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Extreme Value Theory-Based Value at Risk for Stock Portfolio Risk Estimation: A Comparative Study of GEV and GPD Models in Indonesian Banking Stocks

Umar Sodiq[a], Epha Diana Supandi[b]*

[a,b]Department of Mathematics, Faculty of Science and Technology, Universitas Islam Negeri Sunan Kalijaga, Indonesia

*Corresponding author: umarsodiq0001@gmail.com

ABSTRACT

Risk management is a crucial element in stock investment activities to minimize the negative impacts of market uncertainty, particularly during periods of extreme price fluctuations. One effective statistical approach for measuring maximum potential loss in return distributions characterized by fat tails is Value at Risk (VaR) integrated with Extreme Value Theory (EVT). This study aims to analyze stock portfolio risk, estimate potential losses, and evaluate the comparative accuracy of the Block Maxima and Peak Over Threshold methods. The Block Maxima method models maximum extreme values within specific time blocks using the Generalized Extreme Value (GEV) distribution, whereas the Peak Over Threshold method models data exceeding a predefined threshold (u) using the Generalized Pareto Distribution (GPD). The research sample consists of five banking subsector stocks with the largest market capitalization, BBCA, BBRI, BMRI, BBNI, and BRIS for the period from May 1, 2019, to May 31, 2025. Results indicate that VaR estimation at a 95% confidence level using the VaR-GEV method yields a potential loss of 6.64%, while the VaR-GPD method yields 3.13%. Evaluation via the Kupiec backtesting test reveals that the VaR-GEV model is invalid due to being overly conservative with an excessively low violation rate. Conversely, the VaR-GPD model is proven valid, with an actual violation rate of 5.49% that closely aligns with expected values. Given its superior validity and accuracy, the Value at Risk Generalized Pareto Distribution approach is determined to be the optimal model for estimating market risk under extreme conditions.

Keywords: Block Maxima, Extreme Value Theory, Investment, Peak Over Threshold, Value at Risk

1. Introduction

The dynamics and uncertainties of domestic and global financial markets require financial institutions, particularly the banking sector, to possess a robust risk management system. The urgency of implementing effective risk management in Indonesia became increasingly evident when faced with extreme external shocks, such as the pandemic crisis in early 2020, which triggered a drastic contraction in Gross Domestic Product (GDP). Such highly volatile market conditions acted as a massive-scale stress test for the banking subsector. Therefore, the implementation of precise risk management is not merely a matter of compliance with the Financial Services Authority (OJK) regulations, but a crucial necessity to maintain the stability of the financial sector and protect shareholder value amidst uncertainty [1].

In practice, a standard instrument widely used by banks to measure maximum potential losses due to market fluctuations is Value at Risk (VaR) [2].However, there is a significant research gap regarding the application of conventional VaR. The traditional parametric VaR approach generally assumes that asset returns follow a normal distribution, implying that extreme events (tail events) are considered exceedingly rare. In reality, empirical financial data consistently exhibit a fat-tail phenomenon, where massive loss events occur much more frequently than predicted by a normal distribution. This limitation causes conventional VaR to underestimate the risk of extreme losses, which can be detrimental to a financial institution's capital allocation and risk mitigation strategies during a crisis.

In response to the limitations of traditional risk models, the Extreme Value Theory (EVT) approach provides a statistical framework that specifically models the behavior of extreme values at the tail of a probability distribution [3].The application of EVT, through either the Block Maxima or Peak Over Threshold (POT) methods, is highly relevant to the characteristics of the Indonesian capital market, which is prone to high volatility. This is due to EVT's capability to capture the probability of fat-tail risks that are overlooked by the normality assumption. Given that regulators increasingly encourage the adoption of risk metrics that are resilient to tail risk, this study aims to measure and analyze market risk using the Value at Risk (VaR) method combined with the Extreme Value Theory (EVT) approach on banking subsector stocks. It is anticipated that these measurement results will yield more robust projections of extreme losses, serving as a reliable basis for evaluating the readiness of banking risk models.

