*Milica D. Obadović and
Mirjana M. Obadović**

AN ANALYTICAL METHOD OF ESTIMATING VALUE-AT-RISK ON THE BELGRADE STOCK EXCHANGE

ABSTRACT: *This paper presents market risk evaluation for a portfolio consisting of shares that are continuously traded on the Belgrade Stock Exchange, by applying the Value-at-Risk model – the analytical method. It describes the manner of analytical method application and compares the results obtained by implementing this method at different confidence levels. Method verification was carried out on the basis of the failure rate that demonstrated the confidence level for which this method was acceptable in view of the given conditions.*

KEY WORDS: *market risk, Value-at-risk (VaR) model, analytical method, financial market*

JEL CLASSIFICATION: C51, C52, G21

---

*   Novi Sad and The College of Tourism, Belgrade

1. INTRODUCTION

Although in modern parlance the term risk has come to mean "danger of loss", finance theory defines risk as the dispersion of unexpected outcomes due to movements in financial variables (J. P. Morgan[1]). A risk describes selection of such alternatives that do not have a predetermined yield, but for which there is a recognized comparison of alternative yields with their occurrence probabilities. Therefore, a risky investment is one for which the distribution is known with a lesser or higher accuracy.

The total risk of investing in securities is the aggregate of systematic (market risk) and non-systematic risk (specific risk). Systematic risk is a financial risk originating as a consequence of an institutionally and structurally organized market, wherein all the participants have to follow a certain business code. The main elements of systematic risks are the following: significant (sudden) drop in securities price, rapid expansion of securities to other markets, payment delay, banking crisis, payment system crisis etc. Systemic risk is followed and expressed by means of market indexes, as indicators of average market trends and profitability. Non-systemic risk is linked to the operations of the securities issuer and depends on: the issuer's financial status, their market position, attractiveness of their product range, liquidity, solvency, etc.

VaR measures the worst expected loss over a given time interval under normal market conditions at a given confidence level. Based on firm scientific foundations, VaR provides users with a summary measure of market risk. VaR is a method of assessing risk that uses standard statistical techniques routinely used in other technical fields (Jorion 1997: xiv). For instance, a bank might say that the daily VaR of it trading portfolio is $40 million at the 99 percent confidence level. In other words, there is only 1 percent probability from 100 percent, under normal market conditions, for a loss greater than $40 million to occur. VaR measures risk using the same measurement units as banks – e.g. dollars. Shareholders and managers may thus decide whether they consider a given risk level appropriate. In case they are not comfortable with the proffered risk level, the very process leading to VaR calculations may be utilized to make a decision on risk mitigation. Although it virtually always represents a loss, VaR is conventionally reported as a positive number. A negative VaR would imply the portfolio has a high probability of making a profit, for example a one-day 5% VaR of negative $1 million implies

---

[1]   Jorion (1997: 63)

the portfolio has a 95% chance of making $1 million or more over the next day (Crouhy 2001).

It is important to emphasize the following characteristics of VaR. First of all, VaR is an estimated and not a uniquely defined value. VaR evaluations will depend on the stochastic processes that instigate random realizations of market data. This requires the rearranging of past data and determining the size of the historic sample to be used. There is also the question of whether more value should be attached to more recent events than to those that occur further in the past. Basically, the goal is to achieve the best possible evaluation of the stochastic process that generates market data during the particular calendar period to which VaR evaluation is applied. VaR does not refer to the distribution of potential losses in those rare cases when the VaR evaluation is surpassed. It is incorrect to view VaR evaluations as worst-case scenario losses. Analysis of rare but extreme losses has to include alternative tools, such as extreme value theory or simulations made in accordance with the worst-case scenarios of market trends.

VaR has multiple roles:

Informative role - VaR may be used to inform the upper management on the existing risk in the market and investment transactions.

Resource allocation role – VaR may be used to set position limits for traders and to make a decision on where to allocate limited capital resources. The advantage of VAR is that it creates a common denominator, with which it is possible to compare risky activities in different markets.

Performance evaluation role – VaR may be used to adjust risk performance. This is essential for the market environment where traders have a natural tendency to take extra risk. For example, in its 1994 annual report, J.P. Morgan revealed that the daily trading VaR had an average of 15 million dollars at the 95% confidence level. Thus, investors may decide whether they consider this level of risk acceptable. Prior to the publishing of such figures, investors only had a vague idea on the scope of trading activities undertaken by banks.

During the eighties, large financial institutions (Bankers Trust, Chase Manhattan Bank, Citibank and others) began publishing the application of VaR in risk management systems. To implement this concept, a large amount of mutually interchangeable data was required, which was a huge problem until the appearance

of RiskMetrics[2]. It consists of detailed technical documentation, as well as the covariance matrix for several hundred key points, which were updated daily. Since J.P. Morgan's Riskmetrics were published in 1994, there has been a swift expansion of research into VaR methodology. Although the zone of evaluating and analyzing market risk exposure remained the main field of VaR implementation, applications were expanded to other types of risk as well. In the last few years, many financial institutions have accepted VaR as an instrument for evaluating information on their portfolio positions. The regulatory authorities of most countries have recognized and acknowledge the VaR approach as one of several methods for measuring the market risk of financial institutions. Apart from its conceptual appeal, its popularity was promoted by the Basel Committee, which allowed banks to calculate their capital requirements for market risks using VaR methodology. In order to calculate VaR, banks may choose between the historical simulation method, analytical method and Monte- Carlo simulation.

