Bank capital and Value at Risk

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The views expressed are those of the authors and do not necessarily reflect those of the Bank of England. We thank Lina El-Jahel and Adrian Chalcraft for research assistance, Xavier Freixas, Stephen Figlewski, and Bank of England staff for valuable comments, and J.P. Morgan, Tokai Bank Europe and various other financial institutions for generously supplying us with data.

Issued by the Bank of England, Threadneedle Street, London, EC2R 8AH to which requests for individual copies should be addressed; envelopes should be marked for the attention of Publications Group. (Telephone: 0171-601 4030).

Bank of England 1998
ISSN 1368-5562

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Abstract

To measure the risks involved in their trading operations, major banks are increasingly employing Value-at-Risk (VaR) models. In an important regulatory innovation, the Basle Committee has proposed that such models be used in the determination of the capital that banks must hold to back their securities trading. This paper examines the empirical performance of different VaR models using data on the actual fixed income, foreign exchange and equity security holdings of a large bank. We examine how a bank applying the models would have fared in the past if the proposed rules had been in operation.

Journal of Economic Literature Classification Numbers G11, G21, L51.

1 Introduction

1.1 Trading risk and the Basle Accord

In the last decade, banks have greatly increased their holdings of trading assets such as bonds, equities, interest rate and equity derivatives, foreign exchange and commodity positions. Their motive in this has been to make trading profits and to hedge exposures elsewhere in their banking portfolios. The swap market has been especially important in enabling banks to raise funds in a wider range of markets while avoiding mismatched portfolios.

The increase in the relative importance of trading risk in bank portfolios has obliged regulators to reconsider the system of capital requirements agreed in the 1988 Basle Capital Accord. The common framework for treating risk laid down by the 1988 Accord was designed primarily for limiting credit risk and had clear drawbacks in its treatment of trading risk. For example, short positions and holdings of government securities were not covered.[(1)] Also, the counter-party risk of off-balance sheet positions was included but not their position risk.

The capital charge imposed by the 1988 Accord was a minimum of 8% of private sector assets regardless of maturity and made no allowance for the volatility of different security prices. Thus, low-risk short-maturity private sector bonds were penalized much more than longer-dated corporate debt. In certain markets, this placed banks at a competitive disadvantage compared to securities firms for whom capital requirements, at least in the United Kingdom and United States, allow for such risk in a more sophisticated way.

These problems led the European Commission and the Basle Supervisors' Committee to study alternative ways of treating trading book positions. The Commission's Capital Adequacy Directive (CAD), agreed in 1993 and introduced at the beginning of 1996, established EU minimum capital requirements for the trading books of banks and securities firms. The Basle Committee proposals are summarised in a paper issued in January 1996 entitled, 'Overview of the Amendment of

[(1)] Although the latter were included in the United Kingdom.

the Capital Accord to Incorporate Market Risks.' This and earlier papers issued by the Committee[(2)] propose a system comprising two alternative ways of calculating trading book capital. Commercial banks would themselves decide whether they wished to be regulated under the so-called 'standardised' or the 'alternative' model proposed by Basle. G10 supervisory authorities are to implement the two approaches by end 1997.[(3)]

1.2 Additive capital requirements

The CAD and the Basle standardised approach are very similar. Heavily influenced by the systems of capital requirements operated by United Kingdom and United States securities regulators, both systems require firms to hold capital equivalent to a percentage of its holdings in different asset categories, where the percentages are chosen to reflect the price volatilities of generic assets in the relevant categories.

An important drawback of both CAD and the Basle standardised approach is the *additive* nature of the capital required for broad asset categories.[(4)] The requirement is calculated market by market for equity, foreign exchange (FX) and interest rate risk, and then these separate requirements are summed. Thus, for example, the capital requirement for a long position in United Kingdom equities takes into account hedging in the same market but not, say, any offset from holding a short position in United States equities. Nor does it take into account the benefits of diversification from holding long positions in both markets.[(5)]

The effect is to favour specialised market-makers at the expense of globally diversified banks. Banks that run global portfolios have, therefore, pressed the Basle Committee to consider approaches to

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[(2)] See Basle Committee on Banking Supervision (1995a) and (1995b).

[(3)] Jackson (1995) and Kupiec and O'Brien (1995) discuss risk measurement in the context of bank regulation.

[(4)] Dimson and Marsh (1995) discuss at length the implications of the building-block approach.

[(5)] The United Kingdom securities regulators address this problem for equity positions by using a simplified Sharpe portfolio model but this approach was not adopted by either CAD or Basle.

capital requirements that do recognise the benefits of diversification. Clearly, achieving this in a regime in which the supervisors set the percentage capital requirements and hedging allowances for different types of position would have been extremely complex. But, the firms had themselves been developing methods of measuring the risk of given losses on their total portfolio and these internal whole-book or Value at Risk (VaR) models have provided a way of making the problem tractable.[6] Hence, it was possible to develop an alternative to the Basle standardised approach.

1.3 The Basle Alternative Approach

In the Basle 'alternative approach', rather than laying down the percentage capital requirements for different exposures, regulators would establish standards for banks' in-house risk models. These models would then form the basis for the calculation of capital requirements. This would have the key additional advantage of aligning the capital calculation with the risk measurement approach of the particular firm.

Using internal models to generate capital requirements is a radical change in approach but supervisors have for some time been moving steadily in this direction. In the CAD and the Basle standardised method, it is recognised that only by employing the firms' internal models can some positions be correctly processed for inclusion in the capital calculation. This is particularly the case for options, but sensitivity models designed to convert large books of swaps into equivalent bond exposures and to assess the risk on foreign exchange books were also allowed.

It does, however, raise a number of issues for supervisors concerning the safeguards which should be put in place to ensure that the capital requirements generated are adequate. Basle has addressed this in several ways. One is to lay down standards for the construction of the models. For example, they must calculate the distribution of losses over

[6] A systematic description of different approaches to VaR may be found in Jackson (1995). The June 1996 special issue of *Risk Magazine* provides various practitioner perspectives on VaR.

a ten-day holding period using at least twelve months of data and must yield capital requirements sufficient to cover losses on 99% of occasions.

Adopting general standards is necessary both to increase consistency between banks and to ensure that capital requirements really are adequate to the task. In theory, however, they might drive a wedge between the regulatory model and the one which the firm uses for its own purposes. Typically the firms' VaR models use a 95% confidence interval and a 24-hour holding period. Basle will not, however, prescribe the type of model to be used.

1.4 Regulatory safeguards

As a check on the accuracy of the models, under the proposed alternative Basle approach, the supervisors will carry out back-testing, the comparison of actual trading results with model-generated risk measures. This may pose problems, first because trading results are often affected by changes in portfolios in the period following the calculation of the VaR. Because of this, Basle has urged banks to develop the capability to perform back-tests using the losses which would have been made if the book had been held constant over a one-day period. Second, Kupiec (1995) argues that back-testing requires a large number of observations in order to make a judgment about the accuracy of the model. Nevertheless, back-testing and some kind of penalty are essential to provide incentives for firms to increase the accuracy of the models. The Basle proposals envisage that firms that do not meet the back-testing criterion for accuracy should suffer additional capital charges.