2. Theoritical Framework

2.1 Stock Return

The return of an asset is the yield or rate of return obtained from an investment [4]. The return can be calculated using the log return or continuously compounded return formula as follows:

$$R_t = \ln \frac{P_t}{P_t - 1} \tag{1}$$

With,
R_t = Stock return at time t
P_t = Stock price at time t
$P_t - 1$ = Stock price at time $t - 1$

2.2 Portfolio Return

The portfolio return at period t is the weighted average of the returns of the individual assets in the portfolio. If the portfolio consists of N assets, with the weight of the i-th asset being w_i and the return of the i-th asset at period t denoted as $R_{i,t}$, then the portfolio return can be calculated using the following formula [5]:

$$R_{p,t} = \sum_{i=1}^{N} w_i R_{i,t} \text{ , } t = 1,2, \dots, T \tag{2}$$

With,
$R_{p,t}$ = Portfolio return at period t
w_i = weight of the i-th asset
$R_{i,t}$ = Return of the i-th asset at period t
N = Number of assets in portfolio
T = Number of observation periods

2.3 *Extreme Value Theory*

Extreme Value Theory (EVT) is a statistical analytical framework specifically formulated to model the asymptotic behavior of a tail distribution. The primary advantage of this methodology lies in its ability to estimate the probability of extreme events in heavy-tailed data, a characteristic that conventional statistical assumptions often fail to accommodate accurately. Within its implementation framework for identifying and extracting these extreme observations, two fundamental modeling paradigms are utilized: the Block Maxima (BM) and Peaks Over Threshold (POT) approaches [6].

2.4 *Block Maxima*

The block maxima method is an approach for identifying extreme events by partitioning a series of observations into uniform time intervals, where the maximum value from each interval is extracted as the primary sample to represent the extreme conditions of that period [7]. Applying the Fisher-Tippett-Gnedenko theorem (1928), the extreme sample data derived from this method follows the Generalized Extreme Value (GEV) distribution. The cumulative distribution function (CDF) of the GEV distribution is expressed as follows:

$$F(x) = \begin{cases} \exp\left\{-\left[1+\xi\left(\frac{x-\mu}{\sigma}\right)\right]^{-\frac{1}{\xi}}\right\}, & if\ \xi \neq 0 \\ \exp\left\{-\,exp\left[-\left(\frac{x-\mu}{\sigma}\right)\right]\right\}, & if\ \xi = 0 \end{cases} \tag{3}$$

Where $1+\xi\left(\frac{x-\mu}{\sigma}\right) > 0$

$\mu = location\ parameter$
$\sigma = scale\ parameter$
$\xi = shape\ parameter$

2.5 *Peaks Over Threshold*

According to Coles (2001), the Peak Over Threshold (POT) method in Extreme Value Theory identifies extreme values by isolating data that exceeds a specific threshold. Mathematically, for a given threshold u, an observation x is considered extreme if $x > u$ with the excess defined as $y = x - u$. This method applies the Pickands-Balkema-de Haan theorem, which states that for a sufficiently high threshold (u), the distribution of the exceedances will follow the Generalized Pareto Distribution (GPD). The cumulative distribution function (CDF) of the GPD is expressed as follows:

$$F(x) = \begin{cases} 1-(1+\xi\left(\frac{x-\mu}{\sigma}\right)^{-\frac{1}{\xi}}, & if\ \xi \neq 0 \\ 1-\exp\left(-\frac{x-\mu}{\sigma}\right), & if\ \xi = 0 \end{cases} \tag{4}$$

Where μ is the location parameter, $\sigma > 0$ is the scale parameter, and ξ is the shape parameter. The domain is $x \geq \mu$ when $\xi \geq 0$, and $\mu \leq x \leq \mu - \frac{\sigma}{\xi}$ when $\xi < 0$.

