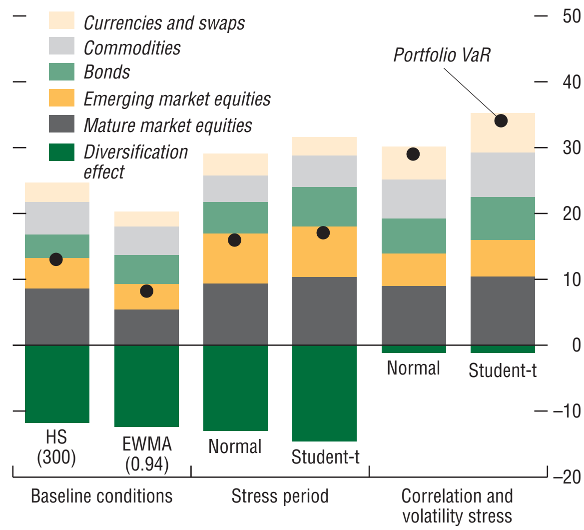
Having analyzed VaR measurement at an individual firm level, a new stylized model of the interaction between different institutions employing VaR-based techniques is now developed. The purpose is twofold.

First, the model demonstrates how the mechanistic application of risk management systems *could* give rise to unduly large price movements and feedback effects. The analysis employs a model that derives institutions' demands for specific assets using a standard portfolio choice model (mean-variance optimization) and by specifying a given risk appetite. Institutions also attempt to maintain a certain level of capital in accordance with perceived risks. A shock to prices changes their VaR measure, which then alters their preferred portfolio (including for a risk-free security linked to their desired capital level). The changes in demand for risky and risk-free assets result in changes in market prices and a feedback to VaR measures.

Second, the model is able to consider the effects of VaR model heterogeneity. To this end, two cases are considered, one in which all actively trading institutions use the same approach, and one in which different segments of the market use alternative models.

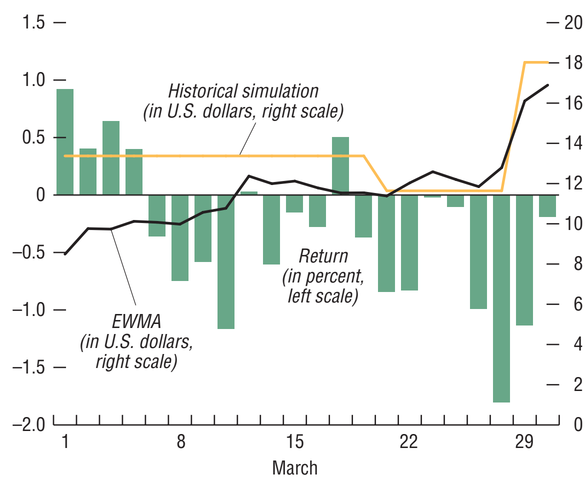
The model setup is such that, each day, a financial institution compares its actual level of capital with its desired level. The latter is a combination of its required capital—expressed as a multiple of the financial institution's VaR—plus

Figure 2.7. August 1998: VaR Estimates at the 99 Percent Confidence Level
(In U.S. dollars)



Sources: Bloomberg L.P.; and IMF staff estimates.
Note: VaR = value-at-risk; HS = historical simulation; EWMA = exponentially weighted moving average. Baseline conditions refer to the period January 1, 1999 to June 21, 2007 and the stress period ranges from July 10, 1998 to August 10, 1998. The figure shows the VaR for a portfolio value of $1,000. The right-hand bars show the VaRs when the correlations between asset classes are increased by 80 percent and the volatilities by 95 percent compared with the baseline scenario.

Figure 2.8. Long-Term Capital Management Scenario: EWMA versus Historical Simulation, March 2007
(Value-at-risk)



Sources: Bloomberg L.P.; and IMF staff estimates.
Note: EWMA = exponentially weighted moving average. The window size for historical simulation is 400 days and the smoothing constant for EWMA is 0.94. The figure shows the value-at-risk for a portfolio value of $1,000. For historical simulation and EWMA, the LTCM scenario for March 2007 is calculated for a 99th percentile VaR.

a buffer. This then directly links an institution's VaR to its demand for risky assets and capital.[13] A reduction in VaR due to lower volatilities frees capital and enables the institution to increase its holdings of risky assets. Conversely, an increase in VaR implies undercapitalization relative to the target level, inducing the institution to exchange risky for safe assets. Since the institution is assumed to be a significant market participant, its trading decisions will alter prices by an additional amount, relative to the average-sized participant, under normal market conditions.

The basic idea is that an adverse shock to the covariance matrix of returns (i.e., higher absolute correlations of returns) results in higher VaR estimates and thus higher target capital levels, inducing sales of risky assets by one institution. This then results in an excess supply of risky assets, assuming other institutions do not increase their holdings by at least the same amount, implying prices of risky assets will fall to clear the market. The institution's action to rebalance its portfolio thus results in additional price pressures. In the model, such price changes also lead to an increase in correlations, as the institution simultaneously sells different types of risky assets. These effects, in turn, feed back into revised VaR measures and renewed portfolio rebalancing.

Results

The impact of the activity described above using a broad portfolio is distinguished for three different situations: one in which all institutions employ HS, one in which all rely on an EWMA measure, and one in which both methods are used in equal proportions. The main focus is on the price dynamics during periods of stress and so, to this end, the data for August 1998 are extracted from the entire sample period and provide the baseline for the exercise.

[13]The multiple used in the model (three) is the same as the Basel market risk framework, in which regulatory capital is three times the VaR measure.