There are several ways of expressing VaR:

1. VaR may be expressed as an absolute amount or as a percentage of market value. For example, VaR is 7 million dollars or VaR is 3.5% of the portfolio value.
2. VaR may be given at an aggregate level, and may be broken down into business units, by risk type, by instrument type, or as a combination of the two.
3. VaR may be given at different confidence levels. As an example, J. P. Morgan's RiskMetrics is used at the 95% confidence level. The Basel Committee selected the 99% confidence level, which reflects the regulator's wish to provide a secure and healthy financial system. Generally speaking, the levels applied in practice are 95%, 97.5%, 99% and 99.9%. The most used confidence levels are 97.5% or 99%. When comparing VaR reports of two institutions, it is necessary to set their confidence levels to be equal.

The first step towards VaR measurement is to select two quantitative factors: the *holding period* and the *confidence level*.

The usual holding period is a day or a month, but institutions may choose other periods (e.g. a quarter or more), depending on their investments and reporting periods. The holding period may also depend on the liquidity of the markets in which an institution operates. All other things being equal, the ideal holding period

---

2   RiskMetrics is a free service offered by JP Morgan in 1994, to promote VaR as a risk measurement tool

in any market is the time required to ensure uniform liquidation of the market positions. The holding period may also be specified by regulations. According to the Basel Agreement, the rules on capital adequacy demand that the internal evaluation models used to determine the minimum regulatory capital for market risk, must reflect a time horizon of two weeks (i.e. 10 working days). Selection of the holding period may also depend on the following factors: the assumption that the portfolio does not change over the holding period is easier to uphold with a shorter holding period; for model validation, so-called back testing, a short holding period is more desirable. Reliable validation requires a large data set and a large data set requires a short holding period. The commercial banks currently have daily VaR reports due to the fast turnover of their portfolios. In contrast, investment portfolios such as pension funds slowly adjust their risk exposure, and hence a one-month period is usually chosen for their investment purposes.

The selection of confidence level depends mostly on the purpose behind the risk measurement. Therefore, a very high confidence level, often as great at 99.97%, is appropriate if used for risk measurement in order to set capital requirements or in order to achieve a low insolvency probability or high credit rating. This choice should reflect the level of a company's aversion towards risk and expenses due to losses caused by exceeding the VaR. The larger the aversion towards risk or expense, the greater is the amount of capital required to cover potential losses, which leads to a higher level of confidence. On the other hand, to validate a model, it is desirable to have relatively low confidence levels, in order to obtain a reasonable proportion of observed losses. In contrast, if VaR is only used by companies to compare the risks in various markets, then the selection of confidence level is irrelevant.

Thus, amongst other reasons, "the best" choice of these parameters depends on the context. It is important to make clear choices in each context and for those choices to be completely clear throughout an institution, so that setting constraints and making other decisions connected to risk may be made in light of this understanding.

2. GENERAL SAMPLE INFORMATION

In this section, the estimation of market risk through application of the analytical Value-at-Risk calculation method is presented. A portfolio was created, consisting of shares of 27 companies that are continuously traded at the Belgrade Stock

Exchange. The data analyzed belong to a yearlong period, between 22 May 2006 and 21 May 2007, for shares from the following companies:

1.   AGBC - *Agrobačka a.d. Bačka Topola BELEX*
2.   AIKB - *AIK banka a.d. Niš BELEX*
3.   ALFA - *Alfa plam a.d. Vranje BELEX*
4.   BMBI - *Bambi Banat a.d. Beograd BELEX*
5.   BNNI - *Banini a.d. Kikinda BELEX*
6.   CCNB - *Čačanska banka a.d. Čačak BELEX*
7.   DNVG - *Dunav Grocka a.d. Grocka BELEX*
8.   ENHL - *Energoprojekt holding a.d. Beograd BELEX*
9.   FITO - *Galenika Fitofarmacija a.d. Zemun BELEX*
10.   IMLK - *Imlek a.d. Beograd, simbol BELEX*
11.   MLNS - *Novosadska mlekara a.d. Novi Sad BELEX*
12.   MTLC - *Metalac a.d. Gornji Milanovac BELEX*
13.   NPRD - *Napred GP a.d. N. Beograd BELEX*
14.   PLNM - *Planum GP a.d. Beograd BELEX*
15.   PRGS - *Progres a.d. Beograd BELEX*
16.   PTLK - *Pupin Telecom a.d. Zemun BELEX*
17.   PUUE - *Putevi a.d. Užice BELEX*
18.   RDJZ - *Radijator a.d. Zrenjanin BELEX*
19.   RMBG - *Ratko Mitrović a.d. Beograd BELEX*
20.   SJPT - *Soja protein a.d. Bečej BELEX*
21.   SRBL - *Srbolek a.d. Beograd BELEX*
22.   TGAS - *Messer Tehnogas a.d. Beograd BELEX*
23.   TIGR - *Tigar a.d. Pirot BELEX*
24.   TLKB - *Telefonkabl a.d. Beograd BELEX*
25.   UNBN - *Univerzal banka a.d. Beograd BELEX*
26.   UNVR - *Univerzal - holding a.d. Beograd BELEX*
27.   ZOPH - *Zorka Pharma a.d. Šabac BELEX*

The initial assumption was that on 22. May 2006, 10,000,000 dinars were invested in a portfolio consisting of these companies' shares. It was additionally assumed that the same amount was invested into each company.

