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MARKET RISK ASSESSMENT USING ANALYTICAL METHOD DURING THE GLOBAL FINANCIAL CRISIS: A CASE STUDY OF THE TRADING PORTFOLIO ON THE BELGRADE STOCK EXCHANGE

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Abstract
This research analyzes the market risk of a portfolio containing continuously traded stocks on the Belgrade Stock Exchange during the global financial crisis of 2008–2009. Utilizing the Value-at-Risk (VaR) model through an analytical approach, it examines potential losses at varying confidence intervals. The method's effectiveness is evaluated based on the failure rate, identifying the confidence level at which the model proves reliable under the specified conditions. The analysis contributes to a better understanding of how traditional risk assessment tools perform in emerging markets during periods of heightened volatility. Additionally, it highlights the importance of model calibration and backtesting in capturing extreme market movements.
Keywords: market risk, Value-at-risk (VaR) model, analytical method, financial market

PROCENA TRŽIŠNOG RIZIKA KORIŠĆENJEM ANALITIČKE METODE TOKOM FINANSIJSKE KRIZE 2008–2009. GODINE

Apstrakt
Ovo istraživanje analizira tržišni rizik portfolia koji sadrži akcije kojima se kontinuirano trguje na Beogradskoj berzi, tokom globalne finansijske krize 2008–2009. godine. Koristeći model Value-at-Risk (VaR) kroz analitički pristup, ispituju se potencijalni gubici na različitim intervalima poverenja. Efikasnost metoda procenjuje se na osnovu stope neuspeha, identifikujući nivo pouzdanosti na kojem se model pokazao pouzdanim u zadatim uslovima. Analiza doprinosi boljem razumevanju načina na koji tradicionalni alati za procenu rizika funkcionišu na tržištima u razvoju tokom perioda povećane volatilnosti. Pored toga, naglašava se značaj kalibracije modela i provere tačnosti u uslovima ekstremnih tržišnih kretanja.
Ključne riječi: tržišni rizik, vrednost izloženog riziku (VaR) model, analitička metoda, finansijsko tržište

INTRODUCTION

In 2007, the United States was hit by a financial crisis originating in the mortgage market, which soon escalated into a global economic downturn. A huge number of debtors were unable to repay their loans, and US banking giants, which had great expectations in terms of earnings arising from these loans, found themselves facing bankruptcy. However, the crisis did not stop with the mortgage market, and in 2008 it spread on the market of stocks and bonds, the prices of which decreased drastically. In September 2008, several large investment banks that had bad mortgage securities in their balance sheets went bankrupt. After September 2008, the crisis deepened and spread across the EU, Russia and other countries, causing panic in the financial and banking markets. The stock market crisis and banking crisis are illustrated by the indicators that show a drastic decline in bank loans and the value of shares and bonds on the stock market that, together with a decline in inflow of net foreign capital, reflected on the decline in economic activity and investors' confidence to invest in the economy. Stock exchange and banking crisis spread to the real economy in many countries and caused a recession.

This paper explores the market risk assessment on the Serbian stock market during the 2008–2009 period, focusing particularly on Value-at-Risk (VaR) modeling. The period under review was notably shaped by the global financial crisis, which had profound impacts on emerging markets like Serbia. The Serbian market, heavily influenced by the global downturn, witnessed extreme market volatility during this period, thus emphasizing the importance of accurately quantifying risk in such turbulent times.

The analytical VaR model used in this research aims to measure potential market risk by calculating the maximum expected loss over a given time horizon at a specific confidence level, while also testing the model's accuracy through backtesting.

Value-at-Risk has become a critical tool in risk management for financial institutions, especially in volatile environments like the one observed in 2008-2009. Various approaches have been developed over time to estimate VaR, including historical simulation, variance-covariance, and models based on time-series data such as GARCH (Generalized Autoregressive Conditional Heteroskedasticity). These models offer different strengths and weaknesses in predicting risk, particularly under conditions of heavy-tailed distributions or market turbulence.