In addition to the parameterization of VaR techniques (the choice of HS window size and EWMA smoothing constant), it is necessary to specify both the institution's risk tolerance and the degree of price impact the institution has in the market. All else being equal, if risk tolerance is very low, the institution will exit the market at the first sign of uncertainty; if risk tolerance is very high, the institution will always seek to increase its risk. Similarly, if its price impact is low, the institution does not affect prices, whereas if its price impact is very high, its trades will dominate price movements. Alternative parameter values can produce both cases in which multiple institutions have no interactive effects and cases in which destabilizing behavior is observed. Parameter values were chosen to reflect information obtained from actual users and industry practice.

The model findings can be summarized as follows:

- Having institutions that employ the same risk model is destabilizing both in terms of covariance structure and volatility of returns, relative to the historical baseline. Conversely, there is a greater tendency toward stability if institutions use different models. As can be seen from Figure 2.9 for the case of one particular asset price, deviations from the historical series are negligible in the case where some institutions use EWMA and others use HS measurement techniques. In contrast, the model with universal use of HS yields markedly different selling and buying patterns when volatility surpasses a certain level.
- Relative to the historical baseline, the model shows how institutions' actions, in accordance with their use of different VaR models, affect the correlation structure of returns (Table 2.1). The positive correlation across the risky assets (the S&P 500 and FTSE 100 indices) increases markedly, while the correlations between this group and the safe asset (10-year U.S. treasuries) generally decline, as the "flight to quality" effect is intensified.
- Volatilities tend to increase relative to the baseline, but only marginally if both VaR

methods are used in equal proportion (Figure 2.10). If only one type of VaR method is employed, volatilities increase dramatically for the risky assets.

- Lower levels of risk tolerance imply a more pronounced tendency toward destabilization. This effect is particularly strong when both institutions employ the same risk model.

Overall, the results of both simulation models show that VaR-based systems provide the scope for self-reinforcing mechanisms to arise. The model in which firms interact shows that diversity across VaR measures is helpful in dampening asset volatility.

Developments in Market Risk Management Practices by Banks and Hedge Funds

This section reviews market risk measurement and management practices, as disclosed in publicly available documents and through staff discussions with individuals from commercial and investment banks, hedge funds, and rating agencies.

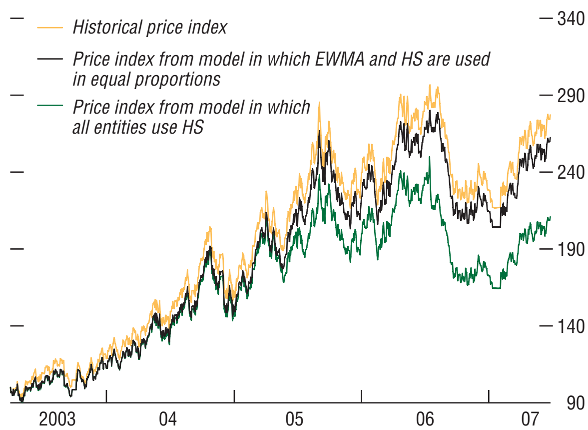
Risk Appetite and Governance

Investment banks and commercial banks active in financial markets explicitly recognize that their business is to take informed risks. To establish its "risk appetite," a board of directors typically reviews the firm's risk-taking periodically in terms of a VaR or ERC framework, while entertaining bids for risk capital (or the risk "budget") from business unit managers reflecting the opportunities they see.

Risk managers today are increasingly involved in assessing risk-taking proposals by business units. Ten years ago, risk management was viewed as a compliance function to police risk limits on traders. Risk managers now increasingly and appropriately regard themselves as being on an equal footing with traders, working to promote and control profitable risk-taking. They often articulate their main objectives as ensuring that there are no P&L "surprises"

Figure 2.9. Asset Price Dynamics Under Alternative Model Specifications

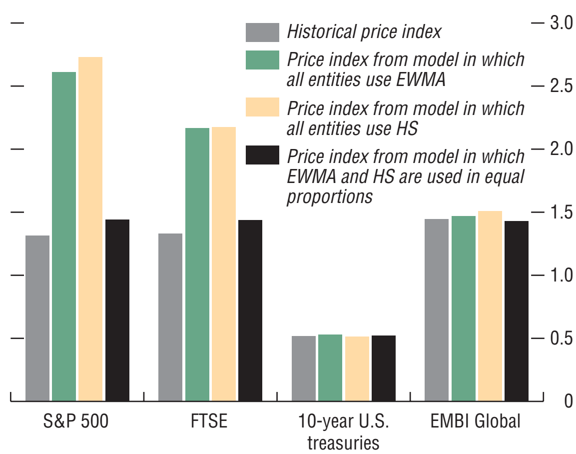
(Index; April 1, 2003 = 100)



Sources: Bloomberg L.P.; and IMF staff estimates.
Note: EWMA = exponentially weighted moving average; HS = historical simulation. The price indices refer to the Commodity Research Bureau energy futures index, one of the assets included in the VaRs of the simulated financial institutions.

Figure 2.10. Selected Asset Volatilities Under the Interactive Model

(Standard deviations; in percent)



Sources: Bloomberg L.P.; and IMF staff estimates.
Note: EWMA = exponentially weighted moving average; HS = historical simulation. The standard deviation is calculated over the stress period August 1998.

