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VALUE AT RISK ESTIMATION USING EXTREME VALUE THEORY APPROACH IN INDONESIA STOCK EXCHANGE

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ABSTRACT

Extreme Value Theory (EVT) is a method used to identify extreme cases in heavy tail data such as financial time series data. This research aimed to obtain an estimate of stock risk through the EVT approach and compare the accuracy of the two EVT approaches, Block Maxima (BM) and Peaks Over Threshold (POT). The method used to estimate stock risk is VaR with the BM and POT approaches, and the Z statistic is used to compare the accuracy. The data used, and the limitation in this research is daily closing price data for non-cyclical consumer stocks included in LQ45 for the period February 01, 2017, to January 31, 2023. Other research limitations are using weekly blocks or 5 working days in dividing BM blocks, using the percentage method in determining threshold values in the POT approach, and using Maximum Likelihood Estimation (MLE) to estimate EVT parameter estimates. The results of the VaR analysis show that the risk level generated by the POT method is greater than the risk level from BM. The results of backtesting between the two EVT approaches in estimating VaR values show that the POT approach is more accurate than the BM approach.

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1. INTRODUCTION

The impact of *Covid-19* is inevitable in various sectors, including the capital market. Investors and capital markets face a high level of uncertainty regarding the impact of *Covid-19*, both physically and financially [1]. Therefore, many investors are interested in investing their shares in the *non-cyclical consumer* sector listed on the IDX and the LQ45 index. This sector is defensive and tends to be stable because it can be supported by stable consumption from the community [2]. In addition, the risk of stocks incorporated in the LQ45 index has a lower value than non-LQ45 [3].

Before investing, investors must better consider the *expected return* and the risk that must be borne. The way to find out the risk of an investment is for investors to measure the level of risk. *Value at risk* (VaR) is a statistical measurement used in measuring the level of risk associated with a company's stock portfolio, and VaR shows the estimated value of the maximum loss that is likely to occur with a level of confidence over a certain period [4].

Many financial time series data have been found to have a *heavy tail* distribution; namely, the tail of the distribution drops slowly when compared to the normal distribution, which can cause considerable financial risk [5]. It indicates the chance of extreme values occurring. In statistics, one of the methods used to identify extreme events is *extreme value theory* (EVT). EVT aims to estimate the probability of an extreme event by looking at the tail of a distribution based on the extreme values obtained [6]. The approaches used in identifying an extreme value using EVT are *block maxima* (BM) and *peaks over threshold* (POT) [7].

This research will discuss the estimation of VaR value to analyze the data of *non-cyclical consumer* sector stocks listed on the IDX and the LQ45 index for the last 5 years, namely PT (LLC) Hanjaya Mandala Sampoerna Tbk (Public company) (HMSP), PT Indofood CBP Sukses Makmur Tbk (ICBP), PT Indofood Sukses Makmur Tbk (INDF), and PT Unilever Indonesia Tbk (UNVR) with the EVT approach, namely *block maxima* and *peaks over threshold*. The use of this method is expected to provide better analysis results. This study aimed to obtain an estimate of stock risk by determining VaR through the EVT approach, both BM and POT, and compared the accuracy between BM and POT in estimating VaR. This research is expected to be a reference in calculating company risk and informing the existence of risk so that anticipation can be made for companies and investors. In addition, investors can find stocks that have a high enough risk.

2. RESEARCH METHODS

2.1 Data Source

The data used in this study were secondary in the form of daily stock closing prices of PT Hanjaya Mandala Sampoerna Tbk (HMSP), PT Indofood CBP Sukses Makmur Tbk (ICBP), PT Indofood Sukses Makmur Tbk (INDF), and PT Unilever Indonesia Tbk (UNVR) obtained from the finance.yahoo.com *website for the* period February 01, 2017 to January 31, 2023. The closing price was chosen because it is often used as an indicator of the next day's opening price.

2.2 Stock *Return*

Calculating the *return of* each stock closing price that will be used as observation data using **Equation (1)** [8].

$$R_t = \frac{P_t - P_{t-1}}{P_{t-1}} \tag{1}$$

with:
R_t : the *return* value at time-t
P_t : stock price at time-t
P_{t-1} : stock price at time-$(t-1)$

2.3 Extreme Value Theory

EVT is a theory that focuses on the behaviour of the *tail of* a distribution. EVT is usually used to model extreme events, such as losses that are rare but have a huge impact. These losses cannot be modelled with the usual approaches, such as the normal distribution, because the sample population of financial data is not normal but rather has a *heavy tail* **[9]**. Two approaches are used in identifying the movement of extreme values. The first approach is the *Block Maxima* (BM) method and the *Peaks Over Threshold (*POT) method **[10]**.