By comparing these methodologies, we aim to provide an in-depth assessment of the applicability and reliability of the VaR model in capturing risk during a major financial crisis. Previous works, including Obadović et al. (2016), offer insight into risk assessment in similar market conditions, contributing to the broader understanding of how risk can be measured and mitigated during extreme economic events.

In the evolving landscape of financial risk management, accurately quantifying potential losses is paramount. Value-at-Risk (VaR) has emerged as a cornerstone metric, offering a statistical estimate of the maximum expected loss over a specified time horizon at a given confidence level (Jorion, 2001). Its widespread adoption across financial institutions underscores its utility in risk assessment and regulatory compliance (Allen, Boudoukh, & Saunders, 2004).

The analytical, or variance-covariance, approach to VaR estimation is renowned for its computational efficiency and straightforward implementation. By assuming normally distributed returns and linear relationships among portfolio assets, this method facilitates rapid risk assessments (Alexander, 2008). However, its reliance on these assumptions can lead to underestimation of risk, especially during periods of market turbulence characterized by non-linear behaviors and fat-tailed distributions (Crouhy, Mark, & Galai, 2001; Shaik, 2022).

Alternative methodologies, such as historical simulation, Monte Carlo simulation, and GARCH-based models, have been developed to address these limitations. These approaches offer enhanced flexibility in modeling complex market dynamics but often at the expense of increased computational demands (Alexander & Baptista, 2004; Wang & Su, 2022). Recent literature also explores the integration of environmental, social, and governance (ESG) factors into VaR models, reflecting the growing emphasis on sustainable finance (Gao & Li, 2023).

Despite the advancements in alternative models, the analytical VaR approach remains a fundamental tool in risk management, serving as a benchmark for evaluating more complex models and providing quick insights into potential exposures (Dowd, 2005). This paper aims to delve into the analytical VaR model's framework, assess its applicability in contemporary financial contexts, and explore its integration with emerging risk factors.

Analytical VaR method

The analytical VaR model, also known as the variance-covariance method, estimates potential losses by assuming that asset returns are normally distributed and that the portfolio's composition remains static over the risk horizon. This method calculates VaR using the portfolio's mean return, standard deviation, and a z-score corresponding to the desired confidence level (Hull, 2012).

It sets the maximum loss that might hit over a chosen horizon at a preset confidence level. In short, VaR states how much the portfolio could lose with a given probability—say 95 % or 99 %. A one-day 5 % VaR of $1 million means the portfolio has a 95 % probability of not losing more than $1 million tomorrow, while a one-day 5 % VaR of –$1 million means the portfolio has a 95 % probability of gaining at least $1 million tomorrow (Crouhy 2001)**.** Financial firms compute VaR through techniques such as historical simulation, the analytical method, and Monte Carlo simulation.

The methodology employed here is identical to that used in the previously published study by Obadović and Obadović (2009), ensuring full comparability of results. The analytical method assumes that market variables follow a normal probability distribution. This assumption allows for the application of statistical tools, such as the Gaussian (Normal) distribution function:

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

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

The normal distribution can also be depicted as a bell-shaped curve. Its essential feature is symmetry, and it is fully specified by only two parameters: μ (mean) and σ (standard deviation). Once these are fixed, the normal distribution is fully determined and is denoted as N(μ, σ^2). The distribution N(0,l) is named the standard normal distribution. This standard form is obtained by rescaling every observation so that its deviation from the mean is expressed in standard-deviation units. The standardized distance of a random variable x_i from the mean is denoted by *z* and is computed with the formula:

$$z = \frac{x_i - \mu}{\sigma} \tag{2}$$

where $-\infty < z < +\infty$. Applying this formula to each observation yields its corresponding z_i value. For every z_i one can find the probability that the random variable x_i lies below or above that standardized value. The probability that z_i is less than a chosen value *y* is written:

$$\text{P}(z_i < y). \tag{3}$$

When the chance that z_i is smaller than 0.5 is required, we write:

$$\text{P}(z_i < 0{,}5). \tag{4}$$

This probability is obtained by evaluating the definite integral of the normal distribution function. Ready-made probabilities for every possible *y* values are provided in standard normal tables.