Let *Vo* be the initial 10,000,000 dinar investment. Since the same amount was invested into each of the 27 companies, it means that invested into every company was:

$$10.000.000 / 27 = 370.370,370 \text{ dinars.} \qquad (1)$$

If $p_{1,1}$, $p_{1,2}$, ..., $p_{1,27}$ are the share prices as of 22 May 2006, and q_1, q_2, ..., q_{27} are the numbers of purchased shares, then:

$$p_{1,1} q_{1,1} = p_{1,2} q_{1,2} = ... = p_{1,27} q_{1,27} = 370.370,370 \text{ dinara}, \qquad (2)$$

$$\text{and } q_{n,n} = 370.370,370 / p_{n,n}. \qquad (3)$$

The number of purchased shares in this example does not change, i.e. it remains constant during the observed analysis period, so only market price fluctuations and their impact on the portfolio value are being followed.

When the market prices of the shares $p_{2,1}$, $p_{2,2}$, ..., $p_{2,27}$ change, in this case, the following day the portfolio value was reduced to 9,930,981.340 dinars. The relative portfolio value change amounts to (9,930,981.340 – 10,000,000) / 10,000,000 = -0.00690 = -0.690 %, which means that a loss of 69,018.66 dinars was made.

A year later, in this case 249 working days, the portfolio value amounted to 24,521,567.951 dinars, i.e. a gain was made of 14,521,567.951 dinars. In this case the investment paid off because a profit of 145.22% was made.

3. CALCULATING VAR VALUES BY APPLYING THE ANALYTICAL METHOD

The analytical method is an approach that assumes market variables have a normal distribution of probabilities and then uses the features of the normal probability distribution to determine VaR. Normal (Gaussian) distribution is given by the following function:

$$f(x) = \frac{1}{\sigma\sqrt{2\pi}} e^{-\frac{1}{2}\left(\frac{x-\mu}{\sigma}\right)^2} \qquad (4)$$

where: x – independent variable, $\pi \approx 3{,}14159$, $e \approx 2{,}71828$, μ - mean (expected) distribution value and σ - standard deviation.

The normal distribution function may also be presented graphically with a bell-shaped curve. The main feature of the normal distribution is that it is symmetrical and that it may be completely determined with only two parameters, as follows: μ (mean value) and σ (standard deviation). If these two parameters are known, then the normal distribution is fully defined. Normal distribution is denoted with

N(μ,σ^2). The normal distribution N(0,l) is called the standard normal distribution. The standard normal distribution is obtained by standardizing deviations of random variable x_i from its mean value, i.e. by showing each value of the random variable through its distance from the mean value expressed in standard deviations. The standard deviation of random variable x_i from its expected or mean value is marked with z and calculated on the basis of the formula:

$$z = \frac{x_i - \mu}{\sigma} \tag{5}$$

where $-\infty < z < +\infty$. Each value of the random variable can be standardized using the previous formula, obtaining the specific value z_i. For each z_i it is possible to calculate the probability of random variable x_i taking a value that is smaller or larger than this value after standardization. The probability of z_i taking a value that is smaller than y may be represented in the following manner:

$$P(z_i < y). \tag{6}$$

If the probability is sought that z_i would be lower than 0.5 for instance, it is presented in the following manner:

$$P(z_i < 0,5). \tag{7}$$

The probability itself is calculated by solving the definite integral of the normal distribution function. The probabilities that z_i will take a lower value than a given value are calculated for all values of y and are given in statistical tables of the normal distribution. As VaR is most often calculated with several standard confidence levels (90%, 95%, 98%, 99%), it is only necessary to know the corresponding values of parameter z.

Knowing these normal distribution properties, the variance-covariance method determines VaR by multiplying the values of the standard deviation for portfolio value change with the corresponding z_i value depending on the confidence level used to determine VaR.

VaR is actually a function of the desired confidence level represented by parameter z_i, the standard deviation of portfolio value σ and portfolio value V. Table 1. shows VaR as a function of σ and V for different confidence levels:

Table 1. *Calculation of VaR for different confidence levels*

Confidence levels	VaR
90%	$-1,28*\sigma*V$
95%	$-1,65*\sigma*V$
98%	$-2,05*\sigma*V$
99%	$-2,33*\sigma*V$

The largest problem in applying this method is calculating the standard deviation of the portfolio value change. Once this value is calculated, VaR is obtained as the product of standard deviation σ, the specific value of parameter z and portfolio value V.