2.6 *Parameter Estimation*

The Maximum Likelihood Estimation method can be employed to determine the parameter estimates for the Generalized Extreme Value distribution using the Block Maxima approach, as well as for the Generalized Pareto Distribution using the Peak Over Threshold approach. This process involves constructing probability density functions, which are detailed in Equation (5) for the Generalized Extreme Value model and Equation (6) for the Generalized Pareto Distribution model [8].

$$f(x;\mu,\sigma,\xi) = \begin{cases} \frac{1}{\sigma}\left[1+\xi\left(\frac{x-\mu}{\sigma}\right)\right]^{-\frac{1}{\xi}-1} \exp\left\{-\left[1+\xi\left(\frac{x-\mu}{\sigma}\right)\right]^{-\frac{1}{\xi}}\right\}, \xi \neq 0 \\ \frac{1}{\sigma} exp\left[-\left(\frac{x-\mu}{\sigma}\right)\right] \exp\left\{-\exp\left[-\left(\frac{x-\mu}{\sigma}\right)\right]\right\}, \xi = 0 \end{cases} \tag{5}$$

with $1+\xi(\frac{x-\mu}{\sigma}) > 0; -\infty < \mu < \infty; \sigma > 0; -\infty < \xi < \infty; -\infty < x < \infty$

$$f(y;\sigma,\xi) = \begin{cases} \frac{1}{\sigma}\left(1+\xi\frac{y}{\sigma}\right)^{-\frac{1}{\xi}-1}, & \xi \neq 0 \\ \frac{1}{\sigma}\exp\left(-\frac{y}{\sigma}\right), & \xi = 0 \end{cases} \tag{6}$$

with $1+\frac{\xi x}{\sigma} > 0; \sigma > 0; -\infty < \xi < \infty; 0 < x < \infty$

2.7 Value at Risk

Value at Risk (VaR) represents the estimated maximum potential loss that may occur at a specific probability level and time interval, making it a primary metric for establishing the loss tolerance limit of an investment [9]. The Value at Risk for the GEV method can be obtained using the following equation:

$$VaR_{p(GEV)} = \hat{\mu} + \frac{\hat{\sigma}}{\hat{\xi}}\left[(-\ln(1-p))^{-\hat{\xi}} - 1\right] \tag{7}$$

With,

$\hat{\mu}$ = Location parameter estimation
$\hat{\sigma}$ = Scale parameter estimation
$\hat{\xi}$ = Shape parameter estimation
p = risk probability

Meanwhile, the Value at Risk calculation for GPD approach is performed based on the following equation:

$$VaR_{p(GPD)} = u + \frac{\hat{\sigma}}{\hat{\xi}}\left[\left(\frac{np}{N_u}\right)^{-\hat{\xi}} - 1\right] \tag{8}$$

With,

u = Threshold
$\hat{\sigma}$ = Scale parameter estimation
$\hat{\xi}$ = Shape parameter estimation
n = Sample total
N_u = Total Exceedances
p = Risk probability

2.8 Backtesting

Backtesting evaluates VaR model accuracy using Kupiec's Proportion of Failures (POF) test to verify if the empirical failure rate matches the expected tail probability. The log-likelihood ratio test statistic is formulated as [10]:

$$LR_{uc} = -2\ln[(1-p)^{T-N}p^{N}] + 2\ln\left[\left(1-\frac{N}{T}\right)^{T-N}\left(\frac{N}{T}\right)^{N}\right] \tag{9}$$

Where N is the number of failures and T is total observations. The VaR model is deemed accurate if LR_{uc} is below the critical χ^2 value with 1 degree of freedom, confirming consistency between expected and actual failure proportions.

3. Methods

This research employs a quantitative approach combining case study and literature review methods. The research object focuses on the daily closing price data of banking subsector stocks listed on the Indonesia Stock Exchange (IDX) during the period of May 1, 2019, to May 31, 2025. The sample selection was conducted selectively based on the criteria of banking stocks that were consistently listed during the research period and included in the top 50 stocks with the highest market capitalization in May 2025. Based on these criteria, five stocks were selected as samples: BBCA, BBRI, BMRI, BBNI, and BRIS. The data collection technique was carried out through non-participant observation, where the researcher collected historical secondary data accessed online via the Yahoo Finance website.