Because VaR is routinely computed at fixed confidence levels such as 90 %, 95 %, 99 % and 99.5 %, the z_i values that match these probabilities are already set.

By relying on the normal distribution, the variance-covariance method derives VaR as the product of the portfolio's standard deviation of value changes by a corresponding z_i value associated with the desired confidence level.

VaR depends only on the chosen confidence level (z), the portfolio's standard deviation (σ), and its current value (V). After the standard deviation of value changes is known, VaR is obtained from:

Table 1
Confidence levels and VaR

Confidence levels	VaR
90%	$-1{,}28*\sigma*V$
95%	$-1{,}65*\sigma*V$
99%	$-2{,}33*\sigma*V$
99,5%	$-2{,}58*\sigma*V$

The hardest part of the approach is estimating the standard deviation of the change in portfolio value. After that figure is in hand, VaR is simply the product of standard deviation σ, the specific value of parameter *z* and portfolio value V.

The standard deviation σ itself is extracted from the covariance matrix built from the assets' historical returns over the past *n* days. The calculation follows this formula:

$$\sigma = \sqrt{wVw^T} \quad , \qquad (5)$$

where $w = (w_1, w_2, \ldots\ldots, w_n)$ represents the weighted portfolio vector (nominal amounts invested into each asset), and *V* is covariance matrix, based on the daily returns of the assets. In this example, an equal amount (4.35%) of the initial portfolio value is allocated to each asset. The covariance matrix *V* is structured as follows:

$$\begin{bmatrix} Var(R_1) & Co\text{var}(R_1,R_2) & \ldots\ldots Co\text{var}(R_1,R_n) \\ Co\text{var}(R_2,R_1) & Var(R_2) & \ldots\ldots Co\text{var}(R_2,R_n) \\ . & . & . \\ . & . & . \\ . & . & . \\ . & . & . \\ Co\text{var}(R_n,R_1) & Co\text{var}(R_n,R_2) & \ldots\ldots Var(R_n) \end{bmatrix}, \qquad (6)$$

where $Var(R_n)$ represents variance of the return rate of asset n, and $Covar(R_n,R_m)$ represents the covariance between the return rates of assets n and m, and it satisfies $Covar(R_n,R_m)= Covar(R_m,R_n)$. Next, the standard deviation of the portfolio is obtained as the square root of its variance:

$$\sigma = \sqrt{\sigma^2}\ , \tag{7}$$

where:

$$\sigma^2 = [w_1, w_2, ..., w_n] \begin{bmatrix} Var(R_1) & Co\operatorname{var}(R_1,R_2) & ......Co\operatorname{var}(R_1,R_n) \\ Co\operatorname{var}(R_2,R_1) & Var(R_2) & ......Co\operatorname{var}(R_2,R_n) \\ . & . & . \\ . & . & . \\ . & . & . \\ . & . & . \\ Co\operatorname{var}(R_n,R_1) & Co\operatorname{var}(R_n,R_2) & ......Var(R_n) \end{bmatrix} \begin{bmatrix} w_1 \\ w_2 \\ . \\ . \\ . \\ . \\ w_n \end{bmatrix}. \tag{8}$$

The volatility needed to build the covariance matrix is computed using the equally weighted historical method:

$$\sigma = \sqrt{\frac{1}{T}\sum_{t=1}^{T}(r_t - r_m)^2}, \tag{9}$$

where r_t represents individual asset return rates and is the mean return rate of the asset. T is the number of observed daily return rates.