As well as back-testing, the system would include the safeguard of an over-riding multiplier. More precisely, Basle is proposing that the capital requirement should be equivalent to the higher of (i) the current VaR estimate and (ii) the average VaR estimate over the previous 60 days multiplied by three. The incorporation of a multiplier has the advantage of making the system more conservative without distorting the treatment of trading books with different risk profiles. However, if the multiplier is too high, it could discourage firms from developing in-house models and lead them to select the standardised rather than the alternative approach since, as mentioned above, banks themselves are to be free to choose which they adopt.

1.5 Value-at-Risk analysis

What then is the nature of the 'whole-book' or VaR models that will be used in capital requirement calculations by banks that take the Basle Committee's alternative approach? The typical VaR models developed by the firms for their internal risk-management purposes attempt to measure the loss on a portfolio over a specified period (often the next 24 hours) that will only be exceeded on a given fraction of occasions (typically 1% or 5%). Two broad types of VaR analysis are employed.

First, under parametric VaR analysis, the distribution of asset returns is estimated from historical data under the assumption that this distribution is a member of a given parametric class. The commonest procedure is to suppose that returns are stationary, joint normal and independent over time. Using estimates of the means and covariances of returns, one may calculate the daily loss that will be exceeded with a given probability. Second, the simulation approach to VaR analysis consists of finding, from a long run of historical data, the loss that is exceeded on a given percentage of the days in the sample. As a non-parametric procedure, the latter imposes no distributional assumptions.(7)

In this paper, we examine various aspects of VaR analysis and its use as an instrument of banking regulation from an empirical point of view.(8) Using data on the equity, interest and FX rate exposure of a bank with significant trading activity, we compare the empirical performance of parametric and simulation-based VaR analysis. Even

(7) The terminology used to distinguish these two forms of VaR analysis varies across authors in a somewhat confusing manner. For example, Laycock and Paxson (1995) refer to what we call parametric and simulation-based VaRs as simulation and back-testing approaches respectively. The former is also often referred to as the variance-covariance approach.

(8) A significant omission in our study is that we do not study the treatment of derivatives in VaR models. Basle Committee on Banking Supervision (1994) discusses some of the problems involved in the risk management of derivatives portfolios. Estrella (1995) argues that the standard approach of linearising non-linear claims such as options can cause problems.

though the proposed Basle Accord Amendment does not specify which approach banks should use, the penalties envisaged for banks whose models fail to forecast loss probabilities accurately makes this an important question. We also look at the impact of window length (ie, the length of returns data used) and weighting factors for the returns. The alternative Basle system requires the use of at least one year of data, and we assess whether this appears sensible.

A finding of considerable practical significance is that adopting different approaches to estimating return volatility for reasonably well-diversified fixed income portfolios makes little difference to the degree to which one can forecast risk. The techniques one employs in calculating volatility can affect forecasting accuracy in a statistically significant way but the improvements are not substantial enough to be economically significant. On the other hand, the various approaches to VaR modelling differ widely in the accuracy with which they predict the fraction of times a given loss will be exceeded. If this latter criterion is applied, simulation-based rather than parametric VaR techniques appear preferable.

Last, we investigate the precise formula for required capital proposed in the Basle alternative approach. As mentioned above, the current proposal is that capital must exceed the maximum of (i) the previous day's VaR, or (ii) three times the average VaR of the previous 60 days. It is interesting to ask with our 'real life' books, how the scaling factor and the fact that one must take the maximum of two quantities affect the outcome.

2 Empirical analysis of VaRs

2.1 Trading books

In this section, we compare the performance of simulation-based VaR methods with parametric VaR analysis that assumes joint normality of asset return distributions. In evaluating different VaR techniques, we employ data on the trading book of a bank with significant trading exposure. From these data,[9] provided to us on condition of anonymity, one may deduce the amounts held by the bank in a number of asset categories. The asset breakdown consists of 14 maturity 'buckets' (ie, intervals along the yield curve) for five different government bond markets (United Kingdom, United States, Japan, Germany and France). The time buckets comprise four bands for maturities less than one year, annual bands for one to ten-year maturities, and a single band for maturities greater than ten years.

Table A shows the break-down of the four different books that we employed in our statistical analysis. The first three portfolios were those held by the bank on three consecutive months. In the table, the foreign exchange exposure for a particular currency represents the total net sterling value of assets denominated in that currency. Hence, for example, if the bank acquires a ten-year Deutsche Mark-denominated bond, both the FX exposure and the six to ten-year bond categories in the Deutche Mark column of Table A increase.[10]

Two features of the data stand out. First, the degree to which the bank's fixed income exposure fluctuates over relatively short periods of time is quite striking. This fact underlines the importance of banks satisfying capital requirements for market risk almost on a continuous basis. Thus, VaR models need to be run daily. Second, the bank's net foreign exchange (FX) exposure is small except for the large short United States dollar position in portfolio 4. This suggests that the bank is systematically hedging the net FX risk in its trading book.[11] Other data in our possession suggest that the months we chose were fairly typical of the bank's general behaviour in that FX risk is systematically hedged while other exposures fluctuate considerably.

The main advantage of using actual books for the predominant bank trading risks is that it ensures that the pattern of risk exposures along the yield curve and between markets is realistic. The amount of exposure taken at different points on the yield curve and between

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(9) The data consisted of sensitivities of the different assets in the book to given market movements.

(10) The practice of considering the exchange rate and foreign currency price risks separately is common among practitioners.

(11) The exposures were the consolidated exposures for the bank and its securities companies, and therefore this did not simply reflect the effect of the Bank of England's guideline on overnight FX exposures that applies to the bank.

markets clearly reflects a bank's investment decisions. Randomly generated portfolios are unlikely to be representative and it would be difficult to build stylised books which were representative without basing them on actual books.

Lastly, most of our data on the bank's portfolio consisted of fixed-income investments in different currencies. However, it is important to examine whether VaR analysis performs differently when applied to portfolios containing equities rather than just fixed-income and FX positions. The bank was kind enough to provide us with data on a single additional portfolio, which we label portfolio 4, which contained equity exposures. The relatively small size of this equity book is typical of what most banks hold.

2.2 Return data

The bond returns employed in our study were based on a time series of zero-coupon yield curves calculated by an investment bank (not the one that supplied us with portfolio data). From this, we calculated holding returns for the maturity categories on which we had portfolio data. For equities, we employed the returns on the French CAC-40, the British FT-All Share, the German DAX, the US S&P Composite and the Japanese Nikkei-225. Including equities and FX positions meant that in total we were dealing with 79 different sources of risk. All returns were calculated as changes in log prices.