Table 2.1. Selected Correlation Coefficients Between Asset Classes in the Interactive Model

	S&P 500	FTSE 100	10-Year U.S. Treasuries	EMBI Global
		Baseline Results		
S&P 500	1.00	0.34	0.35	–0.25
FTSE 100		1.00	–0.14	–0.06
10-year U.S. treasuries			1.00	0.22
EMBI Global				1.00
		All Entities Use EWMA		
S&P 500	1.00	0.79	–0.02	0.05
FTSE 100		1.00	–0.26	0.12
10-year U.S. treasuries			1.00	0.16
EMBI Global				1.00
		All Entities Use HS		
S&P 500	1.00	0.79	0.19	0.14
FTSE 100		1.00	–0.07	0.20
10-year U.S. treasuries			1.00	0.22
EMBI Global				1.00
		EWMA and HS Used in Equal Proportions		
S&P 500	1.00	0.45	0.20	–0.26
FTSE 100		1.00	–0.22	–0.07
10-year U.S. treasuries			1.00	0.21
EMBI Global				1.00

Sources: Bloomberg L.P.; and IMF staff estimates.
Note: EWMA = exponentially weighted moving average; HS = historical simulation.

outside the board's risk tolerance and that their traders have risk-taking capacity when opportunities arise.

A hedge fund's risk appetite and management culture derives primarily from how it markets itself to investors—its desired risk-return tradeoff and resultant strategies—as articulated in the initial offer document and periodic reports. As a whole, hedge funds tend to view their risk appetite more flexibly, with some deliberately positioning themselves to take advantage of volatile or unstable conditions. The absence of direct regulation of the funds facilitates the relative freedom of their approach.

Hedge fund risk managers appear to work more closely with traders than do regulated entities. They modify risk-taking in light of market opportunities, while reinforcing the discipline to stay out of markets if profitable opportunities do not exist (Bookstaber, 2007). Where funds employ purely quantitative strategies, risk control is often built into the process of strategy selection and implementation.

Risk Measurement and Analysis

All of the major investment banks now use VaR as one of their market risk measures, primarily using an HS methodology (Box 2.2) with significance levels ranging from 95 to 99 percent, and holding periods of one to 10 days. Banks use from one to five years of market data to calculate risk factors, with some giving more weight to the most recent observations. Others deliberately use longer time horizons in order to capture more volatile periods.

Published VaRs cannot be meaningfully compared between firms due to the different assumptions that go into their calculations. However, they can provide a useful consolidated guide to a firm's risk profile over time if calculated on a consistent basis (Box 2.3). Also, investment banks have become increasingly transparent and sophisticated in publishing their VaR out-turns and P&L exceptions, although further details—particularly of stress test results—would help investors and credi-

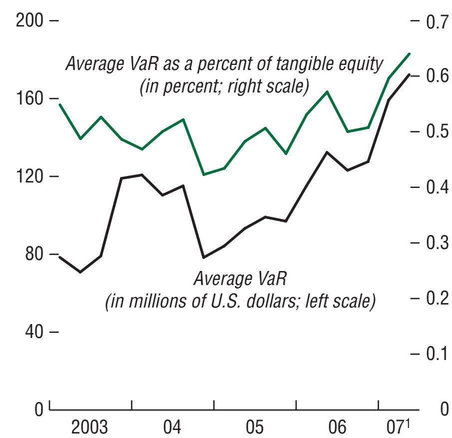
Box 2.3. Risk Measurement and Disclosure Practices of Financial Institutions

All of the major regulated financial institutions publish value-at-risk information with various degrees of detail. The figure shows the recent development of average VaRs for the main U.S. investment banks.[1] Average VaRs have generally been rising as, for instance, these banks have diversified into additional business lines (e.g., commodity dealing and leveraged loans). However, when scaled to tangible equity, VaR measures have been more stable.[2] Nevertheless, given that VaR volatility inputs have been declining, the slightly increasing VaR/tangible-equity trend suggests that outright risk-taking has been rising.

Investment banks typically publish their high, low, and average VaRs for the reporting period broken down into various risk classes (usually interest rate, currency, equity, and commodity risks), plus an implicit diversification benefit. Some also include sensitivity tests (VaR at different horizons, confidence intervals, and using different underlying factor data), and backtesting details (for instance, UBS AG presents its VaR assumption sensitivities and backtesting results). However, only a few institutions currently publish the details of their stress tests and scenario analysis in their annual reports—Société Générale and BNP Paribas being two notable examples.

In addition, most firms assess vulnerabilities to ad hoc shocks (e.g., a 10 to 20 percent stock market crash, or a volatility and/or correlation spike), and across product lines—some institutions even use shock correlations (e.g., assuming a correlation structure of +/–1.0 across all assets). Some firms include these in their published reports, but most do not. Additional disclosure along these lines should be encouraged.

Investment Banks: Average VaR



Source: Fitch.
Note: Average value-at-risk (VaR, ignoring diversification) for five investment banks: Bear Stearns, Goldman Sachs, Lehman Brothers, Merrill Lynch, and Morgan Stanley.
[1]Data through first half of 2007.

[1]The main U.S. broker-dealers are now regulated by the Securities and Exchange Commission under the "Consolidated Supervised Entity" regime. This requires them to maintain regulatory capital based on VaR-type measures, emulating a number of the capital and risk management features of the Basel II Accord for banks.

