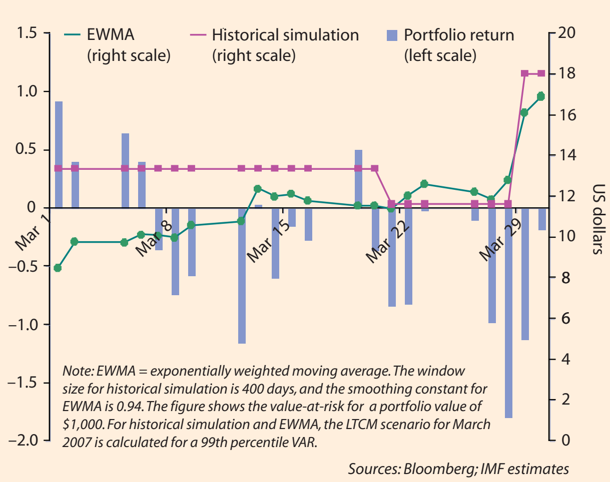
VAR: risk mitigant or amplifier?

Value-at-risk is a far-from-perfect risk measure. Jon Danielsson, Ulrich Klueh and Laura Kodres take a close look at the lessons to be learnt from its use in stressful or volatile periods, such as the current financial crisis

The current financial market crisis has elicited accusations that mechanistic adherence to risk management systems, such as value-at-risk (VAR) market risk measures, may have been a contributing factor. The model in the box opposite explores how, in combination with desired capital levels, risk management techniques – including VAR-type techniques – can lead to destabilising asset price behaviour in certain circumstances.

It is true that VAR-type techniques can help risk managers judge and potentially mitigate risks, thereby protecting their individual institution from adverse events. However, the interaction of rational responses from individual institutions holding similar positions during market stress can collectively cause detrimental asset price dynamics.[1] While difficult to anticipate, risk managers need to be aware that the rigorous use of some risk management techniques can have negative systemic implications.

1. Long Term Capital Management scenario: EWMA versus historical simulation, March 2007 (value-at-risk)



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.

Sources: Bloomberg; IMF estimates

The VAR measure is one of several measures that seek to unify traded positions across a number of different assets to calculate the potential loss on a portfolio that would exceed a given dollar level a certain percentage of the time. That is, 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, often assumed to be 95% or 99% of the time. It is used broadly in the financial industry as one of a number of metrics to assess market risk.

It is easy to demonstrate that the VAR measure – or VAR-type measurements – increases for a given portfolio of assets in stressful times when, as is typically the case, the volatility of the underlying assets rises or the correlations among them increases.

For instance, we took the year of low volatility to March 2007 and added, at the end of the sample period, the rise in volatility and correlations occurring during the summer of 1998 across some well known asset classes. This resulted in a twofold increase in either a historical simulation (HS) or exponentially weighted moving average (EWMA) VAR measure[2] (see figure 1). Because the historical simulation method implicitly weights all previous profits and losses equally, it takes several days of large losses before the VAR measure responds, whereas the exponentially weighted average measure, which weights the recent losses more heavily, responds faster.

Since the VAR measure only addresses the probability that losses exceed the VAR, it has nothing to say about how large actual losses might be. In particular, VAR may be ill equipped to address extreme losses. This can be seen from recent backtesting violations of the VAR measure at relatively high probabilities (99%) across a number of large investment and commercial banks. These violations suggested that even with elevated VAR measures, the model failed to account for the extreme losses that can prevail.[3]

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[1] This article is based on Chapter II of the International Monetary Fund's October 2007 Global Financial Stability Report, by John Kiff, Ulrich Klueh, Laura Kodres, Paul Mills with the aid of Jon Danielsson on risk modelling. Yoon Sook Kim provided research assistance.
[2] The asset classes include mature-market stocks from several countries, emerging-market stocks, 10-year fixed-income securities, commodity prices, foreign currencies and two-year interest rate swap. The portfolio does not include options or other positions with non-linear payoffs.
[3] Asia Risk magazine reported that investment banks reported significantly higher number of value-at-risk exceptions in the third quarter of this year (See Asia Risk, December 2007/January 2008, page 6).