While this model offers simplicity and speed, its assumptions may not hold in real-world markets. Empirical studies have shown that financial returns often exhibit skewness and kurtosis, deviating from normality (Ding, Granger, & Engle, 1993). Moreover, during periods of financial stress, asset correlations can increase, leading to higher portfolio risk than estimated by the analytical model (Ziković & Aktan, 2009).

To enhance the analytical model's robustness, researchers have proposed incorporating alternative distributions, such as the t-distribution, to better capture fat tails (Chen, Liu, & Zhang, 2023). Additionally, adjustments for time-varying volatility through models like GARCH can provide more accurate risk estimates (Wang & Su, 2022).

Serbian Portfolio: Sample Dataset and Primary Value-at-Risk Assessment Results

The paper generates one-day Value-at-Risk estimates at four standard confidence thresholds (90 %, 95 %, 99 % and 99.5 %), for a Serbian equity portfolio composed of 23 continuously quoted companies on the Belgrade Stock Exchange during the two-year period following the global financial crisis (01.01.2008–31.12.2009).
Share-price series were downloaded from the Belgrade Stock Exchange official portal (www.belex.rs) and the ticker symbols and full corporate names that compose the portfolio are listed in Table 2. The sample employed here is a 23-company subset drawn from the original 27 firms examined in Obadović & Obadović (2009), rendering the results sufficiently comparable with the earlier study.

Table 2
Ticker symbols and names of the companies included in the portfolio

Symbol	Company name
1. SJPT	*Soja protein a.d. Bečej*
2. DNVG	*Dunav Grocka a.d. Grocka*
3. FITO	*Galenika Fitofarmacija a.d. Zemun*
4. IMLK	*Imlek a.d. Beograd*
5. NPRD	*Napred GP a.d. N. Beograd*
6. TLKB	*Telefonkabl a.d. Beograd*
7. TGAS	*Messer Tehnogas a.d. Beograd*
8. PUUE	*Putevi a.d. Užice*
9. CCNB	*Čačanska banka a.d. Čačak*
10. ALFA	*Alfa plam a.d. Vranje*
11. ENHL	*Energoprojekt holding a.d. Beograd*
12. MTLC	*Metalac a.d. Gornji Milanovac*
13. BMBI	*Bambi Banat a.d. Beograd*
14. PLNM	*Planum GP a.d. Beograd*
15. PTLK	*Pupin Telecom a.d. Zemun*
16. RMBG	*Ratko Mitrović a.d. Beograd*
17. TIGR	*Tigar a.d. Pirot*
18. BNNI	*Banini a.d. Kikinda*
19. RDJZ	*Radijator a.d. Zrenjanin*
20. AIKB	*AIK banka a.d. Niš*
21. PRGS	*Progres a.d. Beograd*
22. UNBN	*Univerzal banka a.d. Beograd*
23. KMBN	*Komercijalna banka a.d. Beograd*

Source: www.belex.rs

The portfolio-formation and tracking procedure replicates the one in Obadović & Obadović (2009), except that the present study employs a reduced set of 23 companies instead of the original 27. An initial investment of RSD 10 million is still allocated equally across the 23 firms (RSD 434,782.61 per company), the number of shares bought in each firm is held constant throughout the observation period, and all changes in portfolio value are driven solely by market-price movements, thereby preserving full comparability with the earlier study. The amount allocated to each company is obtained by dividing the total investment by the number of firms in the portfolio:

$$10{,}000{,}000 \;/\; 23 = 434{,}782.61 \text{ dinars.} \qquad (10)$$

Let $p_{1,1}$, $p_{1,2}$, ..., $p_{1,23}$ denote the share prices on 1 January 2008 and q_1, q_2, ..., q_{23} the number of shares bought in each firm. Equal cash allocation implies:

$$p_{1,1}\, q_1 = p_{1,2}\, q_2 = ... = p_{1,23}\, q_{23} = 434{,}782.609 \text{ dinars,} \qquad (11)$$