[2]Tangible equity is defined as the book value of a firm's common equity (share capital, additional paid-in capital, and retained earnings) minus intangible assets. Similar trends are apparent in the VaRs of the 20 largest U.S. and European commercial banks (Jeffrey, 2006).

tors more thoroughly assess bank exposure to extreme events.[14]

All major investment banks are working to supplement their VaR calculations with ERC measures designed to ensure that the firm has

[14]Pérignon and Smith (2006) find that VaR disclosure by the largest global commercial banks systematically improved over the decade to 2005, with those in Spain, Canada, and the Netherlands being the most transparent. However, there is a wide divergence of practices, with some of the largest banks publishing very little. Pérignon, Deng, and Wang (2007) find that VaRs published by Canadian banks are persistently too conservative—a conclusion reached by others—as a result of the relative scarcity of exceptions to VaR limits (Jeffrey, 2006).

sufficient capital to survive extreme and prolonged market stress events and meet regulatory requirements, although far less is published about such calculations. The ERC measures are based on VaR principles, but include a wider set of risks (e.g., credit, liquidity, operational, legal, and reputational risks) assessed at higher confidence intervals. These ERC measures are then used to allocate capital to various business units of the institution, linking the expected rate of return and its risk. A few firms are starting to relate traders' remuneration to their ERC measures, rather than outright P&L, given that traders should be rewarded according to their risk-adjusted returns rather than absolute profit if risk measures accurately measure the riskiness of returns and cannot easily be manipulated.

Simulations and stress tests are now nearly universally used by banks to investigate the extreme tails of possible P&L distributions and to condition their risk appetite or add capital. Investment banks tend to run very similar suites of historical stress tests and hypothetical simulations, in part because senior management may dismiss very extreme scenarios as unrealistic. Typical episodes usually include recent equity market crashes or downturns (e.g., 1987, 2001–02), fixed-income and credit stresses (e.g., 1994, 2005), emerging market crises (especially 1997), liquidity stresses (e.g., the collapse of Long-Term Capital Management, the 9/11 terrorist attacks), an oil price shock, and sometimes a pandemic flu scenario.

Sophisticated firms select scenarios that are most suitable for exploring the risks specific to their portfolios and positions. They also adapt historical data from stress periods to take account of market innovations and developments, and make allowance for liquidity risk by assuming that they are unable to trade their position for a period, often at least 10 days, in stressed circumstances. However, there is a tendency to assume that monetary authorities will act to mitigate the severity of a crisis through the provision of emergency liquidity.

The connection between the use of VaR, ERC, and stress tests and limitations on market risk-taking is complex. Position limits are the most common. Investment banks tend to set relatively conservative position limits for untested traders, making sure either the VaR limit or a "stress limit" (or other limit) is close enough to actual positions that it induces periodic and prompt discussions between risk officers and traders about whether further risk-taking is warranted, with somewhat more lenient limits for experienced, successful traders. While flexibility to raise limits at short notice is often delegated to managers, a sharp or sustained rise in volatility is likely to trigger multiple limit breaches across the firm and require a firm-wide reassessment of appropriate exposures.

Most hedge funds calculate a VaR measure, but they tend to put less emphasis on it as a risk measure than do the banks and securities firms, adding other measures to reports to investors. This is because VaR fails to adequately capture the liquidity or credit risks associated with some funds' strategies and positions. According to recent survey evidence, 46 percent of the larger hedge funds use VaR as their primary market risk measure, 40 percent use some sort of volatility metric, and 9 percent use potential future exposure—that is, the potential amount of credit exposure that could be subject to loss following a future default, and so most appropriate for credit funds (Mercer Oliver Wyman, 2006). Other measures can include net asset value (NAV) volatility, leverage (measured by gross assets to NAV), and exposure to changes in market rates (e.g., yield curve shifts).

Since the collapse of Long-Term Capital Management, hedge funds have placed more emphasis than investment banks on stress tests and scenario analyses relative to VaR. Funds frequently supplement the historically stressful scenarios by a suite of hypothetical scenarios that are tailored to the specific risks faced by the fund. Hedge funds are often able to subject their positions to more complex and numerous stress tests with greater frequency than banks, as a result of having far fewer trading positions, more integrated risk management information technology systems, and shorter reporting lines than the trading desks of regulated banks. Compared with most investment banks, hedge funds tend to control risk more flexibly, setting more generous position limits for trusted, active traders to take advantage of opportunities that may arise.

Market Risk Management Challenges

Market Liquidity Risk Management

While both investment banks and hedge funds are fully cognizant of the risks of being caught in "crowded trades," it is difficult to manage liquidity risk in a quantitative manner.[15] Some banks and funds try to assess competitor dynamics when setting limits on their own positions and use various metrics (bid-offer spreads, turnover, surveys of investor risk appetite, and observed order flow) to do so. However, these factors tend not to be formally incorporated into their market risk measures, with most institutions focusing on limiting their own exposure relative to the total market and not taking into account potentially interactive effects. (See Box 2.4 for a review of the Amaranth hedge fund case.) Many use similar, often simple, rules of thumb to constrain position-taking (e.g., a maximum position of 10 percent of average daily turnover in an emerging market security). Comfort from such limitations could prove illusory if a large number of institutions follow the same rule.[16] Indeed, if average turnover is assessed using only the most recent data, position limits could be relaxed as market turnover rises in a crowded trade, only to tighten rapidly when turnover drops in a stressed environment. Risk managers need to factor in the consequences if others follow similar rules for position limits—not all can be the first to exit the burning building.