The standard deviation σ is calculated using a covariance matrix, obtained on the basis of n–days rate of assets return, in the following manner:

$$\sigma = \sqrt{wVw^T}, \tag{8}$$

where $w = (w_1, w_2, \dots, w_n)$ is the weighted portfolio vector (nominal amounts invested into each asset), and V is covariance matrix, obtained on the basis of n–days rate of assets return. In this example the same amount is invested into each asset, so there is 3.7% initial portfolio value invested into each asset. The covariance matrix V looks as follows:

$$\begin{bmatrix} Var(R_1) & Co\,var(R_1,R_2) & \dots\dots Co\,var(R_1,R_n) \\ Co\,var(R_2,R_1) & Var(R_2) & \dots\dots Co\,var(R_2,R_n) \\ . & . & . \\ . & . & . \\ . & . & . \\ . & . & . \\ Co\,var(R_n,R_1) & Co\,var(R_n,R_2) & \dots\dots Var(R_n) \end{bmatrix}, \tag{9}$$

where $Var(R_n)$ is variance of assets return rate n, and $Covar(R_n,R_m)$ is covariance between assets return rates n and m, with $Covar(R_n,R_m)= Covar(R_m,R_n)$. Subsequently, the standard portfolio deviation is calculated as the square root of portfolio variance, in the following manner:

$$\sigma = \sqrt{\sigma^2}, \tag{10}$$

where:

$$\sigma^2 = \begin{bmatrix} w_1, w_2, ..., w_n \end{bmatrix} \begin{bmatrix} Var(R_1) & Co\,var(R_1, R_2) & ....Co\,var(R_1, R_n) \\ Co\,var(R_2, R_1) & Var(R_2) & ....Co\,var(R_2, R_n) \\ . & . & . \\ . & . & . \\ . & . & . \\ . & . & . \\ Co\,var(R_n, R_1) & Co\,var(R_n, R_2) & ....Var(R_n) \end{bmatrix} \begin{bmatrix} w_1 \\ w_2 \\ . \\ . \\ . \\ . \\ w_n \end{bmatrix}. \tag{11}$$

To calculate the covariance matrix in this example, the method of equally weighted historical data was applied, as well as the EWMA (*exponentially weighted moving average*) method, and a decay parameter λ = 0.94 (which suggests how much the value of each observation decreases day by day). According to the equally weighted historical data method, volatility is calculated as follows:

$$\sigma = \sqrt{\frac{1}{T} \sum_{t=1}^{T} (r_t - r_m)^2}, \tag{12}$$

whereas the relevant formula for volatility calculation according to EWMA method is:

$$\sigma = \sqrt{(1-\lambda) \sum_{t=1}^{T} \lambda^{t-1} (r_t - r_m)^2}, \tag{13}$$

where r_t and r_m are individual asset return rates and mean value of assets return rate, respectively. T is the number of observed daily rates of portfolio value change (T = 249).

In this example VaR is calculated for confidence levels of 90%, 95% and 99%, as well as for one-day and ten-days prediction periods (Table 2, Figure 1, Figure 2, Figure 3), by applying the basic analytical method and the following results were obtained:

Table 2. *VaR values calculated for the local market using the basic method*

	1-day	*10-days*
VaR (90%)	1.0338%	3.27%
VaR (95%)	1.4346%	4.54%
VaR (99%)	2.1866%	6.91%

The broken line in the figures 1 - 6 represents data on 88 consecutive VaR values, estimated on the basis of data on 249 value changes for the portfolio consisting of 27 local shares.

The black line in the figures 1 - 6 represents data on 88 consecutive actual portfolio returns to which VaR evaluations are compared.