so the quantity purchased in each company is:

$$q_n = 434{,}782.609 \;/\; p_{n,n}. \qquad (12)$$

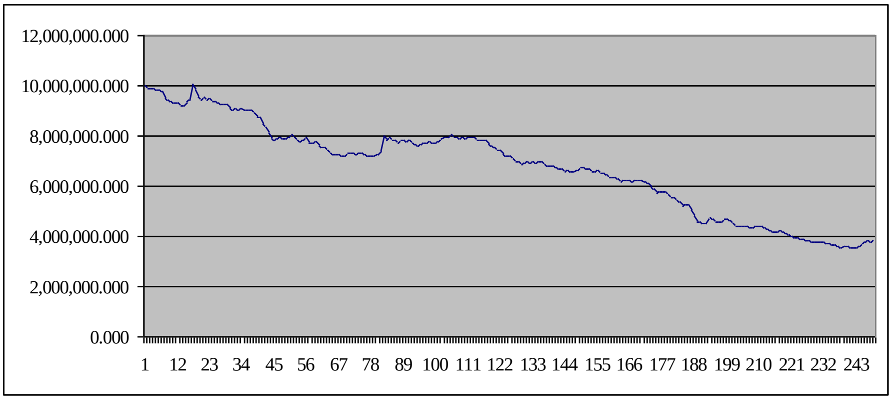
This quantity is held constant throughout the sample period; only market-price movements and their effect on portfolio value are recorded.
After prices change to $p_{2,1}$, $p_{2,2}$, ..., $p_{2,23}$ the next day, the portfolio is worth RSD 9,911,450.35. The relative change is:

$$(9{,}911{,}450.35 - 10{,}000{,}000) \;/\; 10{,}000{,}000 = -0.00886 = -0.886\ \%,$$

i.e. a loss of 0.886 %.
One year (249 trading days) later, the portfolio was worth RSD 3,804,795.13, a shortfall of RSD 6,195,204.87 relative to the starting capital, resulting in a negative return of 61.95%. The chart below illustrates how the portfolio's value evolved throughout 2008.

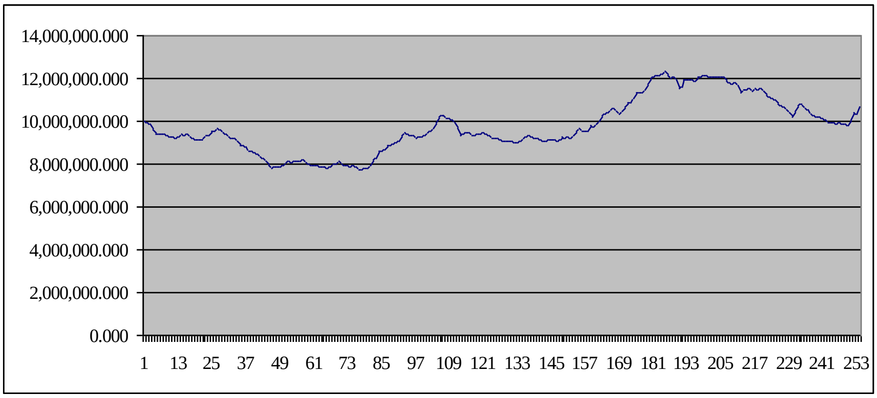
Image 1

Visual overview of portfolio value movements during 2008



At the start of 2009 an investment of RSD 10,000,000 was placed in the portfolio, and after 254 trading days the position ended the year at RSD 10,738,961.11, a gain of 7.39 percent. The chart below tracks the portfolio's value throughout 2009.

Image 2
Visual overview of portfolio value movements during 2009.



Using the standard analytical approach we computed one-day Value at Risk at the 90%, 95%, 99%, and 99.5% confidence levels, and the outcomes are reported in Table 3 and displayed in Figures 3 and 4.