The data analysis technique applied is investment risk measurement using the Value at Risk method with an Extreme Value Theory approach. This analysis utilizes two main methods: Block Maxima, which is modeled with the Generalized Extreme Value distribution, and Peak Over Threshold, which is modeled with the Generalized Pareto Distribution The specific stages of data analysis in this research are as follows:

1. Extracting stock price data from May 2019 to May 2025.
2. Calculating the log return of each individual stock.
3. Conducting descriptive analysis on individual stock returns.
4. Determining portfolio weights based on higher average returns.
5. Calculating the combined portfolio return value.
6. Extracting extreme data using 3 weekly Block Maxima and 10% Peak Over Threshold.
7. Estimating GEV and GPD parameters via Maximum Likelihood.
8. Testing GEV and GPD goodness-of-fit via Anderson-Darling.
9. Calculating VaR using validated BM-GEV and POT-GPD models.
10. Backtesting VaR accuracy using Kupiec's Proportion of Failure Test.
11. Comparing the accuracy of BM-GEV and POT-GPD models.

All stages of data processing, simulation, and complex statistical analysis in this study were executed using RStudio software with the R programming language version 4.5.2.

4. Results and Discussion

4.1 Descriptive Analysis of Stock Return

Daily stock return is a fundamental variable frequently used as the basis in risk calculation. The movement and volatility of stock returns over time can be visually observed using a time series plot. The following is the time series plot of the daily stock returns from the banks used in this research.

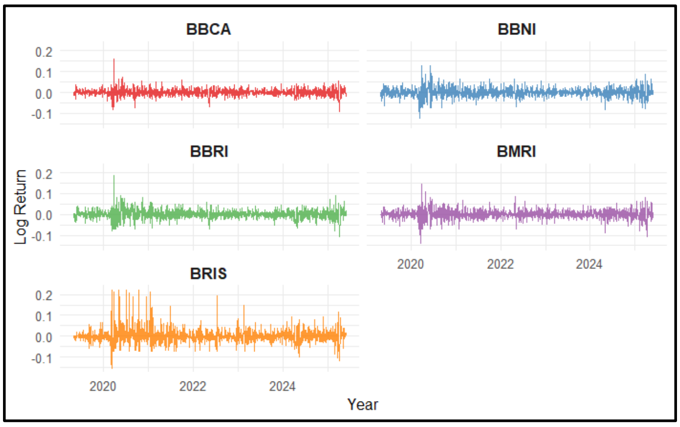

Figure 1. Time Series Plot of Stock Returns

Figure 1 presents the daily log returns of the five banking stocks, exhibiting mean-reversion to zero and distinct volatility clustering. The significant presence of extreme positive and negative spikes particularly around 2020 and most notably in BRIS indicates heavy-tailed distributions. This empirical evidence of extreme return fluctuations directly justifies the application of Extreme Value Theory (EVT) for accurate Value at Risk (VaR) estimation in this study. Furthermore, the detailed descriptive statistical characteristics of the log returns for these five stocks are presented in Table 1.

Table 1. Descriptive Statistic of Stock Returns

Stocks	Mean	Max	Min	Deviation Standard	Skewness	Kurtosis
BBCA	0,000430	0,159849	-0,089153	0,015871	0,571	12,774
BBNI	0,000127	0,127927	-0,124643	0,021943	0,151	7,115
BBRI	0,000306	0,186412	-0106733	0,020970	0,482	9,499
BMRI	0,000457	0,146721	-0,146721	0,021503	-0,049	8,119
BRIS	0,001186	0,223144	-0,155485	0,035342	2,017	14,258

Based on Table 1, BRIS records the highest average return, indicating a superior rate of profitability compared to the other companies. In terms of volatility, BBCA shows the lowest standard deviation, signifying a more stable stock with less dispersion from its mean. Furthermore, looking at the asymmetry of the return distribution, BMRI is the only stock with a negative skewness, which implies a slightly longer left tail and a tendency for extreme negative returns. On the other hand, BRIS exhibits the highest positive skewness. Lastly, all stocks display high kurtosis values, indicating a leptokurtic distribution with 'fat tails'. BRIS has the highest kurtosis, which suggests its return data has the highest frequency of extreme outliers or sudden price movements, making it a highly volatile asset.

4.2 Portfolio

Portfolio asset allocation is weighted according to each stock's mean return, assigning higher proportions to stocks with greater average returns. The calculated portfolio weights for each asset, proportioned according to their mean returns, are detailed in Table 2.