Throughout the analysis we took sterling to be the base currency and employed data from July 1987 to April 1995. Table B shows the annualised sample standard deviations of the daily returns on our 79 different rates of return. The figures in Table B suggest that returns on fixed-income books are much less volatile than returns on books that include significant equity exposure unless the fixed-income portfolio includes very long-dated securities. Even holdings heavily weighted towards long-dated bonds will have relatively low average durations, and hence are likely to exhibit lower volatilities than portfolios that include equities or FX exposure.

Although the returns data covered the period July 1987 to April 1995, estimates of the VaRs were made only for the period June 1989 to April 1995. Data from the earlier period were used in whole or in part (depending on the length of the data window) to construct the first VaR estimate. This meant that it was not possible to compute a VaR estimate for the 1987 equity market crash although the crash did appear in the past data when VaR estimates were calculated using a 24 month window. (This explains the high estimates apparent in Chart 1 for portfolio 4 at the start of the estimation period.)

2.3 Parametric VaR analysis

The first issue we wish to address in our empirical analysis is the sensitivity of parametric VaR analysis to the precise way in which the volatilities are estimated. The approach to volatility estimation typically used in VaR applications is to take a weighted average of the squared deviation from an estimate of the mean return, using a window of lagged data. Thus, if r_t is the holding return at t, a typical estimator for $\sigma^2 = \mathrm{Var}(r_t)$ would be:

$$\hat{\sigma}_t^2 = \frac{1}{T-1} \sum_{i=0}^{T-1} \lambda_i \left(r_{t-T+i} - \overline{r}_t \right)^2 \qquad (1)$$

where $\lambda_i \in [0,1]$, $\sum_{i=0}^{T-1} \lambda_i / T = 1$, and $\overline{r}_t \equiv \sum_{j=0}^{T-1} r_{t-T+j}/T$

In implementing the VaR models, we work out the returns for one-day or rolling ten-day holding periods on a given portfolio and then calculate volatilities, tail probabilities etc, using that single series. This approach yields results that are arithmetically identical to those one would obtain if one estimated a full covariance matrix for n individual asset return series, call it Σ, and then estimated the volatility of a portfolio with portfolio holdings, $a \equiv (a_1, a_2, \ldots, a_n)'$, by calculating the quadratic form, $a'\Sigma a$. The latter approach is that taken by practitioners including JP Morgan in their *RiskMetrics* system and is clearly more efficient if one has many portfolios for which one wants the Value at Risk on a single date. When a large number of VaR calculations are required for a small number of portfolios on different dates, our approach is quicker.

Three choices must be made in implementing the parametric VaR described above, namely (i) what is an appropriate length for the lagged data 'window,' (T); (ii) what weighting scheme should be adopted, $(\lambda_0, \lambda_1, \ldots \lambda_{T-1})$; and (iii) should the mean be estimated using the sample mean, $\sum_{j=0}^{T-1} r_{t-T+j}/T$, or set to zero as some empirical researchers have advocated.[12]

2.4 Forecasting performance and window length

Table C shows two ways of assessing the sensitivity of the VaR results to the choice of T. In the upper block of the table, we show the mean absolute forecast error where we define the forecast error at period t as:

$$\left|\, |r_t - \overline{r}_t| - \hat{\sigma}_t \,\right| \qquad \textbf{(2)}$$

Averaging the absolute forecast errors over the entire sample period yields a measure of the accuracy of the volatility estimates. Standard errors are reported in parentheses under each mean. These are calculated using the technique of Newey and West (1987) and hence are robust to complex patterns of time dependence. The standard errors give a very conservative impression of the statistical significance of differences in mean forecast errors since means calculated under different assumptions are highly positively correlated, reducing the variability of the average difference. Hence, we also give the t-statistics for the difference between each mean absolute forecast error and the other means in the same row of the table. The t-statistics are again calculated using Newey-West techniques.

Note that we tried working with various other measures of forecast accuracy. First, one may define the forecast error as $\left|\, (r_t - \overline{r}_t)^2 - \hat{\sigma}_t^2 \,\right|$ and then employ the sample mean of these absolute differences. In this case, one is evaluating forecasts of the instantaneous variance rather than the instantaneous standard deviation. Since VaR calculations employ the latter, this is probably not appropriate. Second, we experimented by using root mean squares of the forecast errors instead of simply means. The problem with this approach is that it attributes most weight in the comparison to outliers. We thought it better, therefore, to use means.

[12] See, for example, JP Morgan (1995), page 66.

In the lower block of Table C, we provide measures of the degree to which capital requirements based on different VaR models do indeed cover losses that occur with a given probability. Assuming normally distributed returns, one may deduce from the time series of estimated volatilities a corresponding series for what we shall call 1% cut-off points meaning the loss which, according to the model, will be exceeded on average 1% of the time. More precisely, the cut-off points may be obtained by inverting the equation:

$$\text{Prob}\left[\sum_{n=1}^{N} r_{nt} a_n < -\gamma \,\middle|\, \sigma^2, \mu\right] = 0.01 \tag{3}$$

for γ on a period-by-period basis. (In equation (**3**), a_n is the holding of the nth asset. Throughout our analysis, we shall normalise initial wealth to unity so that $\sum_{n=1}^{N} a_n = 1$.) Inverting this equation yields:

$$\gamma \equiv -\mu - \Phi^{-1}(0.01)\,\sigma \tag{4}$$

where $\Phi(\cdot)$ is the cumulative distribution function for a standard normal random variable. As a measure of the performance of different VaR models, the lower panel in Table C shows the proportion of actual portfolio returns that fall below the 1% cut-off points.

As one may see from the upper panel of Table C, the mean absolute forecast errors are relatively insensitive to the length of the data window, though it is true in most cases that a short window yields slightly more accurate forecasts. On the face of it, the insensitivity is surprising since plots of the forecasts based on long or short windows look quite different (see Chart 2). Furthermore, comparisons of the forecasting accuracy of different VaR techniques applied to individual exchange rate returns included in JP Morgan (1995) suggests that different window lengths *do* make a difference (although not a large one). In fact, the forecastability of volatilities and the sensitivity of the forecasts to different techniques depend very much on the return series in question. When we repeated the analyses reported in Table C using the return on a single exchange rate, as in JP Morgan (1995), we found distinctly greater differences between the forecasting performances of different VaR techniques.

However, it is important to note that using a different window size does significantly affect the tail probabilities shown in the lower part of

Table C. In general, the figures in the table show that losses exceed the 1% cut-off points much more than 1% of the time, demonstrating the inaccuracy of the measures of tail probability implied by parametric VaRs based on normal distributions. Hendricks (1996) reaches a similar conclusion in his study of VaR models applied to FX portfolio returns. This is not surprising given the widely documented leptokurtosis of interest rates and stock returns. The results in Table C suggest that a longer data window helps to reduce the tail probability bias, however.