To protect themselves against forced liquidations in illiquid markets, prudent institutions try to carefully manage their maximum liquidity requirements. For most, this is achieved by keeping a proportion of assets invested, unleveraged, and in liquid assets, and by factoring in extra time that may be required to liquidate assets. For hedge funds, requiring investors to submit to initial lock-ups and three-to-six-month notice periods for withdrawals, and retaining the ability to impose "gates" that limit total withdrawals per month as a proportion of NAV, are also used. However, some hedge funds are concerned that their counterparts operate with too great a liquidity mismatch—providing their investors with the ability to withdraw funds too quickly relative to the illiquidity of their assets (e.g., structured credit products), which can potentially lead to panic selling if redemptions are abnormally high.[17] Some hedge funds—especially funds of funds and those trading in liquid markets—offer monthly redemptions to investors and could quickly find themselves forced to liquidate positions in falling markets if investors were to seek withdrawals en masse.

Trading and Banking Book Risks

One of the greatest challenges currently facing investment bank risk officers is how to consistently evaluate and aggregate risks across both their trading and banking books. This can be an issue of methodology—it is not appropriate, for instance, simply to add market and credit VaRs together, but calculating an aggregated VaR is technically challenging. More importantly, with the growing use of securitization and credit derivatives, credit risk is less exclusively a bank-

[15]In a recent survey of large financial institutions, a majority of firms had yet to include liquidity risk in their ERC calculations (Deloitte, 2007a).

[16]See IMF (2007a, p. 92) for a description of the crowded trade that developed in the Brazilian inflation-linked government bond market in May–June 2006.

[17]The problems of the Bear Stearns–sponsored high-yield hedge funds in the summer of 2007 were prompted by requested investor withdrawals and margin calls requiring the potential sale of illiquid asset-backed securities collateralized debt obligations (ABS CDOs) (see Chapter 1). A recent study of 60 hedge funds found that a third did not monitor their liquidity requirements at all (Deloitte, 2007b). About 54 percent of hedge funds use gates or locks to manage investor withdrawals (Mercer Oliver Wyman, 2006).

Box 2.4. The Amaranth Hedge Fund Failure and Liquidity Risk

"We viewed the probability of market movements such as those that took place in September [2006] as highly remote, and our energy-risk models correspondingly discount the [Amaranth] Funds' exposures to the losses associated with such scenarios...But sometimes, even the highly improbable happens...It was not, however, for lack of applying resources or personnel to energy risk analysis that our funds experienced this severe drawdown. For as long as we have had a significant energy business, we have assigned full-time, well-credentialed and experienced risk professionals to model and monitor our energy portfolio's risks."

– From the transcript of a conference call between Nick Maounis, Amaranth CEO, and fund investors, on September 22, 2006

In September 2006, the multistrategy hedge fund Amaranth Advisors lost approximately $6 billion of its $9 billion net asset value (NAV) through trading losses incurred in the natural gas futures markets. This resulted in the fund liquidating its remaining positions to crystallize the largest NAV loss incurred by a hedge fund. What went wrong with Amaranth's risk management?

The fund appears to have significantly underestimated the magnitude of potential losses during an extreme liquidation event. Amaranth's primary trading strategy at the time involved natural gas calendar spread trades (e.g., long March and short April contracts). Forensic risk analysis indicates that its positions had become massive compared with the prevailing open interest in the exchange-traded gas futures markets. For example, Chincarini (2007) estimated that Amaranth's positions may have represented up to 80 percent of the natural gas derivatives open interest on the NYMEX, although potentially spread between positions on two exchanges and over-the-counter transactions. Also, some of Amaranth's positions are estimated to have been hundreds of times greater than average daily trading volumes in some contracts. Liquidity risk may have been particularly acute in some of the fund's 2008–10 positions (Finger, 2006). Once Amaranth's initial losses became known, the terms being offered to unwind its positions deteriorated significantly.

However, Amaranth's positions were nevertheless consistent with running a substantial VaR. Chincarini (2007) estimated that Amaranth's losses were consistent with a 99 percent one-day VaR of between $3 billion and $4 billion on its $9.2 billion of assets, depending on the assumptions used regarding its daily P&L probability distribution. The fund was estimated to be leveraged seven times over. This was incurred in pursuit of a $1 billion expected monthly profit. In other words, "they were chasing an 11% return... for a 'worst-case' [1 percent probability] scenario of a loss of 36%" (Chincarini, 2007, p. 22). In a similar analysis, Finger (2006, p. 5) concluded that the actual $6 billion loss was "well within the realm of the large moves that policies built on [VaR] models are meant to address." Perusal of the fund's monthly P&L data would have indicated that a $6 billion monthly loss was not a remote possibility (Till, 2006).

The absence of wider market disruption from Amaranth's September 2006 closure resulted from the willingness of other market participants with sufficient capital to assume the fund's positions with relative ease. The episode highlights the importance of making allowance for liquidity risk. Nevertheless, if a firm's principals are determined to take substantial risks to achieve high returns, the potential for failure exists, however sophisticated the risk management procedures.

ing book risk and could legitimately be allocated to the trading book.

A particular issue at present is the appropriate treatment of leveraged loans and commitments. Investment banks' credit exposure in such transactions is intended to be short-term and so would naturally be included in the trading book, but since the commitments cannot be traded or easily hedged it is difficult to include them in the market VaR calculation. It appears that most banks assess these transactions on an ad hoc basis, taking into account the existing credit exposure to the borrower and concentration of potential commitments. Nevertheless, the danger is that reported VaR numbers significantly understate the risk that banks are incurring through leveraged loan activities.

Recent events in credit markets have underscored the difficulties risk managers face in adapting their systems to the increased ability to trade credit risk, while taking account of the potential fragility of market liquidity under stressful circumstances.

Observations

While difficult to generalize across banks and hedge funds, there seem to be a number of trends observable in risk management approaches from which one can draw policy implications.