Table 3
One-day VaR estimates obtained with the delta-normal approach across multiple confidence levels

VaR	31.12.2009	31.12.2008
$VaR_{99.5\%}(23)$	2.9989%	4.1609%
$VaR_{99\%}(23)$	2.7020%	3.7912%
$VaR_{95\%}(23)$	1.8909%	2.7815%
$VaR_{90\%}(23)$	1.4585%	2.2432%

Source: Authors' calculation.

From Table 3, it is evident that on 31/12/2008, at a 99.5% confidence level, the maximum estimated one-day loss was 4.1609% of the portfolio value. Scaling the one-day result to a 250-day horizon in the usual way (loss × √250) gives a maximum projected decline of 65.79 percent, underscoring a very high risk exposure.

The figure that follows shows the portfolio returns and the analytically derived VaR figures for the 23-stock portfolio during 2008.

Image 3

2008 portfolio returns and analytical VaR chart

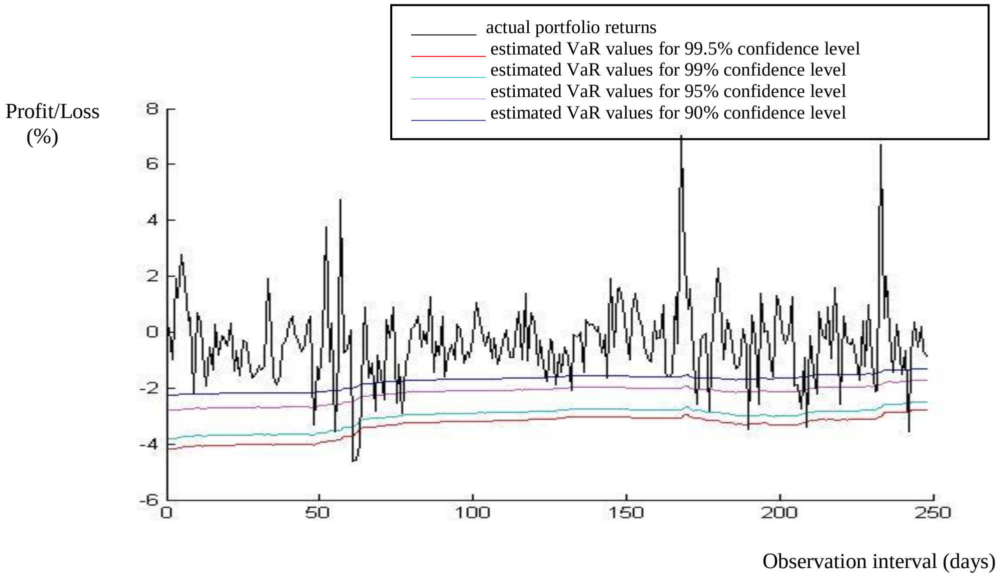


Image 3 plots 248 consecutive daily VaR forecasts (shown in color) at four confidence levels for the 23-share portfolio throughout 2008.

The black line tracks the corresponding 248 realised daily portfolio returns, providing a direct visual benchmark for the VaR estimates.