Table 2. Weight Of Each Stock Based On Mean Return

Stocks	Mean *Return*	Weight
BBCA	0,000430	0,1716
BBNI	0,000127	0,0507
BBRI	0,000306	0,1222
BMRI	0,000457	0,1822
BRIS	0,001186	0,4733

As illustrated in the table, BRIS commands the largest portfolio allocation at 47.33%, corresponding directly to its highest mean return. Conversely, BBNI receives the smallest proportion at 5.07% due to its lowest average return. The remaining capital is distributed among BMRI, BBCA, and BBRI, which account for 18.22%, 17.16%, and 12.22% of the portfolio, respectively.

4.3 Block Maxima Generalized Extreme Value

The Block Maxima approach is employed to identify extreme values. The dataset is segmented into three-week intervals, with each block containing 15 observations. The maximum return value within each block is then selected to form the extreme value dataset, which is subsequently used for distribution modeling and parameter estimation. Following the extraction of these block maxima, the parameters for the Generalized Extreme Value distribution are estimated. The estimation outcomes are presented in Table 3.

Table 3. Block Maxima Parameter Estimation

Location Parameter (μ)	Scale Parameter (σ)	Shape Parameter (ξ)
0,02093909	0,01203623	0,15646255

The location parameter ξ estimated at 0.02093909, indicates the central tendency or the peak of the distribution. The scale parameter σ calculated as 0.01203623, reflects the dispersion or volatility of the extreme data. Furthermore, the shape parameter ξ, which determines the tail behavior of the distribution, is estimated at 0.15646255. This positive shape parameter signifies a heavy-tailed distribution, implying a higher likelihood of extreme market events. Consequently, while such extreme values suggest the potential for substantial returns, they simultaneously expose investors to a significantly heightened risk of severe financial losses.

4.4 Peak Over Threshold Generalized Pareto Distribution

Another approach utilized to handle extreme values is the Peak Over Threshold (POT) method. In this procedure, extreme data extraction is performed by establishing a threshold (u) at the 90th percentile of the entirely sorted dataset, yielding a u value of 0.0193314. From the total observations, data points exceeding this threshold, extracted. Subsequently, the excess value is calculated as the difference between the exceedances and the threshold. These excess values are then modeled, and their parameters are estimated using the Generalized Pareto Distribution. Once the excess values are obtained, the subsequent step involves estimating the parameters for the Generalized Pareto Distribution. The estimation results are presented in Table 4.

Table 4. Peak Over Threshold Parameter Estimation

Scale Parameter (σ)	Shape Parameter (ξ)
0.01794483	−0.06758980

The estimated scale parameter σ is 0.01794483, indicating the dispersion or spread of the excess data above the threshold. Furthermore, the obtained shape parameter ξ is -0.06758980, which dictates the behavior of the distribution's tail. A negative shape parameter signifies a short, bounded tail. This implies that extreme values exceeding the threshold will not increase infinitely but possess an absolute maximum limit. In the context of a stock portfolio, this characteristic suggests that despite the occurrence of extreme events, the magnitude of risk or potential loss derived from the excess data has a definitive maximum bound that will not be surpassed.

4.5 Goodness-of-Fit Test

A goodness-of-fit test is conducted to statistically verify whether the extreme data accurately follows the assumed distributions. The Anderson-Darling test is utilized to assess the Generalized Extreme Value (GEV) distribution for the Block Maxima method and the Generalized Pareto Distribution (GPD) for the Peak Over Threshold method. The hypotheses formulated for this test are as follows:

H_0 : The data follows the specified distribution GEV/GPD

H_1 : The data does not follow the specified distribution.

The significance level α applied in this testing is 0.05. The decision criterion is to reject H_0 if the $p-value < 0{,}05$, and fail to reject H_0 if the $p-value > 0{,}05$. The computation is performed using R software, and the results of the Anderson-Darling goodness-of-fit test are summarized in Table 5.

Table 5. Goodness-of-Fit Test

Method	Assumed Distribution	p-value	Decision
Block Maxima	Generalized Extreme Value	0,06975	Fail to reject H_0
Peak Over Threshold	Generalized Pareto Distribution	0,22611	Fail to reject H_0

Based on the test results outlined in the table, the p-value for both the Block Maxima and Peak Over Threshold methods are greater than the 0.05 significance level. Consequently, the decision is to fail to reject H_0. Therefore, at a 95% confidence level, there is insufficient statistical evidence to reject the null hypothesis. This significantly proves that the extreme loss data from the Block Maxima approach follows the Generalized Extreme Value distribution, and the excess data from the Peak Over Threshold approach follows the Generalized Pareto Distribution.