For instance, UBS announced 16 backtesting exceptions at the 99% level in the third quarter of 2007 – its first exceptions since 1998.[4] These types of backtesting exceptions can be explained by the benign financial market conditions used to estimate the VAR boundary – the low volatilities and correlations – leading up to the recent episode. UBS attributes the violations to the increased market volatility and the wider credit spreads on mortgage-related positions, with 'jump events' and diminished market liquidity occurring in some cases. These conditions, in turn, are themselves related to the interactive effects of multiple institutions using approximately the same model, holding broadly similar positions and reacting simultaneously to the heightened volatility as we explain below.

The stylised model outlined below shows the interaction between different institutions using VAR-based techniques. The purpose of the exercise is twofold. First, the model demonstrates how a mechanistic application of risk management systems can give rise to unduly large price movements and feedback effects. Second, the model is able to consider the effects of VAR model heterogeneity – that is, institutions using alternative modelling assumptions and criteria.

The intuition of the model

The stylised model is set up to reflect, as closely as possible, how VAR risk models are used. The analysis derives a financial institution's demands for risky assets (including a risk-free asset) using a standard mean-variance portfolio model and by specifying a given risk appetite (see box, *The model*). Institutions also try to maintain a certain level of capital in accordance with perceived risks. A shock to prices changes their VAR measure, which then alters their desired portfolio holdings (including of the risk-free asset) linked to their desired capital level. The changes in demand for risky and risk-free assets result in changes to market prices and a feedback to the VAR measure.

The model is set up so that each day a financial institution compares its actual level of capital with its desired level. The desired level of capital is a combination of its required capital – using three times the VAR measure required by regulators – plus a buffer. This desired level links to the institution's desired changes in risky and risk-free assets.

For instance, a drop in VAR due to lower volatility frees up capital and enables the institution to increase its holdings of risky assets. Alternatively, a VAR increase implies an undercapitalisation relative to desired levels. For the institution to return to its desired portfolio holdings, it must liquidate risky assets and swap them for risk-free assets. This adjustment process puts downward pressure on risky asset prices, which again results in a larger VAR, requiring further reductions of risky assets.

Returns are correlated not only through their normal correlation structure, but also through a common factor in the equilibrium pricing equation, reflecting institutions' reaction to the initial rise in correlations (see final equation in box). This implies that volatilities and correlations rise more than they would as a

[4] *See United Bank of Switzerland, Third Quarterly Report, October 30, 2007, pages 20–21. The backtesting exercise was performed from October 2, 2006 to September 28, 2007 using a 1-day, 99% confidence VAR.*

The model

Financial institutions choose portfolios in accordance with a standard mean-variance portfolio optimisation framework, where they maximise expected multivariate normally distributed returns, given a level of risk tolerance, τ. Positions are given by:

$$\theta_t = \tau \Sigma_R^{-1} \mu_R,$$

where μ_R is a vector of mean returns on k assets and Σ_R^{-1} is the inverse of the variance-covariance matrix of the k assets' returns.

An institution's desired risk level is:

$$D_t = \theta_t \cdot P_t,$$

where P is a vector of prices associated with the vector of positions, θ_t. The value-at-risk (VAR) is therefore:

$$VAR_t = (D_{t-1} + \Delta D_t)\, \upsilon t,$$

where the institution updates its desired portfolio daily and υ_t represents its chosen VAR technique. In general, institutions hold more capital at time t, C_t, than required, by a proportion, say α, where α is a constant that is greater than 1, creating a buffer. And the changes in their desired capital holdings reflect the changes in their desired portfolio,

$$\Delta C_t = -\Delta D_t = [\alpha\, C_t(\text{at new } D_t \text{ level}) - C_{t-1}].$$

Institutions update their chosen mean-variance portfolio weights by an amount δ to obtain their new desired portfolio, D_t,

$$\Delta\theta_t = \theta_{t-1}\delta_t.$$

The trades executed by each institution to alter their portfolio weights affect the prices of risky and riskless assets. For simplicity, a residual inverse-demand function for asset i of the following type is assumed:

$$P_t^i / P_{t-1}^i = R_t^i\, I(\Delta\theta_t^i) = R_t^i \exp(\lambda \Delta\theta_t^i),$$

where I is the elastic part of the inverse-demand function and denotes the elasticity coefficient in the demand curve. To allow markets to clear, the changes in the desired portfolios must be able to be accommodated by other agents in the market requiring that there exist a δ_t such that the following equation holds:

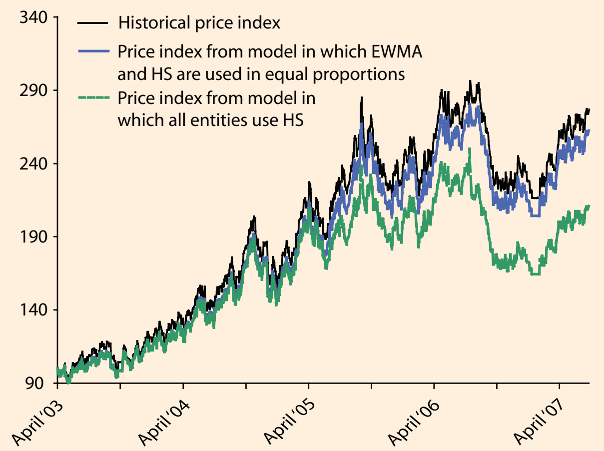
$$\Delta D_t = \Sigma_i P_t^i \Delta\theta_t = \Sigma_i P_{t-1}^i R_t^i \exp(-\lambda\theta_{t-1}\delta_t)\, \theta_{t-1}\delta_t.$$

For a given change in desired portfolio holdings, if λ is small enough, a unique δ exists. Intuitively, this requires that prices are not overly influenced by the institution's changing demands. Assuming such a δ exists, the equilibrium return on asset *i* satisfies

$$\ln(P_t^i / P_{t-1}^i) = \ln(R_t^i) - \lambda\theta_{t-1}\delta_t.$$

Note that the additional term in the above equation says price changes are influenced by the changes institutions make to their desired risky asset positions. These are in turn fed back into the VAR model through the means and variances of the returns to the assets, $\ln(P_t^i / P_{t-1}^i)$, leading to further position adjustments.

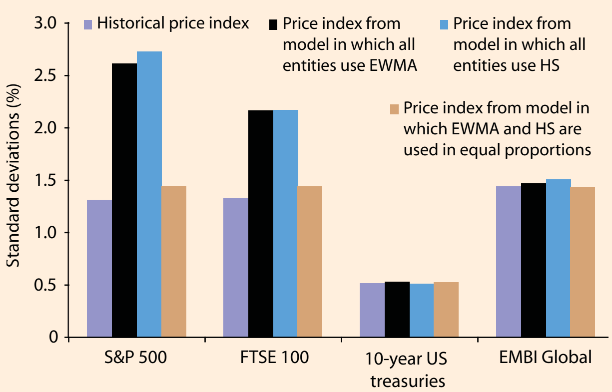
2. Asset price dynamics under alternative model specifications (index: April 1, 2003 = 100)



Note: EWMA = exponentially weighted moving average; HS = historical simulation. The price indexes refer to the Commodity Research Bureau energy futures index, one of the assets included in the VARs of the simulated financial institutions.

Sources: Bloomberg; IMF estimates

3. Selected asset volatilities under the interactive model (standard deviations in %)



Note: EWMA = exponentially weighted moving average; HS = historical simulation The standard deviation calculated over the stress period August 1998.

Sources: Bloomberg; IMF estimate

result of a purely exogenous event, leading to a flight to quality, as institutions seek to dispose of risky (correlated) assets in favour of risk-free securities.

Applications

The model is used to evaluate the effect of simultaneous use of VAR risk management models by multiple institutions on asset price dynamics. It specifically examines whether the use of different VAR parameterisations can help alleviate the systemic implications observed in the model. The sensitivity to various parameters is also examined.

While many financial institutions use a HS method for their VAR calculations, we assume in one of the scenarios that some also use the more traditional EWMA method. We assume that each institution forms a portfolio of nine asset types and holds capital in excess of its regulatory minimums. The main focus is on price dynamics during periods of stress so, to this end, we extract the data for the August 1998 episode from the entire sample period and provide the baseline for the exercise. As well as choosing the HS window and the EWMA smoothing constant, we must specify the institution's risk tolerance, τ, and the degree of price impact, λ.[5]

Risk managers need to be aware that the rigorous use of some risk management techniques can have negative systemic implications

The results can be summarised as follows:

- Having institutions that employ the same VAR model is destabilising both in terms of the 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, for the case of one particular asset, price deviations from the historical price series are negligible in the case where about half the institutions use EWMA and the other half HS measurement techniques. By contrast, the model with universal use of HS yields markedly different selling and buying patterns when volatility exceeds 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 for four basic asset classes in the model (see table opposite). The positive correlations across the risky assets – the S&P 500 and the FTSE 100 indexes – increases markedly, with the correlations between this group and the risk-free asset (here assumed to be the 10-year US Treasury security) generally declining, as the flight-to-quality effect is intensified.
- Volatilities tend to increase relative to the baseline, but only marginally if both methods are used in equal proportion (figure 3). If only one type of VAR method is used, volatilities increase dramatically for the risky assets.
- Lower levels of risk tolerance imply a more pronounced tendency toward destabilisation. This effect is particularly strong when both institutions employ the same risk models.