Figure 1. Graph of VaR values obtained by the analytical method, for a local shares portfolio with the error risk of 0.01 and $\lambda = 1$
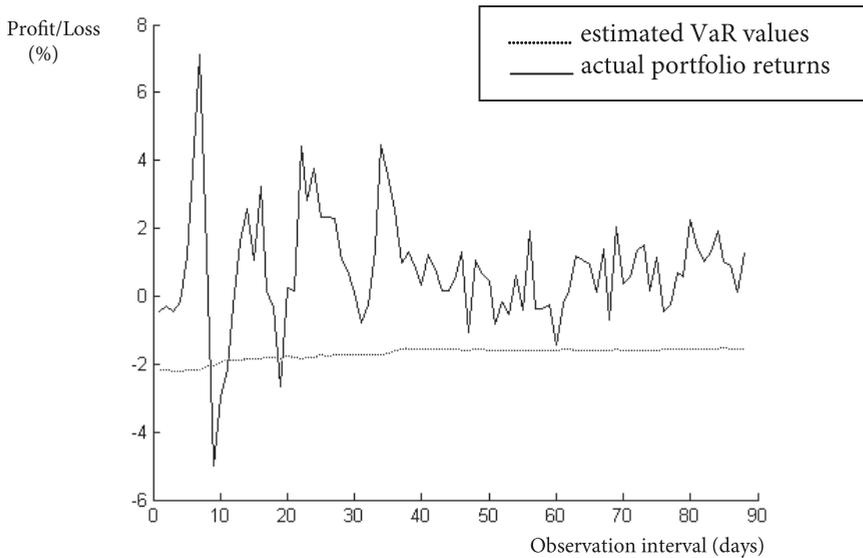
Figure 2. Graph of VaR values obtained by the analytical method, for a local shares portfolio with the error risk of 0.05 and λ = 1
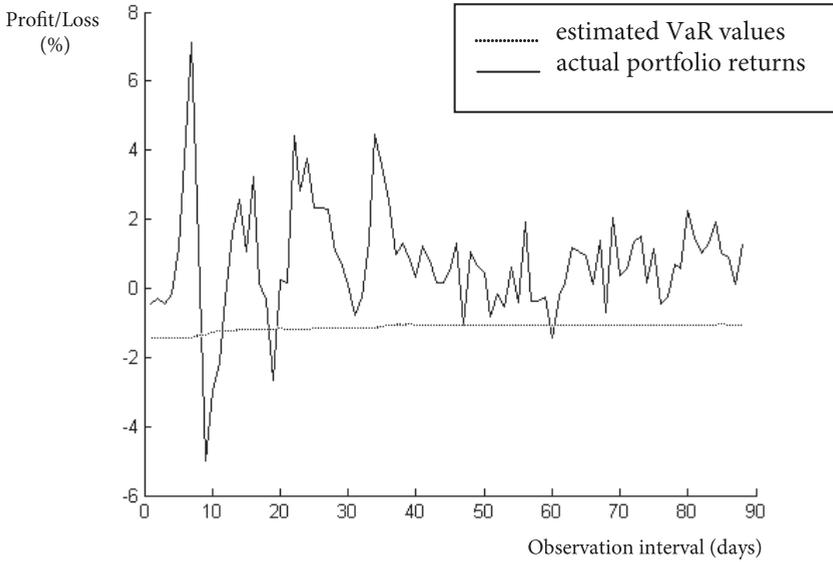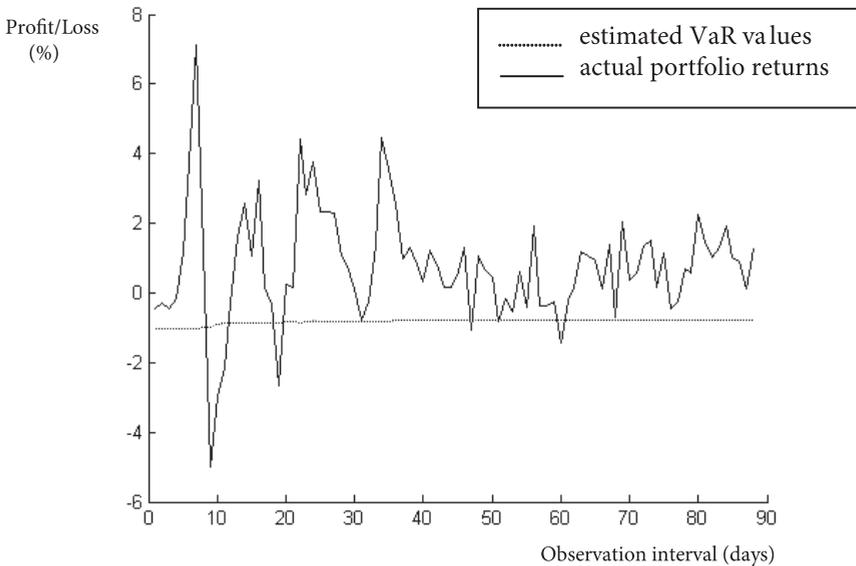

Figure 3. Graph of VaR values obtained by the analytical method, for a local shares portfolio with the error risk of 0.1 and λ = 1

In the following example, VaR values are calculated for confidence levels of 90%, 95% and 99%, for one-day and ten-day prediction periods (Table 3, Figure 4, Figure 5, Figure 6), by applying the analytical EWMA method and the following results were obtained:

Table 3. *VaR values calculated for the local market using EWMA method*

	1-day	*10-days*
VaR (90%)	1.9833%	6.27%
VaR (95%)	2.7439%	8.68%
VaR (99%)	4.1707%	13.19%

Figure 4. Graph of VaR values obtained by the analytical method, for a local shares portfolio with the error risk of 0.01 and λ = 0.94
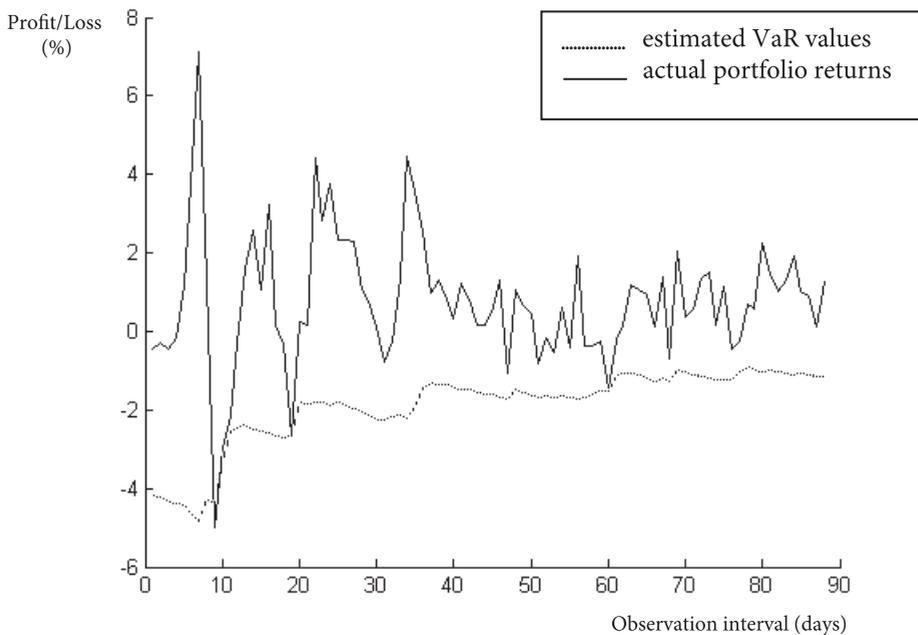
Figure 5. Graph of VaR values obtained by the analytical method, for a local shares portfolio with the error risk of 0.05 and λ = 0.94