4.6 Value at Risk Estimation

The final results of the risk estimation using both Extreme Value Theory approaches at a 95% confidence level are summarized in Table 6.

Table 6. Value at Risk Estimation

Method	Value at Risk Estimation	Percentage
Block Maxima	0.06644736	6.64%
Peak Over Threshold	0.03131952	3.13%

The VaR estimation results in Table 6 above show that using the Block Maxima approach with a confidence level of 95%, an investor who allocates an initial fund of Rp 100,000,000.00 into the investment portfolio with an estimated risk of 0.06644736 will experience a maximum estimated loss of Rp 6,644,736.00. The estimated loss is obtained by multiplying the initial investment amount by the estimated risk. Likewise, using the Peaks Over Threshold approach on the same portfolio with an estimated risk of 0.03131952, the investor will experience a maximum estimated loss of Rp 3,131,952.00. This significant discrepancy highlights how the two models capture extreme data differently. The Block Maxima approach yields a more conservative and pessimistic risk measure because it isolates only the absolute worst-case scenario within each time block. Conversely, the Peak Over Threshold method utilizes a broader set of extreme data above the threshold, providing a more stable estimation. Therefore, risk-averse investors can use the Peak Over Threshold result as a baseline for extreme risk, while treating the Block Maxima estimation as a stricter buffer for severe market crashes.

4.7 Backtesting

The accuracy of the VaR estimations is evaluated using the Kupiec Likelihood Ratio test at a 95% confidence level and critical value = 3.841. The backtesting results, summarized in Table 7, reveal a stark contrast in model performance.

Table 7. Backtesting

	Value at Risk GEV	Value at Risk GPD
Total Data	1.474	1.474
Violations Target	74	74
Actual Violations	7	81
Violations Rate	0,4749%	5,4953%
Deviation	4,5251%	0,4953%
Likelohood Ratio	103.5705	0,7384

The Value at Risk Generalized Extreme Value model generated an Likelohood Ratio statistic of 103.5705, far exceeding the critical threshold, leading to its statistical rejection. With only 7 actual violations out of 1,474 observations against an expected 74, the Generalized Extreme Value approach proves overly conservative. It significantly overestimates risk, establishing excessively high loss limits that demand massive capital reserves. Practically, this results in severe capital inefficiency and high opportunity costs for investors.

Conversely, the Value at Risk Generalized Pareto Distribution model yielded an Likelihood Ratio statistic of 0.7384, well below the critical value, confirming its validity. The model recorded 81 violations, closely aligning with the expected target of 74 or a 5.49% actual violation rate. Consequently, the Peak Over Threshold Generalized Pareto Distribution approach is statistically validated as a highly accurate and appropriate framework for estimating the portfolio's extreme risk without causing unnecessary capital hoarding.

5. Conclusion

Based on the calculation of daily stock returns for the portfolio of the top five banking subsector stocks, BBCA, BBRI, BMRI, BBNI, and BRIS from May 1, 2019, to May 31, 2025 , the risk estimation at a 95% confidence level using the Block Maxima method yielded a potential maximum loss of 6.64%. Meanwhile, with the Peak Over Threshold method, the estimated portfolio risk is lower at 3.13%. Based on both approaches, the Value at Risk Generalized Extreme Value model produces the highest risk level, indicating a highly conservative and pessimistic estimation that anticipates extreme losses by isolating only the absolute worst-case scenarios within each time block. Conversely, the Value at Risk Generalized Pareto Distribution model presents a lower and more stable risk measure by utilizing a broader set of extreme data above a specific threshold, meaning financial institutions can mitigate risk without severe capital inefficiency or unnecessary capital hoarding. Backtesting between the two Extreme Value Theory approaches using Kupiec's Likelihood Ratio test shows that the Generalized Extreme Value model is statistically invalid due to being overly conservative, whereas the Peak Over Threshold Generalized Pareto Distribution approach is proven to be a highly accurate and optimal framework for estimating extreme market risk.

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