Overall, risk management systems at the largest institutions are varied, and risk managers appear cognizant of the implications of the risk measurement models they employ. This increases risk awareness and prevents problems from building up. That said, there are a number of factors that tend toward narrowing the range of risk management practices and approaches, particularly at commercial and investment banks:

- The Basel I and II Accords, as well as other regulatory influences, tend to focus on minimum standards that banks must meet to satisfy risk management requirements—these raise the standard at smaller institutions but could then result in less well-resourced institutions just settling for the minimum risk management systems;
- Rating agencies scrutinize banks' risk management processes using a prescribed methodology as an important element in the rating process;[18]
- Banks employ similarly-trained risk modelers from a limited number of academic institutions;
- Best practices are transferred between institutions through the job mobility of risk professionals; and
- Medium-sized and small banks employ a limited range of risk consultancies to design and build their risk management systems, with a tendency to use "off-the-shelf" risk management packages.

Undoubtedly, these factors raise the quality of risk management at many individual firms and increase their resilience to firm-specific shocks for a given level of capital. But while the risk management "bar" is being raised, the variance around that bar may have narrowed somewhat, especially as new entrants to some markets strive to compete with existing players. This suggests that, if a significant market-wide stress event occurs, the likelihood of a number of the banks acting in similar ways may have increased.

The diversity of strategies and flexibility with regard to risk management approaches used by hedge funds has helped to stabilize markets when stressed in the recent past. For instance, hedge funds bid for distressed assets in the resolution of the Refco brokerage insolvency in 2005 and the Amaranth liquidation in 2006. However, even here, the growing institutionalization of investors (through the participation of pension funds and funds of funds), and the small but growing number of funds issuing publicly traded securities and seeking ratings, could lead to greater similarities in risk management approaches. Regarding systemic stability, this highlights the importance of hedge funds retaining flexibility over strategy or risk-taking in periods of market stress.

The fundamental question is whether this possible convergence of some types of risk management technique actually matters in practice when it comes to amplifying systemic risk. The key issue

[18]An example is Standard & Poor's (2005). The difficulty for supervisors in retaining experienced risk management expertise may also encourage a "check-box" approach rather one that can fully analyze a range of idiosyncratic models.

is how each firm's senior management and risk officers interpret their risk measures to condition their risk appetite in volatile or crisis conditions. Indeed, when asked directly, both banks and hedge funds maintain that they will *not* mechanistically follow VaR-based risk limits when deciding how to react to volatile conditions.

Even if these intentions are carried out, there are a number of other routes whereby risk management techniques could reduce firms' collective ability to take risk in stressful circumstances.

Margin calls. When setting margin requirements for hedge funds and other counterparties, prime brokers often use VaR-based approaches and therefore require a lower percentage of up front collateral if the volatility of the underlying asset is low. This permits counterparties to incur positions with greater leverage. If asset values then fall and volatility spikes up, "variation" margin calls are made first, as the borrower's exposure increases, and margin requirements are raised in the future, as the asset has become riskier. The result is that borrowers are forced to find cash or liquidate other assets to meet the increased margin calls, and lending conditions are tightened, just as asset market conditions become more volatile.[19] If margin requirements were initially set more conservatively, but were less risk sensitive, market dynamics would be more stable.

Large hedge funds address this potential danger by negotiating margin "locks" with their prime brokers. In return for relatively higher margin ratios, prime brokers concede the right to increase margin requirements at short notice, which also cements longer-term relationships with the counterparty.[20]

However, such long-term behavior is likely to be followed only by the well-established prime brokers and their most creditworthy counterparts. Recent competition to provide brokerage services to hedge funds has allegedly resulted in more generous up front margin requirements from new entrants, although the banks concerned fully expect to tighten these requirements as volatility rises, and in some recent cases have allegedly done so.[21]

The commonality of stress tests. As noted earlier, major banks tend to run a similar suite of stress scenarios. However, to prepare adequately for an unprecedented stressful event, an individual firm would need much higher levels of capital to protect itself fully. In the process, the firm could become uncompetitive.

Regulatory capital requirements. With the growing adoption of risk-based bank capital requirements, there is the potential that adverse movements in market risk factors could result in a coincident erosion of regulatory capital—at least among those firms primarily exposed to market risk. Hypothetically at least, sufficiently adverse market moves could begin to erode the cushion of ERC that firms hold above regulatory minima. In turn, this may prompt firms to raise additional capital or reduce the riskiness of their operations (e.g., by closing their most risk capital-intensive positions or assets).[22] Market-makers will find inventory more capital-intensive to hold in volatile conditions and so widen

[19]The process could be exacerbated further by the practice of some brokers that use VaR-based margining across the portfolio of a counterparty's exposures. This saves margin at the outset as the counterparty receives the benefits of netting and diversification in its exposure to a broker, but means that margin requirements could rise swiftly in stressed circumstances if the volatility or correlation of those positions rises.

[20]A similar outcome results if prime brokers calculate average market volatility over prolonged data periods and set the initial margin on the basis of "stressed" liquidity (so reducing the likelihood of having to increase the margin in volatile conditions).

[21]In June 2007, the volatility of the ABX (an index of ABS credit default swaps with significant U.S. subprime exposure) settled at 10 times higher than its pre-February 2007 level (Rosenberg, 2007). As a result, King (2007) estimates that initial margin requirements on the various ABS tranches rose between two and five times.