2.4 Block Maxima

BM is a method that can identify extreme values based on the highest value of observation data grouped by a specific period. This method divides the data into blocks of a specific period, such as weekly, monthly, quarterly, semester or yearly. Each period block formed is then determined to have the highest value. The highest data is included in the sample because this value is the extreme value in a certain period **[9] [10]**. The BM method applies the Fisher-Tippet, Gnedenko (1928) theorem that the extreme value sample data taken from the BM method will follow the *Generalized Extreme Value* (GEV) distribution **[11]**.

2.5 Peaks Over Threshold

POT identifies extreme values by setting a certain *threshold* and ignoring the timing of the *event*. *The threshold* is the maximum limit or limit of the company's ability to bear an operational loss **[12]**. POT sorts from the most significant data to the most minor data and then takes the extreme value that is at the threshold as much as the k value in **Equation (2)** and the $(k+1)$-th value as the *threshold* value. The POT approach applies the *Picklands-Dalkema-De Hann theorem,* which states that the higher the threshold, the distribution will follow a generalized distribution (u). Then, the distribution will follow the *generalized Pareto* distribution (GPD) **[13]**.

$$k = 10\% \times N \tag{2}$$

with:
k : number of extreme data
N : total number of data

2.6 Parameter Estimation

The parameter estimates of GEV for the BM approach and GPD for the POT approach can be estimated using *Maximum Likelihood Estimation* (MLE) by forming a *probability density function* such as **Equation (3)** for GEV and **Equation (4)** for GPD **[14]**.

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

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

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

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

The first derivative of **Equation (3)** and **Equation (4)** is not *closed form*, so numerical analysis is needed to get a *closed from* Equation. One of the solutions for equations that are not *closed* is the Newton-Raphson method **[14]**.

2.7 Distribution Fit Test

The distribution suitability test used to test the extreme data taken using the BM approach has followed the GEV distribution. Also, the extreme data taken with the POT approach has followed the GPD distribution. The techniques used to test the distribution suitability are the *Kolmogorov-Smirnov* test and the *Anderson-Darling* test. The test statistic for the *Kolmogorov-Smirnov* test is shown in **Equation (5) [9]**.

$$D = Max|F_n(x) - F_0(x)| \tag{5}$$

Description:

Max : maximum value
$F_n(x)$: the (empirical) sample distribution function or cumulative probability function that calculated from sample data
$F_0(x)$: cumulative function of GEV distribution

If $D_{count} < D_{table}$ or *p-value* $> \alpha$, then the extreme data taken from the BM approach has followed the GEV distribution. The *Anderson-Darling* test statistic is shown in **Equation (6) [15]**.

$$AD = -n - \frac{1}{n}\sum_{i=1}^{n}(2i-1)(\ln\left(F_0(x_i)\right)) + \ln\left(1-(F_0(X_{n+1-1}))\right) \tag{6}$$

Description:

n : sample size
$F_n(x)$: cumulative distribution function of sample data
$F_0(x)$: cumulative function of GPD distribution

If or if the value of $\text{AD}_{count} < \text{AD}_{table}$ or *p-value* $>\alpha$, then the extreme data taken from the POT approach has followed the GPD distribution.

2.8 Value at Risk

Value at risk (VaR) is a statistical risk measurement method that estimates the maximum loss that may occur on a portfolio at a certain *level of confidence*. The VaR value for BM can be obtained from **Equation (7) [16]**.

$$VaR_{GEV} = \hat{\mu} - \frac{\hat{\sigma}}{\hat{\xi}}[1 - \{-\ln(1 - m\alpha)\}^{-\hat{\xi}}] \tag{7}$$

with:
$\hat{\mu}$: *location* parameter from GEV estimation result
$\hat{\sigma}$: *scale* parameter of the GEV estimation result
$\hat{\xi}$: *shape* parameter of the GEV estimation result
m : the number of observations per *block*
α : significance level

VaR value for *Generalized Pareto Distribution* (GPD) can be obtained from **Equation (8) [16]**.

$$VAR_{GPD} = u + \frac{\hat{\sigma}}{\hat{\xi}}\left[\left(\frac{n}{k}(1-\alpha)\right)^{-\hat{\xi}} - 1\right] \tag{8}$$

with:
u : *threshold* value
$\hat{\sigma}$: *scale* parameter from the GPD estimation result
$\hat{\xi}$: *shape* parameter from the GPD estimation result
n : total number of observations
k : number of observations above the *threshold* value

2.9 Backtesting

Comparing the accuracy value between the BM approach and the POT approach by looking at the results of *backtesting* based on **Equation (9) [17]**.

$$Z = \frac{\sqrt{T}\,(\hat{\alpha} - \alpha)}{\sqrt{\alpha(1-\alpha)}} \tag{9}$$