2.5 Weighting schemes

As mentioned before, a common procedure is to calculate variance estimates for VaR-type analyses using *weighted* squared deviations from an estimate of the mean. Rapidly declining weights mean that variance estimates are largely based on the last few observations although information contained in more lagged observations is not totally ignored. The motivation for this approach is the widely recognised fact that financial market returns are conditionally heteroskedastic.(13)

A range of more or less complicated techniques has been developed to model this feature of financial returns. In particular, Generalised Autoregressive and Conditionally Heteroskedastic (GARCH) models are specifically designed for this purpose. Most implementations of VaR analysis have taken the simpler approach of estimating variances using the weighted average of squared deviations from the mean described above with weights that decline exponentially as the lag length increases. The weights are thus of the form:

$$\lambda_i \equiv T \frac{1-\lambda}{1-\lambda^{T-1}} \lambda^i \qquad i = 0, 1, 2, \ldots, T-1 \tag{5}$$

for a constant $\lambda \in [0, 1]$. Standard results on geometric series imply that $\sum_0^{T-1} \lambda_i = T$.

The upper panel of Table D shows mean absolute volatility forecast errors obtained using different weighting schemes. The calculations are

(13) Some banks' VaR models, for example CSFB's Primerisk, apply different weighting schemes across asset categories. Lawrence and Robinson (1995) argue for asset-specific weighting schemes. We follow *RiskMetrics* in employing a uniform weighting scheme.

carried out using daily returns with 24-month windows of lagged data and means fixed at zero. Once again, the volatility forecasts for the fixed income and FX books are quite insensitive to the precise approach followed although rapidly declining weights ($\lambda = 0.94$) perform somewhat better for all four portfolios, and yield a statistically significant improvement in forecast accuracy for portfolio 4. The lower panel of Table D shows the tail probabilities for different weighting schemes. It is apparent that using weighting schemes with rapidly declining weights increases the upward bias in the tail probabilities. As with window length, there appears to be a trade-off in that weighting schemes may improve the degree to which the VaR calculations track time-varying volatilities (ie, the mean absolute forecast errors may be reduced to some small degree), however, the bias in the tail probabilities is exacerbated.

2.6 Parametric versus non-parametric VaRs

In this section, we compare the performance of parametric and non-parametric-based VaR models. Since non-parametric VaRs do not yield a time series of volatility forecast errors, we restrict our comparison to the tail probabilities that the two kinds of model produce. Table E shows the results for data window lengths ranging from three to twenty four months. For the parametric approach, ten-day return tail probabilities were calculated by scaling up the one-day VaR estimates by $\sqrt{10}$ and then taking the fraction of observations for which the ten-day loss outturns exceed the implied cut-off level. The one-day tail probabilities are calculated as in previous sections. For the non-parametric approach, ten-day return tail probabilities were calculated using ten-day portfolio losses to compute the VaR and then taking the fraction of observations for which the ten-day loss outturns exceed the implied cut-off level. For the one-day tail probabilities, the VaR was computed using one-day portfolio losses and the result compared with the one-day outturns. For both the parametric and the non-parametric approaches, the ten-day return outturns were computed on a rolling basis by summing the log daily returns.

The results in the table suggest that calculating the one-day and ten-day VaR cut-off points from short data windows is inadvisable in that the small sample biases are very substantial. For longer data windows, the non-parametric approach for the one-day returns consistently out-performs the parametric VaR model in that the tail probabilities are matched more accurately. For the parametric approach, the tail probabilities computed using the different lag lengths consistently exceed the 1% level, reflecting the well-known non-normality of financial returns. Looking at the ten-day returns, for some portfolios, the non-parametric approach appears to perform worse than the parametric VaR estimates. In general, the tail probability figures for ten-day returns serve to underline the statistical problems involved in attempting to deduce ten-day volatilities directly from estimates of one-day volatilities.

2.7 The inclusion of estimated means

The last exercise we perform to assess the sensitivity of VaR analyses to different assumptions is to calculate mean absolute forecast errors for parametric VaRs (i) with means estimated from lagged returns, and (ii) with the means set to zero. Fixing the means at zero might seem an unconventional statistical procedure but the estimation error associated with badly determined mean estimates may reduce the efficiency of the estimated volatilities. (Figlewski (1994) makes a similar point in the context of return variance estimation.) If the true mean returns are, as seems likely, very close to zero, fixing them at this level could enhance the forecasts. In fact, the results in Table F show that, for the particular books and return data we employ, the findings are mixed. The mean absolute forecast errors with means set to zero are in some cases lower and in some higher than in cases in which the means are freely estimated. With one-day returns, the differences are very small. With portfolio 1, one-day return forecast accuracy is improved in a statistically significant way but the gain appears economically insignificant.

2.8 'Spike' loss periods

An important question is whether the ability of parametric VaR analysis to 'track' the time-series behaviour of volatility enables it to out-perform simulation-based VaRs in predictions of large, 'spike' losses in portfolio values. It is possible that even if parametric VaRs do not yield lower mean absolute forecast errors as we saw above, they are better at picking out large market movements. This issue is particularly important if VaR analysis is to be used for regulatory purposes since the primary concern of regulators regarding trading-book risks is that banks will be wiped out by sudden large losses that occur before action could be taken to reduce the riskiness of the bank's portfolio. To examine this issue, we split our sample period into six-month intervals and identify, for each of our portfolios, the day within each period on which the largest loss occurred.

Before comparing the performance of the parametric and simulation-based VaR models, let us examine the composition of the spike portfolio losses. Table G provides detailed break-downs of the constituent parts of each of these large value declines for portfolio 4, which as the reader may recall, contains equity as well as interest rate and FX risk. As is apparent from Table G, bond risk is the most important factor in generating large losses, acting as the dominant factor in eight out of twelve cases. FX risk was the most important factor in the remaining four cases. Table A shows that portfolio 4 contains greater FX exposure than the other portfolios, (in particular, a relatively large net United States dollar position).

It is surprising that the equity exposure created no spike losses in the period of our sample. We were concerned that this result reflects the fact that large changes in equity values tend to be negative, and the largest equity exposure in portfolio 4 is a short position in United States equities. As an experiment, we re-ran the VaR calculations assuming that the equity exposures (and the corresponding components of the FX exposures) were of opposite sign. Even with this change, none of the spike losses were attributable mainly to equity losses. One may, therefore, conclude that the relatively small size of the equity exposure is enough to make equity risk minimal even though equity returns themselves are much more volatile than those on bond portfolios.(14)

Table H shows the capital requirement implied by the VaR estimates minus the actual loss sustained.(15) We term this quantity the capital surplus (+) or capital short-fall (-). As one may see, parametric and simulation-based VaR models perform somewhat differently. When capital is based on the simulation-based VaR model, the bank has a capital surplus on 16 of the 48 spike loss dates. When the parametric VaR model is used, the bank has a surplus on nine occasions. Whether the capital surplus is positive or negative, on most spike loss dates the simulation-based VaR model implies a larger capital surplus than the parametric VaR.

The implication is that, though it does not exploit the conditional structure of volatility, the simulation-based VaR seems to do a somewhat better job of establishing appropriate capital requirements; Chart 1 illustrates this, using a 24-month window, for each of the portfolios.