Image 4

2009 portfolio returns and analytical VaR chart

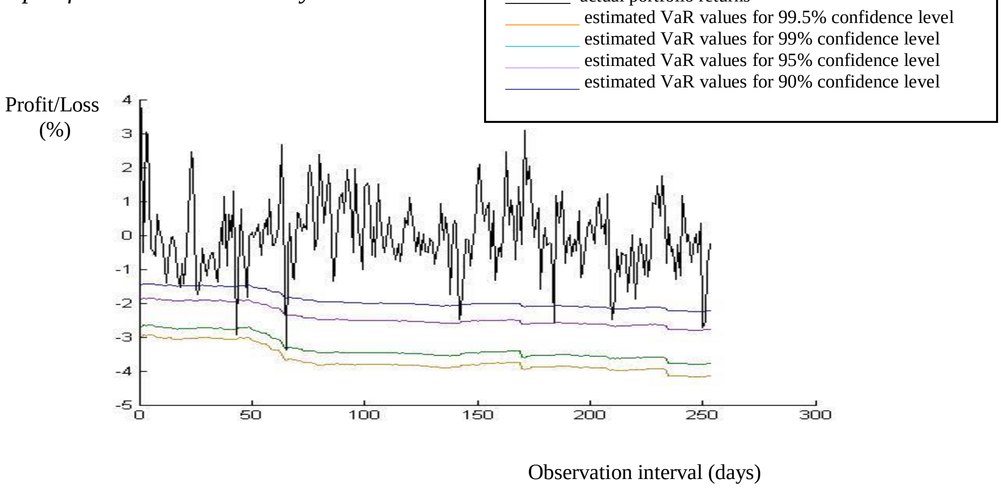


Image 4 plots 248 consecutive daily VaR forecasts (shown in color) at four confidence levels for the 23-share portfolio throughout 2009.

The black line tracks the corresponding 248 realised daily portfolio returns, providing a direct visual benchmark for the VaR estimates.

VERIFICATION OF MODEL ACCURACY

Estimated VaR (Value at Risk) values should not be taken at face value. As previously shown, there were instances where portfolio returns exceeded the estimated VaR values on certain days. Therefore, it is essential to verify the model's accuracy.
The simplest approach to verify accuracy is to calculate the failure rate, which measures how often the actual loss surpasses the estimated VaR value within a given dataset. Let N represent the number of exceedances (instances when losses exceed VaR). At a given confidence level, if N is significantly smaller or larger than expected, it indicates potential inaccuracies in the model.
The table below displays the number of exceedances (N) for various confidence levels in the years 2008 and 2009:

Table 4
Frequency of actual losses exceeding VaR estimates for a portfolio of 23 shares (2008–2009, analytical method)

Delta normal method	2009 T=253	2008 T=248
p=0.005	N = 0	N = 6
p=0.01	N = 2	N = 6
p=0.05	N = 2	N = 21
p=0.1	N = 11	N = 29

Source: Authors' calculation.

where T – the total number of VaR predictions, and N – the number of days actual losses exceeded VaR estimates.
The failure rate (N/T) is then compared to the left-tail probability (e.g., p = 0.01) used for VaR estimation. If these values align, the model is considered accurate. If significant deviations exist, the model should be rejected.
To keep the test transparent, we adopt the 95 % confidence level, roughly two standard deviations under normality, as the cut-off for model acceptance. Kupiec (1995) frames this decision with a likelihood ratio (LR) test whose acceptable region is defined as follows:

$$LR= -2\ln [(1 - p)^{T-N} p^{N}] + 2\ln [(1 – (N/T)^{T-N} (N/T)^{N}].$$

The LR statistic is asymptotically $\chi^2(1)$ distribution under the null hypothesis that p equals the true exceedance probability.

For example, with T = 250 observations and p = 0.10, the expected number of exceedances would be:

$$N = pT = 0.1 \times 250 = 25.$$

The null hypothesis is retained provided N lies inside the 95 percent confidence interval $15 < N < 35$. Values $N \geq 35$ indicate the model understates risk, whereas $N \leq 15$ imply it is excessively conservative.
The table below outlines the acceptable regions for model verification at a 5% significance level ($\alpha = 0.05$):

Table 5
Acceptable regions for model verification at a 5% significance level

Delta normal method	2009 T=253	2008 T=248
p=0.005	0<N<4	0<N<4
p=0.01	0<N<7	0<N<7
p=0.05	5<N<20	5<N<20
p=0.1	15<N<36	15<N<35

Source: Authors' calculation.

