

Fallacies about the effects of market risk management systems

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This paper takes another look at allegations that risk management systems have contributed to increased volatility in financial markets, with the particular example of the summer of 1998. The analysis starts with a review of the literature on the effect of financial engineering on financial markets. The evidence is that financial innovations reduce volatility in financial markets, but they seem to be systematically blamed for the opposite effect. The paper also provides new evidence on the potential effect of VAR-based market risk charges for commercial banks under the Basel Accord. I show that VAR-based regulatory capital charges cannot plausibly be blamed for the volatility of 1998 due to their very slow response to market movements.

The last decades have witnessed a revolution in financial risk management. Quantitative techniques such as option pricing, portfolio insurance, and value-at-risk (VAR) have become essential tools of portfolio management. The concepts of portfolio insurance and dynamic hedging were developed in the late 1970s. VAR was first mentioned in 1993, although the concept goes back to Markowitz (1959). VAR is an aggregate measure of downside risk, defined as the maximum loss over a target horizon such that there is a low, prespecified probability that the actual loss will be larger.

The generalized use of these techniques, however, has raised concerns that they could actually make financial markets less safe than before by causing higher volatility. Such concerns have taken added urgency as regulators are now turning to capital adequacy requirements that reflect the financial risks of regulated institutions. Since year-end 1997, in particular, commercial banks have been allowed to use their internal VAR models to compute their market risk charge (MRC), which should be covered by a minimum amount of capital.¹

Coincidentally, the VAR-based market risk charge came into existence in 1998, a year of considerable turbulence in financial markets, which started with the Russian default and culminated in the near-bankruptcy of Long-Term Capital Management (LTCM).

This episode led to a backlash against risk management techniques. Some observers noted that actual losses suffered by financial institutions did exceed VAR measures, sometimes by large amounts. In fact, this simply reflects well-

Thanks are due to seminar participants at the Bank of England. I also acknowledge useful discussions with Suleyman Basak, Jeremy Berkowitz, Jim O'Brien, and Victoria Saporta.

known limitations of VAR.² Perhaps users were lulled into a false sense of security, which is somewhat astonishing since VAR numbers should be exceeded with some regularity, with a frequency that is inversely related to the confidence level.

More worrisome is the charge that the use of VAR limits led to a “vicious cycle” of position cutting by traders, which put additional downward pressures on prices. Such a claim has been advanced by Dunbar (2000) in his book on LTCM, by Persaud (2000), and has been echoed in the press. The argument is that some shock in volatility, say due to the Russian default, increases the VAR of outstanding positions. In 1999 the *Economist* argued that, as VAR goes up, a “bank is then faced with two choices: put in extra capital or reduce its positions, whatever and wherever they may be. This is what happened last autumn.”³ As the argument goes, several banks could sell the same asset at the same time, creating higher volatility and correlations, which exacerbates the initial effect, forcing additional sales. The purpose of this paper is to assess whether such statements have any foundation in reality.

This line of argument should be a serious source of concern given the generalized trend toward risk-sensitive capital adequacy requirements. The current revision of the Basel credit risk charges, dubbed “Basel II”, also goes in the direction of more sensitive risk charges.⁴ The worry is that the design of such capital adequacy requirements might destabilize the financial system, by inducing banks to tighten credit as credit risk increases, precisely at the wrong time in a recession. This prospect of “procyclicality” is perhaps the most important issue facing bank regulation today.⁵

It is beyond the scope of this paper to discuss procyclicality of credit risk rules. The “vicious circle” argument for market risk charges, however, is being generalized to credit risk as a criticism of any risk-sensitive capital requirements.⁶ We should also note, however, that such criticisms fail to offer plausible alternatives. The history of failures in banking systems and enormous costs to the economy provides a powerful rationale for regulation.⁷ Having no capital requirement at all is not realistic. Alternatively, capital requirements that are not market-sensitive, such as the original Basel 1988 Accord, are open invitations to regulatory arbitrage and can, perversely, induce banks to increase their risks.

This paper will show that capital requirements should be constructed so as to be reasonably “smooth” over time, be they for market or credit risk. This fact has escaped most of the literature on value-at-risk, where the focus has been near exclusively on developing accurate one-day volatility forecasts. One notable exception is Christoffersen and Diebold (2000), who show that there is scant evidence of predictability of volatility at horizons longer than ten days. Other important objectives, beyond accuracy, are the average level of capital as well as fluctuations in capital requirements.

The purpose of this paper is to examine systematically whether market risk charges have had a destabilizing effect, particularly during 1998. The paper

summarizes the literature on topics such as the effect of risk management tools and provides new empirical evidence on the actual behavior of market risk charges. It also draws lessons for the choice of volatility models and smoothing of capital charges.

We analyze three related issues, which are classified into “fallacies”. Critics of financial engineering usually start with the observation that financial markets have recently become more volatile, concurrently with the widespread use of risk management techniques. This is what we call “Fallacy 1: The age of financial instability”, which is analyzed in Section 1. Section 2 then turns to a review of theoretical and empirical evidence on “Fallacy 2: The role of financial engineering”. Finally, Section 3 takes a detailed look at “Fallacy 3: The role of VAR”. The last section contains some concluding observations.

1 Fallacy one: The age of financial instability

Criticisms of modern risk management systems usually start with the casual observation that financial markets have lately become more volatile.^{8,9} After all, there would be less reason for concern if this was not the case.

Each financial crisis seems to generate a period of intense reflection as to the cause of the latest crisis, as well as a flurry of remarks that such crises are becoming more frequent. On the other hand, there is no such rush to explain why markets have lately become so placid.

Given the assertion that (1) financial markets have recently become unstable, and that (2) risk management methods have been developed recently, this association is extended to causation. In other words, risk management techniques are said to lead to higher volatility. Let us first examine the premise of the “age of financial instability” argument.

Among emerging markets, we seem to have experienced many recent financial crises. Even so, however, it is not clear that financial markets or risk management techniques should be blamed. Movements in financial markets inevitably accompany financial liberalization. The flip side of volatility is access to outside capital, which is a substantial benefit if it induces higher long-term economic growth. In addition, one could argue that the recent volatility in emerging markets is due to unsustainable government policies.¹⁰

More fundamentally, emerging markets are the wrong place to look for the effect of risk management techniques, which are certainly more established in so-called “developed” markets. So, the question should be, Is there any evidence that major financial markets have become more volatile in recent times?

To shed some light on this issue, Figure 1 plots the monthly volatility for US equities over the last century. The graph does not give any support to the theory of higher recent risk. Volatility appears to be remarkably stable over these last hundred years. In fact, the largest price moves occurred during the depression of the 1930s. The crash of 1987 was a large loss, but was certainly not out of line with other episodes during this century.