[22]A comparable scenario transpired in the United Kingdom in 2002–03 when life insurance regulatory requirements interacted with equity declines to encourage insurers to sell equities into falling markets due to their relatively high capital charge. The decision by the Financial Services Authority to offer waivers from the regime prior to reform (Tiner, 2003) contributed to stabilizing the U.K. equity market.

spreads or quote smaller size available to trade as a result, thus reducing market liquidity.

Automatic position and stop-loss risk limits. The prevalence of automated portfolio insurance trading strategies, whereby equities were automatically sold if prices fell a specified amount, exacerbated the equity market sell-off in October 1987.[23] A similar self-reinforcing dynamic could be recreated if sufficient numbers of firms and funds were to manage liquidity risk through automated position limits relative to market turnover or through automated stop-loss orders.[24]

Risk managers' reaction to significant market losses. Ultimately, whatever the degree of sophistication of risk measurement, the behavior of firms will depend on how bank risk committees react to recent significant losses resulting from market volatility. Much depends, of course, on the firm's peer group, regulators' expectations, equity analyst reactions, and the margin of risk capital above regulatory minima. For example, if a regulated entity experiences a cluster of VaR exceptions, an initial reaction may be to reduce risky positions to avoid having to explain the violations to the regulator.

Hedge funds' ability to react flexibly. Hedge fund reactions will depend on how they have expressed their risk appetite and limits to investors. If these are relatively tightly defined around specified risk measures or leverage usage, then the franchise value of the fund will depend on adhering to these prior commitments to investors and potentially closing out their long or short positions in stressful conditions. Conversely, hedge funds with greater risk tolerance, low exposures, or access to resilient sources of capital or funding could well take the opportunity to increase their risk-taking positions.

[23]Presidential Task Force on Market Mechanisms (1988); New York Stock Exchange (1990).

[24]Garleanu and Pedersen (2007) describe a model whereby markets in which traders are constrained by VaR-based risk limits display lower prices when volatility increases.

Policy Implications

Systemic risk is addressed both by improving risk management at individual financial institutions (to reduce counterparty risk for others) and by facilitating diversity in terms of both the risk management approach and market participants, with a view to broadening the scope for contrarian behavior during periods of stress.[25] In addition, while some institutions have specific plans in place, others would benefit from considering beforehand how they would react to stressful scenarios and making provision in benign periods for such events.

A number of implications for policymakers and risk managers arise from the preceding analysis.

Stress tests to augment market risk models more systematically. Banks' market risk-based models can be augmented with stress tests to establish the appropriate level of capital. As has been shown in this chapter, VaR and related ERC models generally cope well when outcomes remain within the normal range of experience, but they have well-known limitations when stressed. Hence, as is becoming standard practice, regulators need to use their discretion under the second pillar of the Basel II Accord to ensure that their systemically important institutions assess their exposure to extreme events. As product innovation enables more of a bank's banking book to be hedged or traded, stressing risk exposures (both on- and off-balance-sheet) for credit spread widening and liquidity shocks will become especially important, including attempting to anticipate the actions of other firms when modeling liquidity shocks.[26]

[25]Stabilizing speculators need both available risk capital and appetite to enter into volatile markets to take positions when they believe prices are significantly different from their fundamental value. If risk capital is unavailable, prices may diverge from fundamentals for prolonged periods (Shleifer and Vishny, 1997).

[26]"Liquidity-adjusted" VaRs were conceptualized in the late 1990s and are now being implemented. At their simplest, L-VaRs impose limits on trading positions linked to the markets' underlying turnover. At their most complex, L-VaRs incorporate liquidity-inspired adjustments into the VaR's volatility and correlation structures.

Stress tests to be adapted to the most relevant scenarios. Some regulators are already aware of the tendency of firms to take suggestions from regulators as to what the scenarios are that they are "expected" to run rather than the threats most relevant to their institution, and thus avoid providing such suggestions. For their part, authorities need to maintain a "constructive ambiguity" about their reaction in a crisis to ensure that firms do not automatically assume in their stress tests that intervention or regulatory relief will automatically be forthcoming.

Reactions to stressful events better anticipated. Supervisors and central banks can consider how they would expect financial institutions to react in stress scenarios and what their own response would be. Given the potential for firms' collectively to be vulnerable to systemic stress, it would be prudent for monetary authorities and bank regulators to include within their own private risk management plans scenarios where system-wide liquidity injections and regulatory relief may be necessary, and to have thought through the circumstances in which such action may be appropriate (e.g., in internal "crisis simulations").

Supervisors remain flexible when assessing risk management systems and models. When assessing banks' capital models and risk management systems, regulators can recognize the tendencies that push firms toward standardization on what is currently believed to be best practice. While maintaining sound minimum requirements, bank supervisors can avoid being too rules-based with regard to model details and use the discretion they retain under international agreements to allow firms to tailor models to their own requirements and parameters in order to foster innovation and a diversity of approaches.

Banks improve their risk management reporting. Consistent with the spirit of the second pillar of the Basel II Accord, banks themselves can further improve the comprehensiveness of their risk management reporting in order to provide assurance to counterparties, creditors, and shareholders as regards their exposure to tail events and the contingency plans and preparations they have made. In particular, external assessment of the robustness of VaR models would be aided by publishing more results of backtesting exercises and exception reporting.[27] Also, the understanding of a firm's vulnerability to tail events would be facilitated by publishing the details and results of a selection of stress tests (Box 2.3) as well as a firm's VaR under a hypothetical extreme market stress event.[28]

Stabilizing benefits of hedge funds be taken into account. Regulatory authorities can consider the stabilizing benefits that hedge funds can bring in times of stress when assessing risk management requirements. Unregulated liquidity providers (i.e., hedge funds) often provide bids or offers in stressed circumstances when assets are deemed to be fundamentally misvalued and they have access to sufficient capital. Because they are not required to calculate and hold a minimum of economic capital, such pools of private capital can have the freedom to take advantage of the possible herd behavior of others that could result from those that apply more rigid risk management procedures required of regulated institutions. Naturally, some hedge funds have managed risk injudiciously, and no doubt others will occasionally do so, and it is not yet clear whether, overall, hedge funds have a stabilizing or destabilizing influence in markets. But it is the primary responsibility of their investors and counterparties to ensure that hedge funds' risk man-

[27]As an example of how detailed stress test disclosure can be, Société Générale's annual report lists 11 of its 18 historical stress tests and displays the year-end potential losses associated with these and seven other extreme, but plausible, hypothetical scenarios.