2.9 Basle alternative approach capital calculations

A last but nevertheless important question is how much of a capital cushion the proposed Basle alternative approach would deliver for actual books, given not only the 99% confidence level but also the multiplier of three. We look at this issue for our portfolios by comparing the capital requirement that would be generated by one part of the proposed two-stage test, namely three times the 60-day average of the VaRs calculated to cover a ten-day holding period using the parameters laid down by Basle. A bank would be required to hold capital equivalent to the greater of (i) this amount and (ii) the VaR for the current book. With a multiplier of three, the first of these tests will

(14) The more 'spiky' and volatile nature of equities has been recognised by regulators, for instance, in the CAD building-block approach. Under the CAD, a single position in a ten-year government bond would carry a capital requirement of 2.4%, whereas a single position in an equity index would carry a charge of 8%. For a single equity, the charge would be 12%.

(15) The capital 'requirement' is the VaR for the whole book produced using a 99% confidence level. We do not incorporate in this calculation any other aspects of the Basle proposals such as the three-times multiplier.

'bite', unless the bank's current book is abnormally risky.

We compared the ten-day returns which would have been secured on our four portfolios during the period July 1989 to April 1995 with the capital requirement based on three times the 60-day average of the daily VaRs. (The Basle requirement would usually be calculated using the 60-day average for VaRs for different books held on different days.) In performing the calculations, we used the parametric approach with a 24-month window of past returns data, equal weights, and a zero mean. We calculated the capital requirement implied by multipliers of two and two and a half as well as three. None of the portfolios had a single loss outlier (losses which exceeded the capital requirement) when the multiplier was either two and a half or three. Three of the portfolios had a single (marginal) loss outlier for a multiplier of two.

2.10 The Basle approach to back-testing

The proposed alternative Basle approach envisages that banks will suffer increases in their capital requirements if, over a 250-day period, their VaR models under-predict the number of losses exceeding the 1% cut-off point. Such losses are termed 'exceptions'. If a bank's VaR model has generated zero to four exceptions, it is said to be in the Green Zone; if five to nine, it is in the Yellow Zone; and if there are more than ten exceptions, it is in the Red Zone. The capital requirement for banks whose models are in the Yellow Zone may be increased by regulators; if they are in the Red Zone, the requirement would almost certainly be increased.

We ran back-tests for all four of our portfolios, comparing the VaR figures calculated for one-day holding periods (again, using the parametric approach) with the actual return on each book. The number of exceptions for each portfolio over the different 250 day periods are set out in Table I. The results vary for different portfolios. For three of the six periods, if portfolio 2 were held, the model would generate more than four exceptions. The highest number of exceptions was seven, which occurred twice for portfolio 2 and once for portfolio 4. According to the Basle guidelines, this would normally lead to an increase in the multiplier of 0.65 unless the supervisor could be persuaded that special factors had affected outcomes.[16] The fact that the model moves from the Green to the Yellow Zone so much from period to period underlines the difficulty of distinguishing between good and bad models using samples of a mere 250 observations. However, our results suggest that a grossly inaccurate model would be picked up by such back-testing.

3 Conclusion

In writing this paper, we have sought to provide practical analysis of help to those contemplating the use of VaR models either for risk measurement within a bank or for regulatory control of bank risk-taking. We have related our results at various points to the recommendations and provisions of the alternative approach of the Basle Accord amendment. A strength of our study is our use of data on the actual trading books of a bank active in a wide range of markets. Judgments of whether one approach dominates another seem to be sensitive to the kind of portfolios held. Studies that analyse VaR modelling on the basis of, for example, a single equity index or FX rate seem to us to be ill-advised, therefore, and it is important to look at realistic portfolios.

The main conclusions that emerge from the empirical section of our study are as follows. Simulation-based VaR techniques yield more accurate measures of tail probabilities than parametric VaR models. This arises from the severe non-normality of financial returns. We are not convinced by the common argument that mismeasurement by parametric VaRs of the *level* of tail probabilities does not matter since they correctly rank different portfolios. Different asset returns will be more or less fat-tailed leading to varying biases.

Parametric VaR analysis tracks the time-series behaviour of volatility better and appears to yield slightly superior volatility forecasts compared to non-parametric, simulation-based techniques (though the differences are generally not statistically significant). However, with

[16] A supervisor can disregard the Yellow Zone if they believe there is a good reason for the poor performance unrelated to the model. However, the Red Zone can only be disregarded in extraordinary circumstances.

reasonably well-diversified fixed-income books, the gains in forecasting accuracy are relatively slight. The parametric VaR models that yield the best forecasts have relatively short window lengths and large weighting factors. But such models are very poor at fitting the tails of return distributions and capital requirements based on them tend to be too low.

What are the implications of the proposed amendment to the Basle Accord for banks? The amendment proposes that the value at risk calculated using VaR techniques should be scaled up by a factor of three. With such a high scaling factor, only extremely risky portfolios will ever fail to be covered. Even so, the back-testing provisions proposed by Basle are likely to affect banks quite significantly. Under the proposed amendement, if a bank's VaR model under-predicts the number of large losses, the capital requirement will be adjusted up. A bank holding the portfolios we employ in this study would find its capital requirements adjusted fairly frequently if it was using the parametric approach.

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Table A. Portfolio amounts (£millions)

	FFr	£	$	Yen	DM
Portfolio 1					
FX	-10.89	–	-46.02	4.31	40.95
3-12 month	24.04	56.82	-191.56	-590.78	462.35
2-5 year	-11.45	-336.42	83.13	1247.51	-139.10
6-10 year	-3.52	-14.62	69.96	-65.45	-144.32
11+ year	0.00	0.00	-3.19	5.52	-41.66
Portfolio 2					
	FFr	£	$	Yen	DM
FX	-5.95	–	5.72	-22.23	10.20
3-12 month	64.96	40.01	-135.10	-529.87	629.90
2-5 year	-130.29	-268.84	-33.18	1194.70	-178.89
6-10 year	19.39	11.17	0.93	-58.66	-107.47
11+ year	0.00	0.00	-2.71	5.20	-8.76
Portfolio 3					
	FFr	£	$	Yen	DM
FX	-9.86	–	33.50	-5.59	22.48
3-12 month	-237.72	105.39	4.56	-1314.62	11.69
2-5 year	43.46	-245.85	11.11	346.49	89.64
6-10 year	39.53	22.44	0.26	-58.31	-69.96
11+ year	0.00	-26.70	-2.72	4.75	-8.81
Portfolio 4					
	FFr	£	$	Yen	DM
FX	28.51	–	-132.10	11.84	-26.08
3-12 month	-11.00	2.22	-153.15	-341.36	-327.05
2-5 year	-160.38	13.88	24.53	357.72	559.87
6-10 year	179.83	-53.34	53.92	40.87	-398.86
11+ year	43.13	39.72	29.90	0.00	0.00
Equities	1.50	2.81	-37.69	6.06	8.24

Table B. Standard deviations of daily return

	FFr	£	$	Yen	DM
FX	6.32	–	10.74	10.00	6.63
<3 months	0.90	0.48	0.31	0.22	0.25
3-6 months	1.09	0.86	0.53	0.34	0.45
6-9 months	1.31	1.32	0.83	0.53	0.67
9-12 months	1.49	1.76	1.16	0.70	0.88
1-2 years	2.63	3.33	2.09	1.30	1.72
2-3 years	3.62	4.42	3.10	1.95	2.27
3-4 years	4.59	5.53	4.13	2.67	2.93
4-5 years	5.58	6.57	5.15	3.43	3.50
5-6 years	6.65	7.55	6.14	4.36	4.06
6-7 years	7.99	8.55	7.13	5.62	4.97
7-8 years	9.36	9.80	8.13	6.73	6.19
8-9 years	10.15	10.97	9.08	7.66	7.34
9-10 years	10.40	12.05	9.94	8.43	8.53
11+ years	11.45	13.66	11.63	10.09	10.50
Equities	19.48	14.24	16.51	22.43	20.02

Note: standard deviations are annualised (multiplied by $\sqrt{250}$) and in percent.