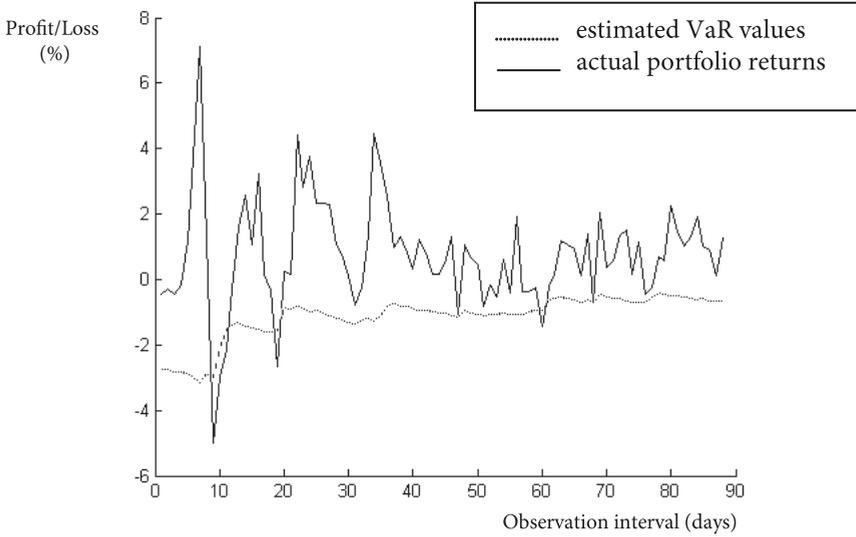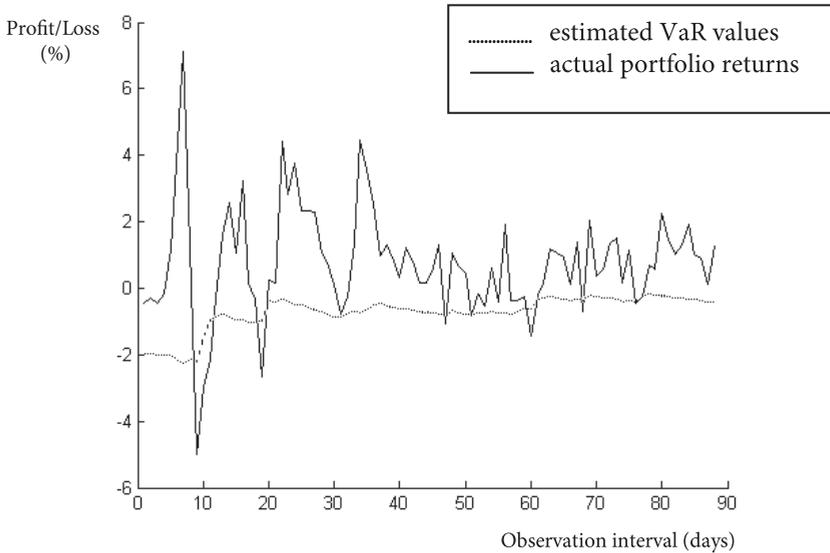**Figure 6.** Graph of VaR values obtained by the analytical method, for a local shares portfolio with the error risk of 0.1 and λ = 0.94

MODEL VERIFICATION BASED ON THE FAILURE RATE

The above demonstrates how to evaluate the basic parameters for VaR measurement, mean value, standard deviation and quintile, based on actual data. These evaluations should not be taken for granted and the accuracy of a model should be verified.

The simplest way of verifying model accuracy is to record the *failure rate,* which gives the proportion of how many times VaR has exceeded the expectations in a given sample.

In order to determine whether these models predict risks well, VaR is evaluated for 88 consecutive days, for a local shares portfolio. The following tables demonstrate how many times the loss was larger than predicted by VaR.

Table 4. *Review of the calculated values – how many times the actual loss exceeded the previous day VaR for a portfolio consisting of local shares using the analytical method (T = 88)*

analytical method	$\lambda = 1$	$\lambda = 0.94$
p = 0.01	N = 4	N = 2
p = 0.05	N = 5	N = 6
p = 0.1	N = 7	N = 9

where T – total number of consecutive VaR predictions, and N – number showing how many times the actual loss exceeded the VaR from the previous day.