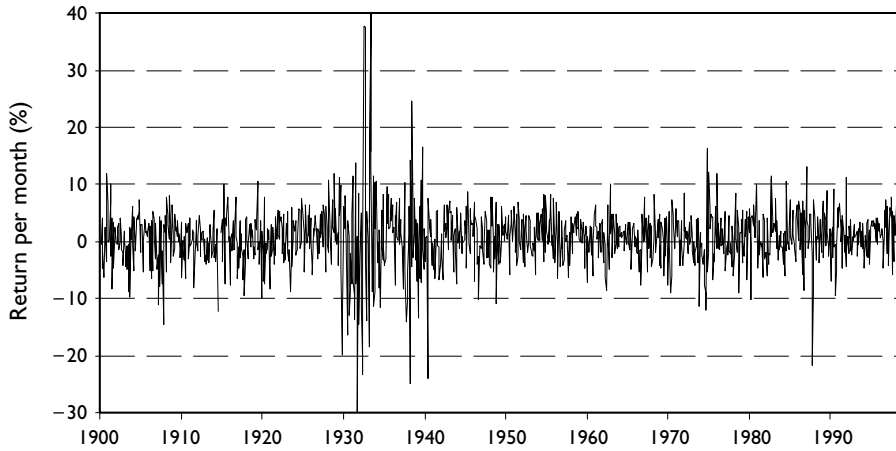
FIGURE I Monthly returns on US equities 1900–2000.

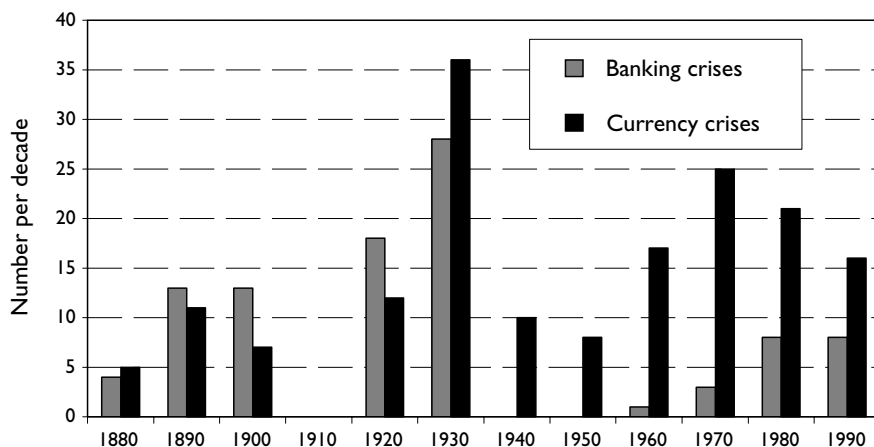
Table 1 gives another perspective, counting occurrences of monthly losses greater than 5% on US stocks by decade. Moves greater than 5% are also reported for gold and the Deutschmark/US dollar exchange rate. The table gives no indication that these markets have recently become more volatile. Instead, the 1990s experienced about half the occurrences of large losses seen in the 1980s. Volatility in these markets seems to be going down, not up.

Alternatively, we can examine the frequency of financial crises during this century. Bordo *et al.* (2001) provide a list of currency and banking crises since 1880 for a fixed sample of 21 countries.¹¹ Figure 2 displays the number of crises per decade. As these authors indicate, “crises were chronic problems not just of the 1990s but in the preceding years as well”.

TABLE I Occurrences of large monthly market movements.

Decade	Losses	Moves	Moves
	> 5% S&P	> 5% Gold	> 5% DM/US\$
1900s	14		
1910s	10		
1920s	9		
1930s	35		
1940s	11		
1950s	5		
1960s	10		
1970s	14	40	8
1980s	9	41	21
1990s	5	18	12

Source: Author's calculations.

FIGURE 2 Frequency of financial crises (21-country sample).

This evidence is supported by long-term histories of other markets. Anderson and Breedon (2000), for example, examine 50 years of asset price volatility in the United Kingdom. They report that the volatility of stocks and interest rates went up in the early 1970s, which was a period of high inflation, but have been on a downward trend thereafter. Turning to causes of price volatility, they find no evidence of any link to financial innovation or regulation. Instead, asset price volatility seems strongly influenced by inflation risk, output growth risk, and macroeconomic policy regimes. In other words, asset price volatility is mainly driven by fundamentals. Even so, recent volatility has been lower than average.

Thus, the argument of “the age of financial instability” seems to be flawed, as financial markets have been no more unstable recently than over the past century.

2 Fallacy two: The role of financial engineering

The second major fallacy consists of blaming modern financial engineering, such as portfolio insurance or VAR systems, for creating excess volatility in financial markets.

2.1 The role of portfolio insurance

Portfolio insurance aims at achieving payoff patterns similar to long option positions. As is well known, a long position in a put can be replicated by holding a fraction, Δ , of the asset with some borrowing or lending B . The put is replicated by

$$p = \Delta \times S + B \quad (1)$$

For instance, with $S = \text{US\$}100$ and 26% annual volatility, a one-year at-the-money put could be replicated by a position of $\Delta = -0.47$ in the asset plus lending out $B = \text{US\$}57$, for a total outlay of $p = \text{US\$}10$.

A key insight of the Black–Scholes (1973) option pricing model is that, for long option positions, the hedge ratio is an increasing function of the spot price. If S drops to, say, US\$90, Δ goes to -0.62 , which requires selling 0.15 units of the asset. This leads to a pattern of trading where falls in S create lower (negative) deltas, and hence more selling. Long option positions can be dynamically replicated by selling in falling markets.¹² Absent any other effect, this could be thought of as increasing volatility.

Indeed, portfolio insurance has been widely blamed for aggravating the crash of 1987. The so-called “Brady Report”¹³ took the position that portfolio insurance was the central cause of the 1987 crash. This view is widely disputed, however.

Miller (1991) argued that the crash of 1987 was due to a breakdown in market structures, ie, the additional uncertainty due to the inability of the New York Stock Exchange to handle abnormal trading volumes. In fact, one of the few recommendations of the Brady Report was to institute trading halts, which hopefully should give enough time to prepare for markets to clear.

On the theoretical front, the latest work is that of Basak (2002), who considers a general-equilibrium model of the economy with portfolio insurance. Such models are useful, as they consider total allocation effects in a multiple-period framework. Basak’s conclusion is that market volatility actually declines when more investors behave as portfolio insurers. The intuition is that portfolio insurers, who are more risk-averse than others, can shift consumption from good states of the world to bad ones, increasing the value of the market in bad states of the world. On the other hand, adding “trend-chasers” has an ambiguous effect on market volatility.