Table C. Parametric VaRs and window length

		3 months Data	6 months Data	12 months Data	24 month Dat
Mean Absolute Forecast Error					
Portfolio 1	Mean	26.71*	26.79	27.02	27.1
	Standard Error	(0.85)	(0.73)	(0.64)	(0.60
	t-statistic	–	[0.20]	[0.57]	[0.79
Portfolio 2	Mean	17.26*	17.32	17.40	17.2
	Standard Error	(0.55)	(0.47)	(0.42)	(0.41
	t-statistic	–	[0.21]	[0.39]	[0.08
Portfolio 3	Mean	5.43	5.42	5.44	5.40
	Standard Error	(0.21)	(0.17)	(0.15)	(0.14
	t-statistic	[0.23]	[0.18]	[0.72]	–
Portfolio 4	Mean	77.12*	78.11	78.10	78.6
	Standard Error	(2.10)	(1.85)	(1.78)	(1.72
	t-statistic	–	[0.89]	[0.68]	[0.99

Tail Probabilities

	3 months Data	6 months Data	12 months Data	24 month Dat
Portfolio 1	1.71	1.38	1.32*	1.32
Portfolio 2	2.11	1.91	1.58	1.51
Portfolio 3	1.58	1.32	1.45	1.25
Portfolio 4	1.71	1.65	1.71	1.38

Note: calculations employ equal weights ($\lambda_i = 1 \forall i$),
zero means, and daily returns.
Forecast errors are x1e4.
Asterisks indicate lowest in the row.
Newey-West standard errors are in parenthesis.
T-ratios are given for difference from lowest
mean absolute error in the same row.

Table D. Parametric VaRs and exponential weights

		Equal Weights	λ =0.97	λ =0.94
		Mean Absolute Errors		
Portfolio 1	Mean	27.17	26.37	26.11*
	Standard Error	(0.60)	(0.84)	(0.94)
	t-statistic	[1.67]	[1.33]	–
Portfolio 2	Mean	17.29	17.05	16.86*
	Standard Error	(0.41)	(0.53)	(0.60)
	t-statistic	[1.08]	[1.26]	–
Portfolio 3	Mean	5.40	5.36	5.30*
	Standard Error	(0.14)	(0.19)	(0.22)
	t-statistic	[0.71]	[1.03]	–
Portfolio 4	Mean	78.60	76.49	75.62*
	Standard Error	(1.72)	(1.98)	(2.15)
	t-statistic	[2.18]	[1.61]	–
		Tail Probabilities		
		Equal Weights	λ =0.97	λ =0.94
Portfolio 1		1.32*	1.32*	1.72
Portfolio 2		1.51*	1.71	1.91
Portfolio 3		1.25*	1.45	1.45
Portfolio 4		1.38*	1.65	1.65

Note: calculations employ zero means,
daily returns, and a 24-month window.
Forecast errors are x1e4.
Asterisks indicate lowest in the row.
Newey-West standard errors are in parenthesis.
T-ratios are given for difference from lowest
mean absolute error in the same row.

Table E. Parametric and Simulation VaRs: tail probabilities

	3 months Data	6 months Data	12 months Data	24 months Data
Portfolio 1				
one-day return parametric	1.71	1.38	1.32	1.32
ten-day return parametric†	1.78	1.05	1.32	1.05
one-day return simulation	1.71	0.79	1.38	0.92
ten-day simulation††	3.69	1.97	2.30	1.78
Portfolio 2				
one-day return parametric	2.11	1.91	1.58	1.51
ten-day return parametric†	0.79	0.72	0.99	0.92
one-day return simulation	1.78	0.99	1.18	1.18
ten-day return simulation††	2.63	1.32	1.45	1.65
Portfolio 3				
one-day return parametric	1.58	1.32	1.45	1.25
ten-day return parametric†	1.58	1.12	1.05	1.05
one-day return simulation	1.51	0.86	1.18	0.86
ten-day return simulation††	3.09	1.32	1.58	1.18
Portfolio 4				
one-day return parametric	1.71	1.65	1.71	1.38
ten-day return parametric†	1.12	1.12	1.18	0.92
one-day return simulation	1.38	0.72	1.38	0.92
ten-day return simulation††	3.09	1.58	1.38	1.25

† Calculated by multiplying the one-day VaR estimate by $\sqrt{10}$ and comparing with the subsequent realised ten-day log returns.

†† Calculated by estimating the VaR from the portfolio losses over ten-day periods and comparing these with the subsequent realised ten-day log returns.

Table F. Parametric VaRs: sample mean inclusion

MEAN ABSOLUTE FORECAST ERRORS				
			Sample Mean	Zero Mean
Portfolio 1	one-day return	Mean	27.30	27.17*
		Standard Error	(0.61)	(0.60)
		t-statistic	[2.01]	–
	ten-day return†	Mean	82.54	81.58*
		Standard Error	(2.44)	(2.46)
		t-statistic	[0.95]	–
Portfolio 2	one-day return	Mean	17.31	17.29*
		Standard Error	(0.41)	(0.41)
		t-statistic	[0.56]	–
	ten-day return†	Mean	51.27	50.67*
		Standard Error	(1.34)	(1.38)
		t-statistic	[0.86]	–
Portfolio 3	one-day return	Mean	5.39*	5.40
		Standard Error	(0.14)	(0.14)
		t-statistic	–	[1.14]
	ten-day return†	Mean	16.34*	16.38
		Standard Error	(0.45)	(0.49)
		t-statistic	–	[0.23]
Portfolio 4	one-day return	Mean	78.53*	78.60
		Standard Error	(1.73)	(1.72)
		t-statistic	–	[0.34]
	ten-day return†	Mean	237.69	232.23*
		Standard Error	(7.23)	(7.65)
		t-statistic	[1.68]	–

Note: equal weights, one-day returns, 24-month window.
Forecast errors are x1e4.
Asterisks indicate lowest in the row.
Newey-West standard errors are in parenthesis.
T-ratios are given for difference from lowest
mean absolute error in the same row.
†Calculated by mutiplying one-day returns by $\sqrt{10}$.