Subsequently, at the given confidence level, we need to know whether N is too small or too large, under the null hypothesis that p is a true probability. Once the failure rate is calculated as N/T and compared to the left tail probability, e.g. p = 0.01, which is used to determine VaR evaluation, if they match the VaR evaluation was correct, and if they differ significantly the model has to be rejected.

For the sake of illustration, the confidence level is set at 95 percent. This number does not refer to the quantitative level *p* that was selected as the VaR, which might be *p* = 0.01 for instance. This confidence level refers to the decision on whether to reject the model or not. It is generally set at 95 percent because this corresponds to two standard deviations under a normal distribution.

Kupiec (1995) developed the confidence regions for such a test. These regions are defined by the tail points of likelihood ratio:

$$LR = -2\ln\left[(1-p)^{T-N}\, p^N\right] + 2\ln\left[(1-(N/T)^{T-N}\,(N/T)^N\right], \qquad (14)$$

which is distributed through χ^2 test with one degree of freedom under the null hypothesis that p is a true probability.

For example, with data for the portfolio consisting of local shares (T = 88) it could be expected that N = pT = 10% × 88 = 8.8 deviations will be observed. However, the regulator will not be able to reject the null hypothesis as long as N is within the confidence interval [2 < N < 15]. Values of N greater or equal to 15 suggest that VaR model represents the probability of large losses lower than they actually are; values of N that are less than or equal to 2 suggest the VaR model is too conservative. The following table shows the regions in which the model is not rejected on the basis of significance α = 0.05.

Table 5. *Model verification: Regions in which the model is not rejected at the significance level of 0.05*

	Portfolio consisting of local shares (T = 88)
p = 0.01	N < 4
p = 0.05	N < 9
p = 0.1	2 < N < 15

However, this table still shows the disturbing fact that for small values of VaR parameter *p*, it becomes harder to verify the deviations. For example, the rejection region of 95 percent for p = 0.01 and T = 88 is [N < 4]. Therefore it is impossible to state with certainty whether N is abnormally small or the model systematically overestimates the risk.

It should also be emphasized that this interval, expressed as the N/T ratio, decreases with larger samples, i.e. with more data it should be easier to reject a faulty model.

Revealing systematic ambiguities becomes harder with lower p values, because they correspond to rare occurrences. This explains why some banks prefer higher values for p, e.g. 5 percent (which translated as the confidence level c = 95%), in order to be able to observe a sufficient number of deviations to validate the model.

The following table presents whether a model is acceptable or not, on the basis of Kupiec likelihood ratio.

Table 6. *Model verification for a portfolio consisting of local shares using the analytical method (T = 88)*

analytical method	λ = 1	λ = 0.94
p = 0.01	rejected	accepted
p = 0.05	accepted	accepted
p = 0.1	accepted	accepted

5. CONCLUSIONS

Analytical approaches provide the simplest and most easily implemented methods to estimate VaR. They rely on parameter estimates based on market data histories that can be obtained from commercial suppliers or gathered internally as part of the daily mark-to-market process. For active markets, vendors such as RiskMetrics™ supply updated estimates of the volatility and correlation parameters themselves. But while simple and practical as rough approximations, analytic VaR estimates also have shortcomings. Perhaps the most important of these is that many parametric VaR applications are based on the assumption that market data changes are normally distributed, and this assumption is seldom correct in practice. Assuming normality when our data are heavy-tailed can lead to major errors in our estimates of VaR. VaR will be underestimated at relatively high confidence levels and overestimated at relatively low confidence levels.

Market value sensitivities often are not stable as market conditions change. Since VaR is often based on fairly rare, and hence fairly large, changes in market conditions, even modest instability of the value sensitivities can result in major distortions in the VaR estimate. Such distortions are magnified when options are a significant component of the positions being evaluated, since market value sensitivities are especially unstable in this situation.

Analytic VaR is particularly inappropriate when there are discontinuous payoffs in the portfolio. This is typical of transactions like range floaters and certain types of barrier options.

In summary, analytic approaches provide a reasonable starting point for deriving VaR estimates, but should not be pushed too hard. They may be acceptable on a

long-term basis if the risks involved are small relative to a firm's total capital or aggregate risk appetite, but as the magnitude of risk increases, and as positions become more complex, and especially more nonlinear, more sophisticated approaches are necessary to provide reliable VaR estimates (Koenig 2004: 81).

Using the analytical method on the portfolio consisting of shares traded in the local market, it has been shown under null hypothesis that p = 0.05 is an accurate probability, based on the Kupiec likelihood ratio distributed through χ^2 test with one degree of freedom, so this method is accepted in all cases except when applying the basic analytical method to the portfolio at the confidence level of 99%, wherein this model shows the probability of larger losses to be smaller than it actually is.

Applying this method in local market conditions is risky at a confidence level of 99%, because that level corresponds to extremely rare events. This explains why some banks prefer lower confidence levels, in order to be able to observe a sufficient number of deviations for the purpose of model validation. A multiplication factor is thus applied to transform VaR into secure capital to be set aside for protection from market risk.