One drawback of theoretical models is that it is sometimes difficult to tell whether their implications depend heavily on their assumptions, which can be subject to differences of opinion. Still, theoretical models provide little support for the view that portfolio insurance increases market risks.

As for the empirical evidence, the challenge is to design tests that separate out the effect of risk management tools from other effects. One such paper is that of Roll (1988), who examines the crash of 1987 across the world. He concludes that portfolio insurance should not be blamed as the average decline in the five markets in which it was used was less than the average decline of the 18 markets in which it was not used.

2.2 The role of other automatic trading rules

Even so, it should be pointed out that many other trading rules, long established before portfolio insurance or modern risk management techniques, can also contribute to a practice of selling in a falling market.

Technical trading rules Trend-following systems also sell after price drops.

Margin calls Leveraged investments can lead to margin calls for long positions after prices have fallen, leading to forced liquidation if investors cannot come up with the required additional margin.

Rebalancing with leverage Schinasi and Smith (2000) demonstrate that the practice of rebalancing to fixed weights with leverage also creates similar trading patterns. This has nothing to do with margin calls but instead is due to the fact that, after a price fall, total wealth drops faster than the price, necessitating a decrease in the risky position.¹⁴

Stop-losses The practice of cutting losses after a fall in the price may be prudent but also involves selling an asset after its price has fallen.

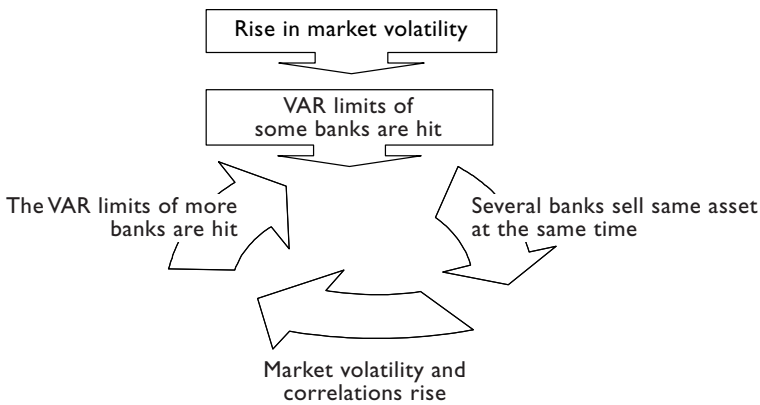
Each of these rules could be “blamed” for increasing risk. Margins for individual investors, for instance, have long been considered with suspicion. Indeed, there was a widely held view that the crash of October 1929 was “caused” by the financial liquidation of shares in response to margin calls. As a result, the Securities and Exchange Act of 1934 transferred margin-setting authority to the Federal Reserve System.

Since then, however, this view has been discredited.¹⁵ Hsieh and Miller (1990), for instance, examine the presumed line of causation from lower margins to higher volatility. They find no empirical evidence to support this. Instead, they show that higher-margin credit volume (or more borrowing) is related to lower volatility. Since lower margins leads to higher-margin credit volume, the line of causation is actually opposite to the common view: lower margins create more speculation, more liquidity and actually lower volatility.

Similar suspicions seem to surround any financial innovation. After equity options were introduced on the Chicago Board Options Exchange in 1973, the SEC imposed a moratorium that suspended the introduction of new options. The fear was that these new instruments could destabilize markets. In fact, subsequent academic research has found that the introduction of options is actually associated with lower volatility of underlying stocks.¹⁶

In a special category are contingent requirements. These involve securities with clauses that give investors apparent protection in case the borrower’s credit rating or stock price deteriorates. One type involves options that give investors the right to sell their stock or bonds to the firm in exchange for a fixed amount of cash. Another are “ratings triggers”, which create additional requirements for the borrower should its credit rating decline. While some are benign, such as the obligation to increase coupon payments, others can require full repayment of the debt. Such clauses are popular with borrowers, who can lower their costs, and investors, who believe that such securities are safer than otherwise.

Contingent requirements can cause serious trouble. They create calls on liquidity precisely in states of the world where the company is faring badly, putting further pressures on the company’s liquidity. Indeed, triggers in some of Enron’s securities forced the company to make large cash payments and propelled it into bankruptcy. Rather than offering protection, these clauses can trigger bankruptcy, affecting all creditors adversely. While these clauses are highly inadvisable, they are in a special category because they create direct claims on a company’s liquidity. Also, because the clauses are borrower-specific, they do not create systemic risk.

FIGURE 3 The VAR vicious circle hypothesis.

Otherwise, all of these rules generate patterns of trading similar to portfolio insurance, but have been in existence for much longer. The latest innovation is that of risk-sensitive capital requirements, such as those based on VAR.

3 Fallacy three: The role of VAR

As explained in the introduction, VAR has been blamed for causing increased volatility during summer 1998. The argument is that some exogenous volatility shock, eg, the Russian default, led to an increase in VAR measures. With commercial banks subject to VAR-based capital adequacy requirements, an increase in VAR, assuming it is binding, should lead to a requirement to raise additional capital or to cut positions so as to reduce VAR.¹⁷ Since raising capital in a hurry is not feasible, commercial banks presumably cut positions, provoking sales that further increased volatility.

This VAR “vicious circle” hypothesis, due to Persaud (2000), is described in Figure 3.¹⁸ The troubling conclusion is that VAR tools increase volatility and are inherently dangerous.

This story, however, has several flaws. First, it assumes that all VAR-constrained traders have the same positions. Otherwise, they could simply cross their trades with little effect on prices. Ultimately, positions cannot be directly compared as these data are proprietary and jealously guarded. Berkowitz and O’Brien (2002), however, address this issue indirectly by looking at correlations of daily trading revenues for a group of six US commercial banks. The average correlation for P&L is 0.12 only for the period January 1998 to March 2000.¹⁹ This provides no support for the hypothesis that these commercial banks had nearly identical positions.

Second, the Basel risk charges apply only at the highest level of commercial banks. Other financial institutions, such as investment banks or hedge funds, do

not have such regulatory requirements. Even for commercial banks, actual capital ratios were far in excess of regulatory requirements, so that market risk charges were not binding. The fact that VAR-based market risk charges were introduced in 1998 and that markets experienced a crisis in 1998 is pure coincidence.

Third, as we will show below, capital adequacy requirements move so slowly that they could not possibly have caused panic selling. To prove this, we need to review the structure of the Basel VAR approach.