Table G. 'Spike losses' — portfolio 4

Date		Fr.	UK	US	Jap.	Ger.	TOTAL
03/07/89	FX	0.13	–	-2.03	-0.01	-0.11	-2.02
	Bond	0.26	-0.09	-0.05	-1.61	-1.12	-2.61
	Equities	0.01	0.02	-0.12	0.04	0.09	0.03
	Total	0.39	-0.07	-2.20	-1.58	-1.14	-4.60
21/02/90	FX	0.01	–	-0.72	0.06	-0.02	-0.67
	Bond	1.35	0.02	0.04	0.46	-4.22	-2.36
	Equities	-0.01	-0.02	0.03	-0.16	-0.06	-0.23
	Total	1.34	0.00	-0.65	0.35	-4.30	-3.26
06/08/90	FX	-0.04	–	-0.87	0.05	0.04	-0.82
	Bond	-3.18	-0.32	-2.41	-1.47	2.99	-4.38
	Equities	-0.07	-0.07	0.98	-0.16	-0.39	0.29
	Total	-3.28	-0.38	-2.30	-1.58	2.64	-4.90
11/02/91	FX	-0.04	–	-0.56	0.04	0.06	-0.50
	Bond	0.75	-0.04	-0.13	-1.65	-1.38	-2.45
	Equities	0.01	0.04	-0.81	0.00	0.10	-0.66
	Total	0.73	-0.00	-1.50	-1.61	-1.23	-3.61
01/09/91	FX	-0.03	–	-2.08	0.11	0.06	-1.95
	Bond	0.35	-0.06	0.03	-1.09	-1.10	-1.88
	Equities	-0.00	-0.01	0.04	-0.03	-0.06	-0.05
	Total	0.32	-0.07	-2.01	-1.01	-1.10	-3.87
18/11/91	FX	-0.18	–	-1.35	0.09	0.15	-1.28
	Bond	-0.50	0.07	-0.04	-0.04	-0.14	-0.67
	Equities	-0.04	-0.04	-0.22	-0.15	-0.07	-0.52
	Total	-0.72	0.03	-1.60	-0.11	-0.06	-2.47

Table G. 'Spike losses' — portfolio 4 continued

Date		Fr.	UK	US	Jap.	Ger.	TOTAL
23/09/92	FX	0.09	–	0.03	-0.08	-0.17	-0.13
	Bond	-3.25	-0.05	-0.34	-0.06	-2.33	-6.02
	Equities	-0.00	-0.00	-0.02	0.00	0.03	0.01
	Total	-3.16	-0.05	-0.33	-0.14	-2.46	-6.15
05/01/93	FX	0.47	–	-3.14	0.26	-0.46	-2.87
	Bond	-0.30	-0.24	-0.13	0.06	-0.54	-1.15
	Equities	0.01	-0.01	0.08	-0.05	0.11	0.13
	Total	0.18	-0.25	-3.19	0.27	-0.89	-3.89
13/04/93	FX	0.09	–	-2.46	0.20	-0.11	-2.27
	Bond	0.31	0.06	-0.23	-0.81	-0.20	-0.88
	Equities	0.02	0.02	-0.06	0.22	0.06	0.26
	Total	0.42	0.08	-2.75	-0.40	-0.25	-2.89
01/03/94	FX	0.05	–	0.01	0.04	-0.03	0.07
	Bond	-1.51	-0.17	-1.07	-1.79	0.86	-3.68
	Equities	-0.03	-0.03	0.18	0.06	-0.08	0.09
	Total	-1.50	-0.20	-0.88	-1.69	0.75	-3.52
28/06/94	FX	0.00	–	0.58	-0.02	-0.01	0.55
	Bond	-0.23	-0.08	-0.78	-1.44	-3.15	-5.67
	Equities	0.01	0.01	0.09	0.08	0.10	0.29
	Total	-0.22	-0.07	-0.11	-1.37	-3.06	-4.82
03/10/94	FX	0.10	–	-0.07	0.09	-0.10	0.02
	Bond	-1.64	-0.06	-0.49	-1.19	-0.03	-3.42
	Equities	-0.02	-0.03	0.07	0.02	0.00	0.04
	Total	-1.57	-0.09	-0.49	-1.08	-0.13	-3.36

Note: figures are daily returns in percent.

Table H. Model performance on 'spike' loss dates

	Portfolio 1		Portfolio 2	
Model	Sim.	Var./Cov.	Sim.	Var./Cov.
Period 1	-1.63	-1.51	-0.49	-0.47
Period 2	-0.56	-0.64	-0.42	-0.43
Period 3	-0.75	-0.89	-0.48	-0.54
Period 4	0.03	-0.08	-0.29	-0.39
Period 5	0.28	0.11	0.15	0.02
Period 6	-1.08	-1.34	-1.05	-1.22
Period 7	-1.81	-2.09	-1.39	-1.51
Period 8	0.04	-0.24	-0.31	-0.35
Period 9	0.40	0.15	-0.08	-0.10
Period 10	0.11	-0.08	0.06	0.00
Period 11	-0.07	-0.10	-0.04	-0.04
Period 12	-0.16	-0.08	0.18	0.12
	Portfolio 3		Portfolio 4	
Model	Sim.	Var./Cov.	Sim.	Var./Cov.
Period 1	-0.06	-0.05	-0.81	-0.58
Period 2	-0.08	-0.10	0.05	-0.15
Period 3	-0.11	-0.13	-1.62	-1.95
Period 4	-0.10	-0.12	-0.32	-0.53
Period 5	-0.09	-0.12	-0.62	-0.79
Period 6	-0.08	-0.16	0.79	0.58
Period 7	-0.75	-0.80	-3.19	-3.29
Period 8	-0.01	-0.10	-0.34	-0.79
Period 9	0.16	0.06	0.66	0.13
Period 10	0.04	-0.03	-0.54	-0.47
Period 11	0.03	0.01	-1.28	-1.40
Period 12	0.04	0.04	0.29	-0.09