[28]In order roughly to approximate "stressed VaRs" to compare across firms, rating agencies are forced simply to add VaRs across business units, assuming correlation structures go to unity in a crisis (Fitch Ratings, 2007). When considering U.S. bank holding companies with large trading operations, Hirtle (2007) finds that greater transparency, particularly over stress test results and VaR components, is associated with significantly higher risk-adjusted returns by the bank—although the direction of causation was not determined.

agement systems are sufficiently robust, and they should require that such information be available for this purpose. Consequently, care needs to be taken when devising industry or supervisory "codes of hedge fund best practice" to ensure that those codes do not inadvertently restrict how funds model and manage their risk-taking, while appropriately providing guidance in other areas, such as disclosure and customer protection.

Conclusions

Do market risk management techniques amplify systemic risks?

Not surprisingly, there is no straightforward answer to this question. First, it is important to emphasize that, particularly in less volatile environments, financial systems are more stable if firms are risk-sensitive and react to the signals their models are sending. If firms were not generally risk-sensitive, the likelihood of asset bubbles and crises would be even greater. VaR-type techniques reveal aspects of a firm's risk-taking, particularly regarding correlated exposures, that would not necessarily be apparent if risks were managed in silos within a firm.

Having said this, risk management techniques are not a panacea for all ills. The modeling work presented in this chapter suggests that a VaR-type risk management framework certainly has the potential to encourage firms to increase their risk appetite in a benign environment, as well as to reverse it when volatility returns. This result holds with a surprising degree of uniformity even when varying the timeframe over which the data are selected or the weights given to recent data. The model of price dynamics involving multiple firms using VaR measures also demonstrates that there is potential for a destabilizing feedback mechanism to develop whereby the movement of market prices is amplified. Results from the model indicate that a diversity of risk management models can be a stabilizing influence.

The question is: Do the principal institutions actually operate in ways whereby these theoretical results could hold? To put it another way: Will enough firms be constrained to follow their risk management measures sufficiently closely to amplify market volatility by their actions? When risk managers at major institutions are asked the question directly, the answer is most definitely that they do not follow their risk management systems inflexibly. They claim to understand the limitations of their VaR and ERC models and to apply judgment to these outputs when deciding whether the firm's risk appetite should be curtailed in stressed circumstances.

Other evidence, however, suggests that price pressures and risk management systems could interact in a destabilizing manner. First, VaR-type measures are now nearly universal in banks, and nearly all use short time-period HS.

Second, published investment bank VaRs have been generally rising over the past three to four years despite falling volatility, indicating they have added to their risky positions. The surprising lack of exceptions to their daily VaR limits that firms publish indicates that either (1) their models are too conservative and are not calibrated finely enough to show exceptions in practice; (2) banks prefer to show a high VaR with few exceptions; or (3) their models have been overly influenced by benign conditions to report low VaR usage in practice. The danger is that, with the recent move to higher volatility, some firms will recognize that their underlying positions were much riskier than they perhaps realized and cut them.

Third, as described above, there are a number of indirect ways in which greater volatility can encourage selling into falling markets—from automatic stop-loss triggers and rules of thumb to ERC minimum requirements. It is worth highlighting the potential interaction of the exposure of some leveraged hedge funds to increasing volatility, triggering both margin calls from prime brokers and redemption requests from investors at a time of reduced trading liquidity. Long-Term Capital Management and Amaranth highlighted how quickly supposedly well-resourced risk management architectures can be overwhelmed in unfavorable market conditions. Given the difficulty of incorporating liquidity risk into the market risk management systems of large trading institutions, more risk managers also need to consider what the market dynamics will be if the majority of their counterparts are also following similar rules.

One should not lose sight of the improvements in risk measurement and control over the last decade and the positive role of these improvements in reducing the likelihood of idiosyncratic failure from uninformed risk-taking. These advances should induce greater risk sensitivity on the part of financial institutions, leading to early unwinding of unanticipated exposures and better risk control. At the same time, it is important not to place undue confidence in all aspects of firms' risk management systems—for instance, the ability to measure and assess vulnerability to extreme events is still not well developed. Also, the co-vulnerability of firms seems to have increased so that, when systemic firms come under pressure, they are more likely to be under stress together rather than alone (Chan-Lau, Mitra, and Ong, 2007; and IMF, 2007b). Raising the general quality of market risk management, while reducing its variance, has probably reduced the likelihood of failure of individual systemically important institutions, while possibly increasing the tendency of institutions to act similarly in stressful periods. In such circumstances, from a systemic perspective, it is important to ensure that there are market participants that are either sufficiently disparate in their holdings and strategies, or are able to take large contrarian positions during periods of stress. Over the medium term, the general trend toward greater involvement of an increasing variety of players in global financial markets should help to improve market resilience.

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