3.1 The Basel VAR

To use the internal model approach, banks first have to satisfy various qualitative requirements. The bank must demonstrate that it has a sound risk management system, which must be integrated into management decisions. Notably, the bank has to use the regulatory VAR forecast directly for management decisions. This point is important, as it forces commercial banks to use the same parameters as dictated by the Basel rules.

When this is satisfied, the market risk charge is based on the following quantitative parameters for VAR: (1) a horizon of 10 trading days, or two calendar weeks; (2) a 99% confidence interval; and (3) an observation period based on at least a year of historical data and updated at least once a quarter. In practice, banks are allowed to compute their 10-day VAR by scaling up their one-day VAR by the square root of 10.

The market risk charge (MRC) is then computed as the higher of the previous day's VAR, or the average VAR over the last 60 business days, times a "multiplicative" factor k

$$MRC_t = \max \left(k \frac{1}{60} \sum_{i=1}^{60} VAR_{t-i}, VAR_{t-1} \right) \quad (2)$$

where k is to be determined by local regulators, subject to an absolute floor of 3.²⁰

Apparently, the effect of these rules on the MRC has not been fully appreciated. This is the first paper, to our knowledge, that specifically analyzes the time-series behavior of the market risk charges. By now, there is an enormous literature on VAR, derived from statistical time-series techniques which focus narrowly on one-day VAR accuracy issues.²¹

Here, two smoothing mechanisms are involved. The first is the requirement that the model be based on at least a year of historical data. More precisely, the "average life" of weights on past observations must be at least six months. This requirement can be traced to the observation of Jackson, Maude and Perraudin (1997) that short windows can lead to inaccurate VAR. But, as we will show, this requirement also has the effect of creating VAR measures that are very stable over time. The second mechanism consists of taking the average VAR over 60 days.

3.2 Modelling daily VAR

Let us examine first the requirement of a minimum window for computing daily VAR numbers. With the historical simulation method, the window must be at least one year. Requiring at least 250 days seems reasonable as this would yield an expected 2.5 observations in the left tail. But then, as shown by Pritsker (2001), the VAR risk forecast will not be very responsive to changes in recent volatility due to the fact that each observation in the 250-day window has a relatively small weight of $1/250$. We would need to have several observations below the previous quantile to start moving VAR measures.

Alternatively, consider parametric VAR models based on the standard deviation. Such models can accommodate time variation in risk more easily. More recent models mix historical simulations with parametric volatility modelling.²² Consider, for instance, a simple RiskMetrics-type exponentially weighted moving average (EWMA) forecast. The conditional variance forecast is

$$h_t = \lambda h_{t-1} + (1 - \lambda) r_{t-1}^2 \quad (3)$$

where $\lambda < 1$ is the decay factor and r the rate of return on the asset.

With a position of W_{t-1} in the risky asset, VAR can be computed as $VAR = W_{t-1} \times 2.33\sqrt{h_t}$ at the 99% level assuming a conditional normal distribution. This could be extended to other parametric distributions, however, with a different multiplication factor.

Replacing recursively, this yields geometrically declining weights:

$$h_t = (1 - \lambda) [r_{t-1}^2 + \lambda r_{t-2}^2 + \dots] \quad (4)$$

The average life is then

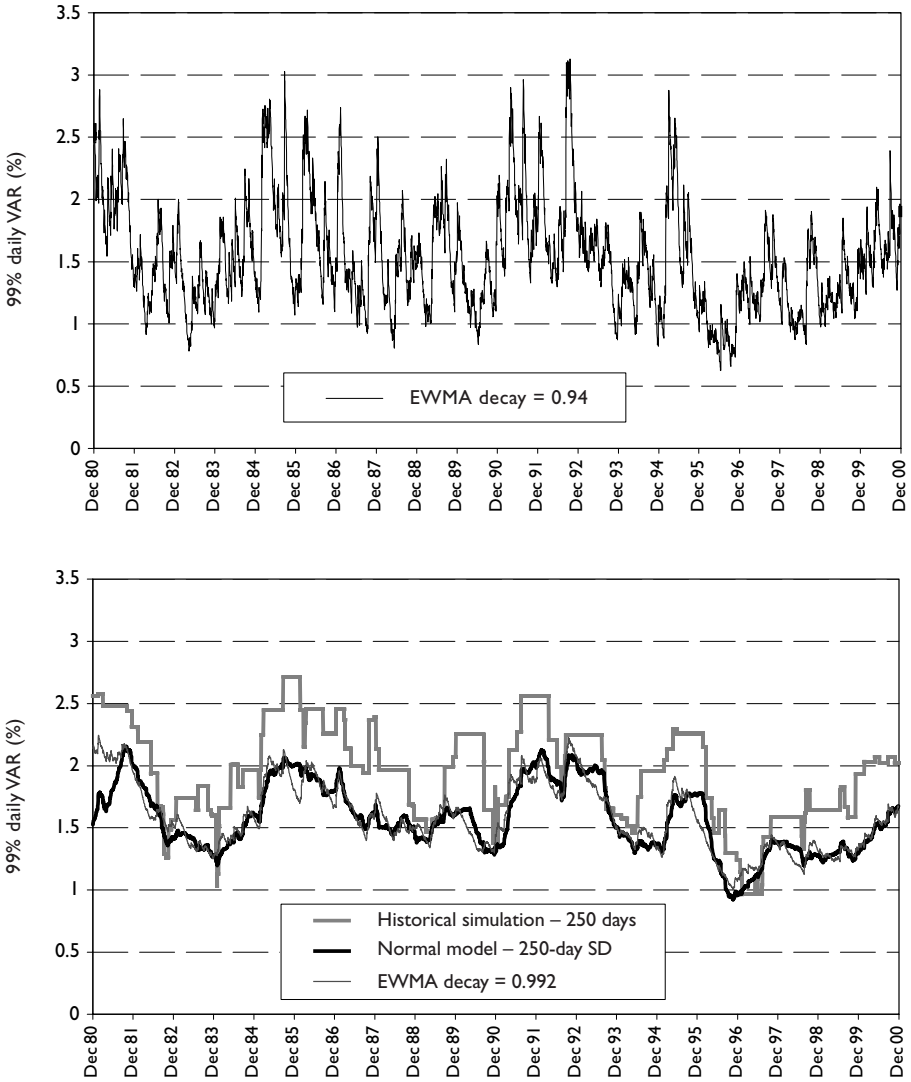
$$\sum_{i=1}^{\infty} i \lambda^{i-1} (1 - \lambda) = \frac{1}{(1 - \lambda)} \quad (5)$$

For example, the average life of the RiskMetrics model with $\lambda = 0.94$ is 16.7 days, or 0.067 years, assuming a 250-day year. This is not allowed under the Basel rules, however. We need λ to be at least 0.992 to achieve an average life of half a year. Alternatively, banks could use a moving average over one year, with equal weights within the window

$$h_t = \frac{1}{250} \sum_{i=1}^{250} r_{t-i}^2 \quad (6)$$

Figure 4 compares the evolution of daily VAR models for the Deutschmark/US dollar rate since 1980. First, note that the historical simulation model generally yields a higher 99% VAR than the other models. This reflects the well-known observation that daily financial series have tails fatter than the normal.²³

FIGURE 4 Comparison of VAR models: Deutschmark/US dollar rate.