REFERENCES

Alexander, C. (2008), *Market Risk Analysis, Volume IV: Value at Risk Models*, John Wiley & Sons Inc.

Alexander, C. (2005), 'The present and future of financial risk management', *Journal of Financial Econometrics*, Volume 3, pp. 3-25.

Bekaert, G. et al. (1998), 'Distributional characteristics of emerging market returns and asset allocation', *Journal of Portfolio Management*, Volume 24, pp. 102-16.

Bingham, N. H. and R. Kiesel (2000), *Risk-Neutral Valuation, Pricing and Hedging of Financial Derivatives*, Springer-Verlag, London.

Bluhm, C., L. Overbeck and C. Wagner (2001), *An introduction to credit risk modeling*, Chapman & Hall, Boca Raton, Florida.

Chen, S. X. and C. Y. Tang (2005), 'Nonparametric inference of value-at-risk for dependent financial returns', *Journal of Financial Econometrics*, Volume 3, pp. 227-55.

Crosbie, P. (1999), *Modeling default risk*, KMV Corporation.

Crouhy, M., R. Mark and D. Galai (2001), *Risk Management*, McGraw-Hill, New York.

Danielsson, J. and C. de Vries (1997), 'Tail index and quantile estimation with very high frequency data', *Journal of Empirical Finance*, Volume 4, pp. 241-57.

Davis, M. H. A. at al. (1991), *Mathematical Finance*, IMA Volume 65, pp. 47-62, Springer-Verlag, New York.

Ding, Z., C. W. J. Granger and R. F. Engle (1993), 'A long memory property of stock market returns and a new model', *Journal of Empirical Finance*, Volume 1, pp. 83-106.

Dorfman, M. (2005), *Introduction to Risk Management and Insurance*, Prentice Hall, New Jersey.

Dowd, K. (2005), *Measuring market risk*, Wiley, West Sussex.

Dowd, K. (1998), *Beyond Value at Risk, The new science of risk management*, Wiley, West Sussex.

Esch, L., R. Kieffer and T. Lopez (2005), *Asset and Risk Management*, Wiley, West Sussex.

Fabozzi, F. J., L. Martellini and P. Priaulet (2006), *Advanced Bond Portfolio Management*, John Wiley & Sons Inc., Hoboken, New Jersey.

Fernandez, C. and M. Steel (1998), 'On Bayesian modelling of fat tails and skewness', *Journal of the American Statistics Association*, Volume 93, pp. 359-71.

Finger, C. C. (1999), *Conditional approaches for creditmetrics portfolio distribution*, CreditMetrics™ Monitor.

Gencay, R. and F. Selcuk (2004), 'Extreme value theory and value-at-risk: relative performance in emerging markets', *International Journal of Forecasting*, Volume 20, pp. 287-303.

Gencay, R., F. Selcuk and A.Ulugulyagci (2003), 'High volatility, thick tails and extreme value theory in value-at-risk estimation', *Insurance: Mathematics and Economics*, Volume 33, pp. 337-56.

Hall, P., C. L. Wolff and Q. Yao (1999), 'Methods for estimating a conditional distribution function', *Journal of American Statistical Association*, Volume 94, pp. 154-63.

Ho, L.C. et al. (2000), 'Value at Risk: Applying the Extreme Value Approach to Asian Markets in Recent Financial Turmoil', *Pacific-Basin Finance Journal,* Volume 8, pp. 249-275.

Holton, G. A. (2003), *Value at Risk: Theory and Practice*, Academic Press, Amsterdam.

Jorion, P. (2001), *Value at Risk*, McGraw-Hill, New York, NY, .

Jorion, P. (1997), *Value at Risk: The New Benchmark for Controling Market Risk*, McGraw-Hill, Chicago, IL, .

Loretan, M. and P.C.B. Phillips (1994), 'Testing the covariance stationary of heavy-tailed time series', *Journal of Empirical Finance*, Volume 1, pp. 211-48.

Karatzas, I. and S. E. Shreve (1998), *Methods of Mathematical Finance*, Springer-Verlag, New York.

Koenig, D. R. (2004), *Volume I: Finance Theory, Financial Instruments and Markets*, PRMIA Publications, Wilmington, DE.

Koenig, D. R. (2004), *Volume II: Mathematical Foundations of Risk Measurement*, PRMIA Publications, Wilmington, DE.

Koenig, D. R. (2004), *Volume III: Risk Management Practices*, PRMIA Publications, Wilmington, DE.

Lamberton, D. and B. Lapeyre (1996), *Introduction to Stochastic Calculus Applied to Finance*, Chapman & Hall, London.

Marrison, C. (2002), *The Fundamentals of Risk Measurement*, McGraw-Hill, New York .

Morgan Guaranty Trust Company (1994), *RiskMetrics-Technical Document*, Morgan Guaranty Trust Company, Global Research, New York, NY, .

Pestman, W. R. (1998), *Mathematical Statistics*, Walter de Gruyter, Berlin-New York.

Silva, A. and B. Mendes (2003), 'Value-at-risk and extreme returns in Asian stock markets', *International Journal of Business*, Volume 8, pp.17-40.