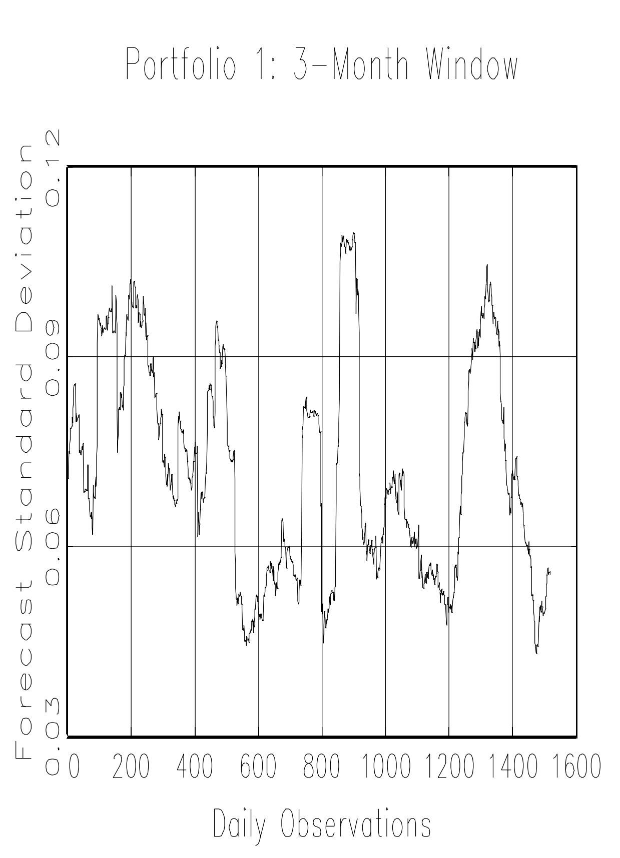
Note: the table shows the capital shortfall (-) or surplus (+) for the largest loss in each six-month period. Parametric approach uses zero mean. Figures are expressed as daily returns in percent. Equal weights, daily returns, 24-month window.

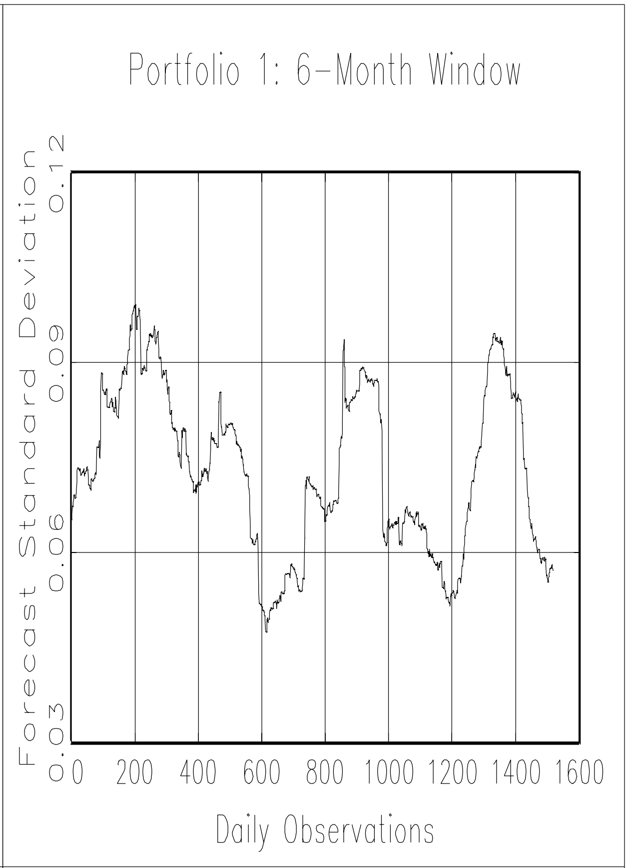
Table I. Back-testing results

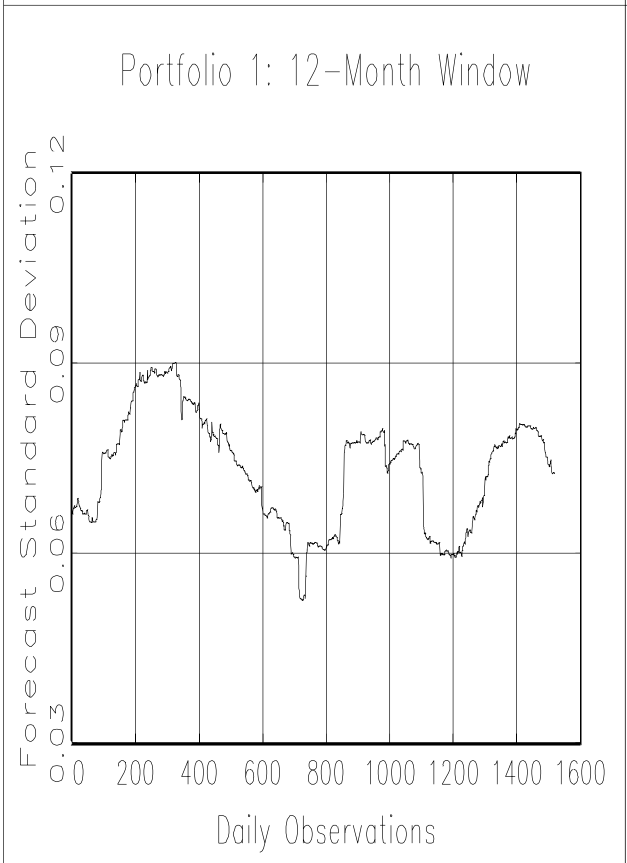
Portfolio	1	2	3	4
Period 1	6	7	4	3
Period 2	4	7	5	3
Period 3	3	2	4	1
Period 4	4	5	4	4
Period 5	1	1	2	3
Period 6	2	1	0	7

Note: the table shows the number of exceptions in each 250-day period.
Green zone = 0–4 exceptions
Yellow zone = 5–9 exceptions
Red zone = 10+ exceptions.

Chart 1: Plots of Forecasts







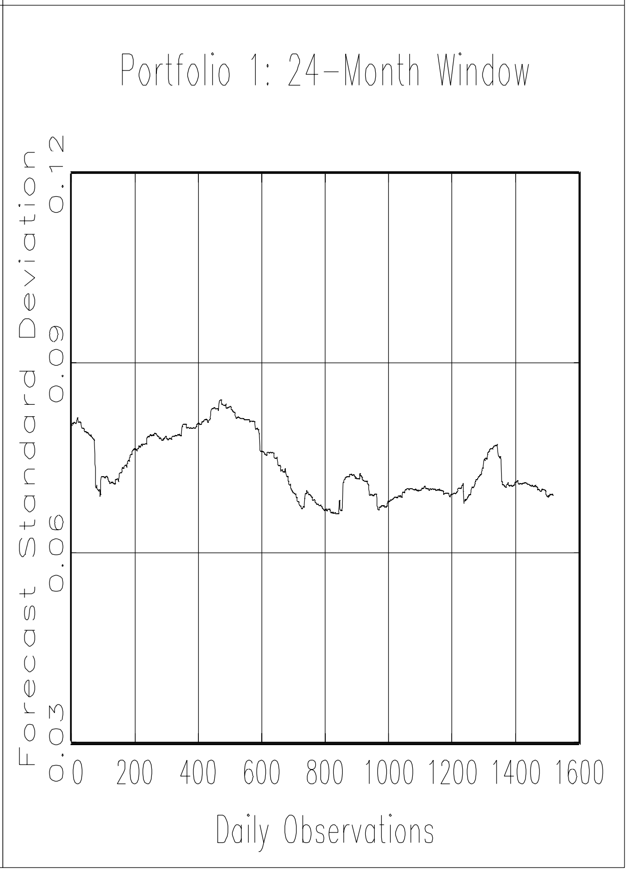


Chart 2: Comparison of Simulation and Parametric based VaRs