In the top graph, the EWMA with $\lambda = 0.94$ is indeed very volatile, due to the higher weight on recent data. This is not relevant, however, since such fast-moving models are not allowed under the Basel rules. The bottom graph shows that the normal-MA model based on a moving window of 250 days is much smoother. The historical simulation method is more volatile, but still much smoother than the EWMA model with decay of 0.94. Finally, the EWMA with 0.992, which is the minimum decay allowed under Basel rules, is nearly as smooth as the normal model.

TABLE 2 Required return for last VAR term to be binding.

	Model					MA
	EWMA, decay (λ)					
Parameters	0.92	0.94	0.96	0.98	0.992	250 days
Required return	10.4 σ	12.0 σ	14.7 σ	20.8 σ	32.9 σ	46.5 σ

Source: Author's calculations.

The fact that banks are constrained to use slow-moving VAR forecasts explains the finding by Berkowitz and O'Brien (2002) that banks' VAR forecasts can be beaten by a simple Garch model applied to the history of P&L. At first sight, these findings are surprising since Garch models have no information on changing positions. One interpretation is that "these results may reflect substantial computational difficulties in constructing large-scale structural models of trading risks for large, complex portfolios." Another interpretation, however, is that the banks's structural models are simply hamstrung by the Basel requirements. And this may be a rational outcome since the purpose of these VAR models is to produce a smooth capital requirement and not necessarily to measure the next day's risk with utmost accuracy.

3.3 Which VAR is binding?

The market risk charge is composed of the maximum of two terms. Which of these terms in Equation (2) will be binding? The first term, which is three times the 60-day average, will in general be higher than yesterday's VAR, and thus will be binding. The bank would have to experience an enormous increase in the previous day's VAR for it to become the dominant factor.

To see this point, assume that VAR is stable at VAR_0 for the last 60-day period, except for a spike on the last day. The second term in Equation (2) will be binding when

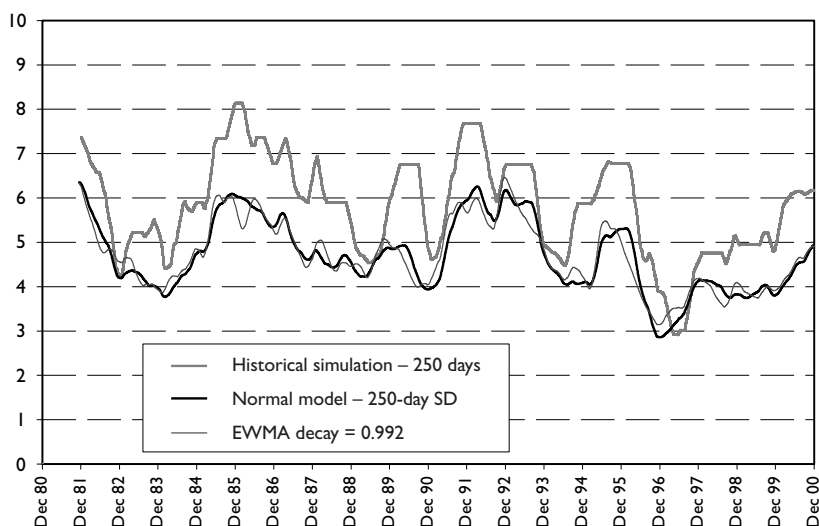
$$VAR_{t-1} > 3(1/60) [VAR_{t-1} + 59VAR_0] \quad (7)$$

which implies

$$VAR_{t-1} > (3 \times 59/57) \times VAR_0 = 3.11 \times VAR_0 \quad (8)$$

This could happen in one of two ways. Assuming stable risk factors, this could be achieved if the exposure W_{t-1} , or size of positions, is multiplied by a factor greater than 3.1. Alternatively, with constant exposures, this could also be achieved by an increase in the volatility of risk factors $\sqrt{h_t}$. The latter is much less likely, however.

Table 2 displays the required latest return, expressed in terms of volatility, such that the second term is binding, for various values of the decay parameter for the EWMA model, as well as the 250-day MA. Lower values for λ imply

FIGURE 5 Market risk charge: Deutschmark/US dollar rate.

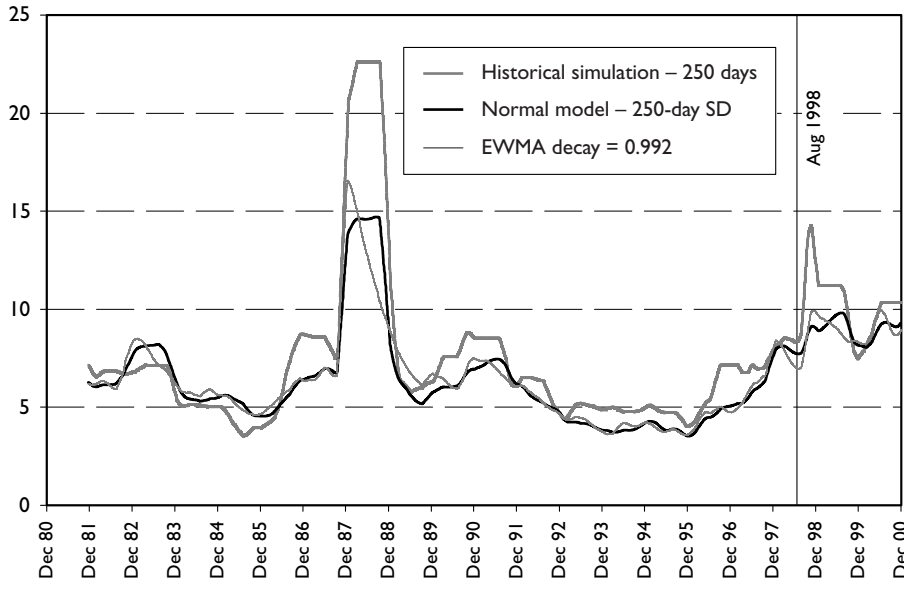
greater weight on the last observation. Hence, a smaller movement is required for the latest observation to be binding.