The final verification, based on Kupiec's Likelihood Ratio test, determines whether the model is acceptable or rejected at different confidence levels:

Table 6
Model verification results using kupiec's likelihood ratio test

Delta normal method	2009 T=253	2008 T=248
p=0.005	accepted	rejected
p=0.01	accepted	accepted
p=0.05	rejected	rejected
p=0.1	rejected	accepted

Source: Authors' calculation.

CONCLUSION

Value-at-Risk projections give managers an early view of the downside a portfolio may face within a fixed horizon. Among the many techniques discussed in the literature, we rely on the simple variance–covariance approach, producing one-day VaR figures at 90 %, 95 %, 99 % and 99.5 % confidence levels for an equally weighted basket of twenty-three liquid Serbian stocks recorded daily on the Belgrade Stock Exchange from 1 January 2008 through 31 December 2009. To verify the model's accuracy, a 5% significance level (α = 0.05) was employed. The results revealed the following findings:

- **In 2009**, the analytical VaR method overestimated risk at lower confidence levels (90% and 95%).
- **In 2008**, no clear pattern emerged across different confidence levels. At higher confidence levels (99.5% and 95%), the method underestimated risk, while it performed acceptably at lower confidence levels.

These results underscore the sensitivity of the analytical VaR method to extreme market conditions, such as those experienced during the 2008 financial crisis. The model's limitations become especially evident when return distributions deviate from normality, which is a fundamental assumption of the analytical approach. While the analytical method is computationally efficient and easy to interpret, its reliability may be compromised during periods of high volatility or market stress.

The analytical VaR model remains a valuable tool in financial risk management due to its simplicity and effectiveness. Its ease of implementation makes it particularly useful for preliminary risk assessments and regulatory reporting. However, the model's reliance on assumptions, such as normal distribution and static correlations, can limit its accuracy in volatile market conditions.

Enhancements to the model, including the adoption of alternative distributions and the integration of volatility modeling techniques like GARCH, show promise in addressing the limitations of the basic VaR method (Alexander & Baptista, 2004; Wang & Su, 2022). Moreover, the inclusion of environmental, social, and governance (ESG) factors in VaR assessments reflects the evolving nature of risk considerations in modern finance (Gao & Li, 2023).

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REZIME

Ovo istraživanje bavi se procenom tržišnog rizika portfolija sastavljenog od akcija kojima se kontinuirano trguje na Beogradskoj berzi u periodu globalne finansijske krize 2008–2009. godine, koji je bio obeležen izraženom nestabilnošću, povećanom volatilnošću i značajnim padovima tržišnih vrednosti. Cilj rada je da se ispita primenljivost i pouzdanost analitičke metode Value-at-Risk (VaR) u uslovima ekstremnih tržišnih kretanja, sa posebnim fokusom na tržište u razvoju. U istraživanju se koristi analitički VaR model, koji polazi od pretpostavke normalne raspodele prinosa, kako bi se procenili potencijalni maksimalni gubici portfolija za različite nivoe poverenja i vremenske horizonte. Dobijeni rezultati se zatim upoređuju sa stvarnim ostvarenjima gubitaka, pri čemu se efikasnost modela ocenjuje primenom backtesting procedure, odnosno analizom stope neuspeha (failure rate). Na taj način identifikuje se nivo poverenja na kojem analitički VaR model pokazuje najveći stepen pouzdanosti u posmatranom periodu. Rezultati istraživanja ukazuju na ograničenja tradicionalnih modela za procenu rizika u periodima finansijskih kriza, kada dolazi do odstupanja od standardnih statističkih pretpostavki. Ipak, analiza pokazuje da pravilna kalibracija modela i kontinuirana provera njegove tačnosti mogu značajno unaprediti kvalitet procene tržišnog rizika. Rad doprinosi boljem razumevanju ponašanja analitičkih metoda za merenje rizika na tržištima u razvoju i pruža korisne smernice za njihovu primenu u uslovima povećane neizvesnosti i sistemskih šokova.