Overall, the results of both simulation models show that VAR-based systems – or those that act like VAR – provide the scope for self-reinforcing mechanisms to arise. Moreover, diversity across VAR measures may be helpful in dampening asset volatilities.

It is important to note several provisos. First, the results are based on a situation where all institutions start by holding roughly

[5] *In the baseline scenario, the window for the HS implementation is 400 days; the EWMA smoothing constant is 0.94; the risk tolerance parameter is 0.8; and the degree of price impact is 0.25.*

the same portfolio. To the extent that institutions hold very different portfolios, the self-reinforcing behaviour will be reduced.

Second, the model assumes that no one institution takes into account the behaviour of the others. Our interviews with major international financial institutions suggests that this is generally the case. While most risk managers acknowledged that institutions were likely to rush for the exits during a period of stress, especially in so-called 'crowded trades', they also believed they were positioned closest to the exit for a quick escape.

Third, the model does not attempt to calibrate or price market liquidity. The flight to quality is based on the underlying risk/return characteristics of the assets. In the turmoil that began last August, there has also been a flight to liquidity. Such a reaction would reinforce the effects observed in the model.

Conclusion

The widespread use of the VAR-type model risk management techniques is not fundamentally flawed, as its implementation serves to unify several disparate risks under one roof, providing an estimate of potential consolidated portfolio losses under normal market functioning.

Most users recognise that VAR gives inaccurate measures of individual institution risk if applied in situations of extreme volatility. But they do not so often appreciate that systemic problems can arise from using the model. These occur when institutions all use similar techniques and parameterisations – as seems to be the case currently – and many institutions hold similar positions.

In fact, any type of risk-mitigation technique using volatility or correlations and forcing actions based on reactions to higher levels of these variables – such as stop-loss orders, margining systems, and so on – will produce similar results. Specifically, heightened volatility and correlations that occur in stressful situations exacerbate negative asset price dynamics, as a flight to quality leads to fire sales of risky assets.

There are several ways of avoiding these detrimental effects. The most obvious would be to more closely tailor the model to individual institutions' risk-taking activities so that similar models do not signal position alterations simultaneously.

To ensure large increases in volatility or correlations do not imply large position changes, longer sample periods that include a full cycle of volatility changes could help to better calibrate the VAR model. The fact that many institutions calibrate their VAR models using just one year of data suggests that the low volatilities of the past year provided a false sense of security against more volatile conditions.

More reliance on institution-specific stress tests, especially those that truly stress positions beyond historical norms would help highlight areas where problems are likely to arise. The interactions among various types of assets across the credit or business cycle may also pick up relationships that are hidden if only short periods or upswings are examined.

From the regulatory point of view, when assessing institution's risk models and risk management systems, regulators can recognise the tendencies that encourage standardisation and instead use their discretion to welcome and encourage institutions to tailor models to their own requirements. In this way, supervisors or regulators could point out that some of the standardisation may be related to commonly perceived cyclical characteristics that may not last.

Supervisors could use their discretion under Basel II to consider through-the-business-cycle movements in risk levels, both for individual assets and, more importantly, for their correlations and dependencies. During downturns, and especially in stressful times, correlation structures often change dramatically. Overall, fostering innovation and diversity of approaches will help ward off a commonality of position-taking and responses.

Better disclosure by institutions to their counterparties, creditors and shareholders concerning their risk management systems – emphasising exposures to tail events and contingency planning and preparation – should help assure others of the robustness of approaches to risk management.

Understanding and explaining poor results and model failures would also demonstrate conscientious risk management frameworks. Ideally, institutions should attempt to take into account others' behaviour during periods of stress in their own contingency-planning exercises.

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Selected correlation coefficients between asset classes in the interactive model

	S&P 500	FTSE 100	10-year US 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 US 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 US 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 US 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 US Treasuries			1.00	0.21
EMBI Global				1.00

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