The table shows, for instance, that with $\lambda = 0.94$, we require a shock 12 times the daily standard deviation. This happened only once in our equity and currency sample, during the crash of October 19, 1987. With the lowest decay allowed, $\lambda = 0.992$, we need a movement of 32.9 times the standard deviation for the latest VAR to be binding. With a simple moving average over the last year, the required move implies a factor of 46.5. It is highly unlikely that an exogenous shock to volatility could induce yesterday's VAR to be binding. Therefore, in what follows we will assume that the market risk charge is driven by three times the average VAR. This is not to say, however, that the second term in the market risk charge is useless. It serves to catch banks that suddenly increase their positions.

3.4 Evaluation of the Basel market risk charge

The contention is that VAR-based capital requirements experienced sharp increases during summer 1998, leading to forced position cutting. The question is, how did the increased volatility of financial markets affect the Basel capital requirements?

Figure 5 displays movements in the market risk charge for a fixed position in the US dollar/Deutschmark exchange rate. Note how smooth the lines are compared to those in the previous graph. This is due to the averaging over the last 60 days. The figure does not include the normal-EWMA model with decay of 0.94 since it is not allowed. The graph shows no evidence of sharply higher market risk charge during 1998. The fluctuations in MRC in 1998 are actually lower than over the rest of the sample period.

FIGURE 6 Market risk charge: US equities.

One could argue that volatility was confined to other markets, however. So, we turn to US equities. Figure 6 plots the MRC for a fixed position in US stocks. There is some evidence of an increase in the MRC during 1998, but not out of line with the history of the last 20 years.

Figure 7 gives more detail for 1998. The graph shows that the increase in the MRC was very slow. It was barely noticeable for the normal model with a 250-day MA and for the EWMA with decay of 0.992. There is a greater increase for the historical simulation method, but, due to the averaging process, the MRC only reached a peak by the end of November, by which time the crisis was over.

Finally, Figure 8 plots the MRC for a short position in 10-year Treasury notes. Again, there is no evidence of sharp movements in the MRC for the historical simulation and MA models. While the 1980s were much more volatile than the 1990s for Treasuries, 1998 was certainly not an eventful year in terms of the Basel market risk charge. In conclusion, it seems inappropriate to blame increases in VAR models for position cutting.

3.5 Objective functions for VAR models

The previous section indicates that smoothness in the VAR-based capital charge is a desirable property. This has been largely ignored in the VAR literature, which has focused on purely statistical issues such as bias and bunching.

“Bias” indicates the extent to which the quantile is well calibrated. It is measured as the percentage of exceptions, or losses worse than the 99% VAR.

FIGURE 7 Market risk charge in 1998: US equities.

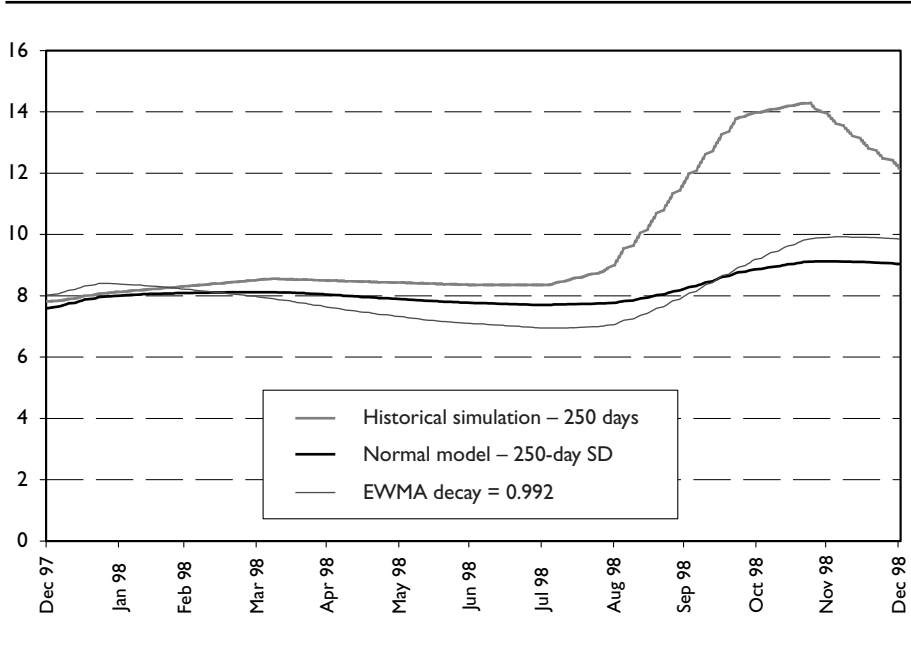
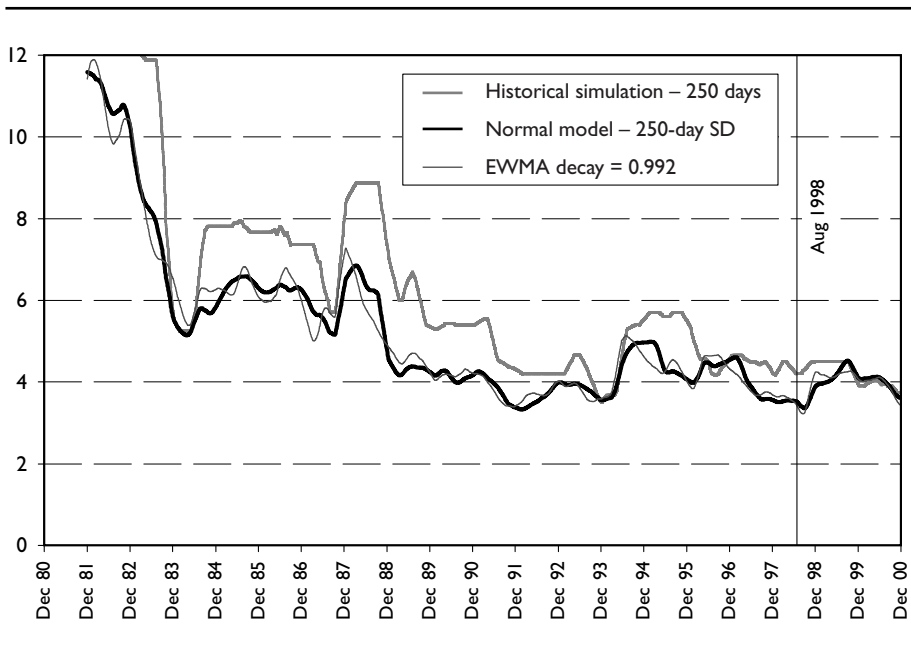


FIGURE 8 Market risk charge: US Treasuries.



Normally, this should be 1%. Whether deviations are significant can be tested, for instance, with a *t*-statistic.

“Bunching” indicates the extent to which exceptions are grouped in time. Ideally, deviations should be uniformly spread over time. This can be measured, for instance, by the Ljung–Box *Q*-statistic of autocorrelations in exceptions, which is distributed as a χ^2 statistic. With 15 lags, we cannot reject if the number is less than 25 at the 95% confidence level. The quest for low bunching has led to more responsive VAR measures, such as Garch or EWMA models.

These statistical measures, however, do not consider the effect on capital charges. All else equal, a bank would want low and stable capital charges. The problem is that these economic goals are in direct conflict with the statistical objectives.

Lower charges could be achieved at the cost of more exceptions. There is no question, however, that a VAR system should be as unbiased as possible. This is why the Basel Committee has established a backtesting framework with penalties for banks that incur too many exceptions.

Similarly, less variable capital charges could be achieved at the expense of more bunching. Less variability is economically beneficial. If capital cannot be raised quickly, or positions adjusted quickly, more variable capital charges imply that the institution has to hold more spare capital to absorb peaks in the capital charge. Whether bunching is intrinsically bad, however, is not so obvious.

These tradeoffs are illustrated in Table 3, which compares the performance of five VAR models in terms of various objective functions. The table reports bias and bunching, as well as the average and standard deviation of the one-day 99% VAR forecast and the capital charge based on the 60-day average.

The simulations use daily data from 1980 to 2001, for US stocks, US bonds (represented by a short position in 10-year Treasury notes), and the Deutschmark/US dollar rate. This represents about 5,050 *ex-post* observations. All models are purely anticipative, based on the last 250 days of data.

The “normal” and “Student” models are based on the historical standard deviation and the appropriate deviate, eg, 2.33 for normal data, and the corresponding number from the Student distribution, with degrees of freedom estimated by matching the kurtosis over the last year. The EWMA methods use a decay $\lambda = 0.94$. “EWMA + N” assumes a conditional normal distribution; “EWMA + HS” bootstraps the scaled residuals.²⁴

The left columns give the bias for each model and market. The “normal” model substantially understates tail probabilities and appears badly biased in all markets. The tail percentage ranges from 1.52% to 1.90%, which is significantly higher than the expected 1.00%. This reflects the well-known observation that financial series have fatter tails than the normal distribution. More unexpected is the observation that the EWMA + N model has even worse bias for these three markets. The other models, the Student, HS, and EWMA + HS, are much better calibrated.

The next column shows that the first three, unconditional, models all have too much bunching. The statistics reject the hypothesis of no bunching. The EWMA models generally deal well with heteroskedasticity.

TABLE 3 Comparison of performance of VAR models.

VAR model	Bias		Bunching	One-day VAR			Capital (60-day)		
	Exceptions	t-test	Ljung-Box	Average	S.d.	S.d.	Average	S.d.	S.d.
	Per cent		χ^2 -test	Level	Change		Level	Change	
US equities									
Normal	1.52	3.74*	84.06*	2.243	0.830	0.029	2.236	0.814	0.007
Student	1.11	0.78	73.31*	2.503	0.936	0.036	2.495	0.915	0.008
Hist. sim.	1.17	1.20	68.67*	2.593	1.310	0.072	2.583	1.274	0.013
EWMA + N	1.74	5.30*	36.72*	2.170	1.058	0.168	2.167	0.903	0.019
EWMA + HS	0.97	-0.22	18.99	2.749	1.563	0.247	2.742	1.330	0.029
US bonds									
Normal	1.66	4.68*	47.50*	1.680	0.586	0.012	1.694	0.607	0.003
Student	1.08	0.56	46.84*	1.877	0.651	0.019	1.892	0.675	0.003
Hist. sim.	0.78	-1.57	39.28*	2.020	0.787	0.033	2.037	0.809	0.005
EWMA + N	1.98	6.95*	28.88*	1.584	0.617	0.094	1.600	0.597	0.010
EWMA + HS	1.02	0.13	12.02	1.977	0.755	0.126	1.990	0.697	0.013
DM/US\$ rate									
Normal	1.90	6.46*	21.91	1.564	0.265	0.009	1.566	0.265	0.002
Student	1.21	1.53	27.93*	1.762	0.277	0.017	1.765	0.276	0.002
Hist. sim.	0.92	-0.58	36.08*	1.926	0.372	0.030	1.930	0.361	0.004
EWMA + N	2.07	7.72*	17.83	1.516	0.419	0.080	1.519	0.343	0.009
EWMA + HS	0.80	-1.42	23.88	1.915	0.627	0.119	1.920	0.517	0.013

The table compares the performance of various VAR models in terms of various objective functions. Rejection at the 95% significance level is denoted by *.

"Bias" is measured as the percentage of exceptions, or losses worse than the 99% VAR; the t-statistic tests whether the actual percentage is significantly different from 1.00. "Bunching" is measured by the Ljung-Box Q-statistic of autocorrelations in exceptions with 15 lags; the χ^2 -statistic tests whether the deviations are independent over time, and cannot reject if the number is less than 25 at the 95% confidence level. The "One-day VAR" columns give the average and standard deviation of the VAR forecast. The standard deviation is reported for the level of VAR and the one-day change. The "Capital" columns give the average and standard deviation of the market risk charge using the average of the VARs over the last 60 days.

Daily data are used from 1980 to 2001, which represents about 5,050 *ex-post* observations. All models are based on the last 250 days of data. The "normal" and "Student" model are based on the standard deviation and the deviate (eg, 2.33 for normal data) and the corresponding number from the Student distribution, with degrees of freedom estimated by matching the kurtosis over the last year. Historical simulation ("Hist. sim.") is a bootstrap method using the empirical 99% quantile. The exponentially weighted moving average ("EWMA") methods use a conditional forecast of the variance with decay $\lambda = 0.94$, the same as RiskMetrics. The "EWMA + N" method assumes a conditional normal distribution. The "EWMA + HS" method bootstraps the scaled residuals.

The last six columns give the average and standard deviation of the one-day VAR and of the 60-day average. Focusing first on the average, the table shows that models that have high bias have low average VAR, and vice versa. A greater percentage of exceptions leads to low average capital charges. This is why back-testing is needed.

Standard deviations are reported for VAR measures in levels, ie, relative to the long-term average, and in daily changes. The latter measure gives a better indication of short-term fluctuations in VAR. The table reveals a number of interesting relationships. First, fluctuations for the normal and Student models are systematically less than those based on historical simulations. This is due to sampling variability in the historical simulation estimator.²⁵ Second, fluctuations for the EWMA models are systematically greater than those based on unconditional distributions. Third, as previously noted, fluctuations in the 60-day average are much smaller than those in the one-day VAR, by a factor of five to 10. Table 3 also demonstrates the intrinsic conflict between low bunching and stable capital charges. The EWMA models have lower bunching than the others but much more variable capital charges.

Overall, the best model across these conflicting objectives seems to be the “Student” model. It offers low bias, relatively low average capital, and low volatility in the capital charge.

4 Conclusions

This paper has taken another look at allegations that risk management systems contribute to increased volatility in financial markets, in particular during the summer of 1998. We started by showing that major financial markets have been no more volatile in recent years, which have witnessed many financial innovations.

The debate about the role of financial engineering bears an eerie resemblance to discussions of portfolio insurance, which has been widely blamed for the crash of October 1987. There is still considerable controversy, however, about the actual effect of portfolio insurance. The same rush to judgment was also observed with margins during the crash of 1929 and when futures and options were introduced. Instead, the empirical evidence suggests that financial innovations provide a stabilizing influence.

This paper provides new evidence that VAR-based regulatory capital charges for commercial banks cannot plausibly be blamed for the volatility of 1998. Market risk charges move very slowly in response to changing market conditions due to the averaging over the last 60 days and slow updating imposed by the Basel rules.

A new insight of this analysis is that risk-sensitive systems should incorporate smoothing mechanisms. The quest for accuracy in VAR measures, which would dictate fast-moving systems such as Garch, should take second place to stability in the market risk charge.

This is not to say, however, that VAR systems should be viewed as a panacea. They provide no guarantee that large losses will not occur. In addition, traders could wilfully attempt to “game” their VAR by altering the distribution of P&L to satisfy a fixed VAR at the expense of a small probability of large losses. Such possibilities have been analyzed by Ju and Pearson (1999), but are more likely at

the level of traders' desks than the whole institution. Artzner *et al.* (1999) propose instead a "tail loss measure", which is the expectation of the loss once VAR is exceeded. Such measures could usefully supplement VAR numbers.²⁶ This explains why the industry and regulators emphasize the importance of stress tests, which precisely examine the effect of unusual market movements.

Overall, it is fair to conclude that there is no evidence to support the assertion that VAR-based risk management systems destabilize the financial system.

1. The Basel Committee on Banking Supervision (BCBS) amended the original 1988 Basel Accord to add a capital charge for market risks. See BCBS (1996).
2. See the first edition of Jorion's (2000) book on VAR.
3. As quoted in the *Economist*, June 12, 1999. See also the string of *Economist* articles (October 17, 1998; November 14, 1998) on the same theme. This line of argument is even recognized by central bankers – see Clementi (2001).
4. See BCBS (2001).
5. See for instance Ervin and Wilde (2001) and Borio, Furfine and Lowe (2001).
6. See Danielsson *et al.* (2001).
7. See, for instance, Caprio and Klingebiel (1999). Hogarth and Saporta (2001) estimate that typical losses from banking crises cost an average of 15% to 20% of annual GDP.
8. See "The age of financial instability", *Financial Times*, 13 June 2001.
9. It could be argued that greater volatility in financial markets is actually beneficial if it dampens volatility in the real economy. Consider, for example, the choice between a flexible exchange rate and a fixed rate, including the extreme case of a common currency. A common currency transmits shocks across economies and may create greater volatility in output and employment. Perhaps it is better for risks to appear in financial markets, where they can be hedged and diversified, rather than being shifted to the real economy.
10. More generally, the late Fischer Black (1995) even argued that governments are responsible for creating systemic risk. He included as examples interference with business and with the enforcement of contracts, as well the creation of debt guarantees. Indeed, he suggested that banking systems that go bankrupt are nearly always due to governments.
11. A "currency crisis" is defined from either a change in parity value, or large jump in a combination of the spot rate, interest rate, or level of reserves. A "banking crisis" is identified with the erosion of most of the capital of the banking system. The countries are Argentina, Australia, Belgium, Brazil, Canada, Chile, Denmark, Finland, France, Germany, Greece, Italy, Japan, The Netherlands, Norway, Portugal, Spain, Sweden, Switzerland, the UK, and the USA.
12. See Rubinstein (1985) for alternative paths to portfolio insurance.
13. Formally, the *Report of the Presidential Task Force on Market Mechanisms* (1988).
14. Consider for instance a position of US\$100 invested as 200% in a risky asset worth US\$100 and -100% in cash. If the price falls to US\$80, the portfolio is now worth US\$60, or US\$160 in the asset and -US\$100 in cash. Rebalancing to fixed weights, we have US\$120 in the asset and -US\$60 in cash. Hence, this involves selling the asset after the price fell.

15. See the review by Kupiec (1998).
16. See Detemple and Jorion (1990) for evidence on US stocks. Similar results were found for Canadian and UK stocks. As options involve high leverage and the equivalence of short-selling, these results can be interpreted in terms of mitigation of short-sales constraints.
17. There could be some feedback effect due to marking-to-market losses on capital. Many banks did suffer trading losses in 1998, which could lead to position cutting. This has nothing to do with VAR, or any risk-sensitive risk measure, however. Any rule based on, say, the ratio of notional to capital would give the same results.
18. Persaud (2000) also references work on “herding” by Morris and Shin (1999). The problem with the theoretical literature on herding is that these models are very sensitive to the assumptions. Heinemann (2000), for example, has shown that the conclusions of Morris and Shin (1998), which are the basis for their more recent paper, can be overturned in a more general model. Bikhchandani and Sharma (2001) provide a useful review of the literature on herding in financial markets.
19. In a personal communication Berkowitz and O’Brien report that correlations over longer periods rise by a factor of two. Even a correlation of 0.24, however, is not very high.
20. Ignoring the specific risk charge, which is explained in more detail in BCBS (1996).
21. See Hendricks (1996), Jackson, Maude and Perraudin (1997), Christoffersen (1998), Lopez (1999), among others.
22. See for instance Boudoukh, Richardson and Whitelaw (1998) and Hull and White (1998).
23. See Hendricks (1996).
24. This has been used, for instance, by Hull and White (1998).
25. As Jorion (1996) has argued, methods based on the sample standard deviation are more robust as this statistic uses the whole distribution. The historical simulation method uses the 1% quantile, which is much more imprecisely estimated, especially in a sample as short as 250 days.
26. Basak and Shapiro (2001) examine the effect of this gaming at the level of the institution on financial markets. They show that strict VAR limits could induce banks to take on more risk in bad states of the world, ie, after VAR limits have been breached, which could cause higher volatility in financial markets. The authors show that these shortcomings are remedied by tail loss measures.

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