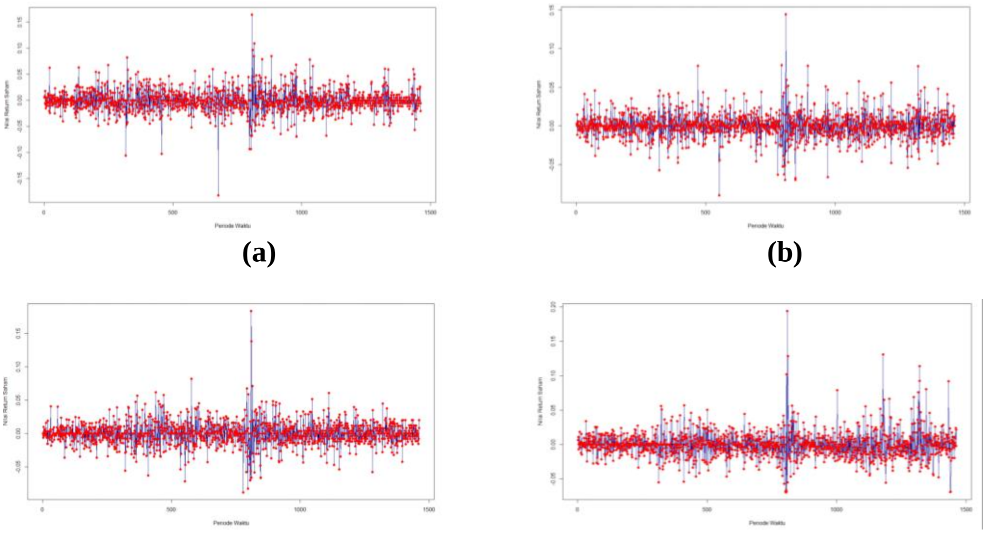
Description:
T : number of observation data
$\hat{\alpha}$: number of *failures* divided by the number of observations
α : confidence level

If the loss that occurs on that day is greater than the estimated VaR value, it is recorded as a *failure* event. Furthermore, the Z value obtained can be used for *backtesting* hypotheses by comparing with the *chi-square* value with a degree of freedom of 1 (one). With a confidence level of 95% and a chi-square value of $\chi_{(1;0.05)2} = 3.831$, If the statistical value does not exceed the *chi-square* value for the 95% confidence level ($Z_{stat} < 3.831$) then the VaR model is said to be valid **[18]**.

3. RESULTS AND DISCUSSION

3.1 Descriptive Statistics of Stock *Return*

Figure 1 shows that the value of stock *returns* in the four companies often *fluctuates* and is full of uncertainty. The ICBP stock *return* plot looks more stable than the others. This is indicated by points that have increased or decreased still around the average. Meanwhile, for the HMSP, INDF, and UNVR stock *return* plots, it appears that there are often stock *returns* that *are* too high or stock *returns* that are too low. Fluctuations that occur in HMSP, ICBP, INDF, and UNVR cause extreme values to occur in specific periods.



(a) (b)

(b) (d)

Figure 1. Time Series Plot of Stock Returns, (a) HMSP, (b) ICBP, (c) INDF, (d) UNVR

Table 1. Descriptive Statistics of Stock Returns

Size	HMSP	ICBP	INDF	UNVR
Mean	-0.000679	0.000254	0.000050	-0.000203
Variance	0.000465	0.000272	0.000326	0.000366
Minimum	-0.182143	-0.089588	-0.087948	-0.069231
Maximum	0.164502	0.144578	0.183168	0.193833

Based on Table 1, it is known that the average value of ICBP stock returns is higher than the average value of stock *returns of* other companies. The high average value of stock returns indicates that the company has a relatively high rate of return. Conversely, the small average value of the company's *return* indicates that the company has a relatively low rate of return. Furthermore, the lowest variance value is also owned by ICBP. The variance value shows how far the stock *return* price data spreads from its average value. Therefore, the smaller variance value indicates that the company is stable because it has not experienced many significant changes over time. Conversely, the more excellent variance value indicates that the company is unstable because it often experiences changes over time.

3.2 Identify Extreme Values and *Heavy Tail.*

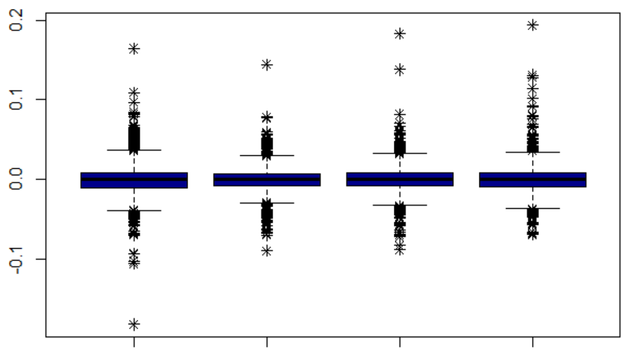


Figure 2. Boxplot of Stock Returns of HMSP, ICBP, INDF and UNVR

In Figure 2, it can be seen that the *return* values of HMSP, ICBP, INDF, and UNVR stocks have extreme values. The existence of extreme values is indicated by the presence of black dots that cross the upper and lower limits.

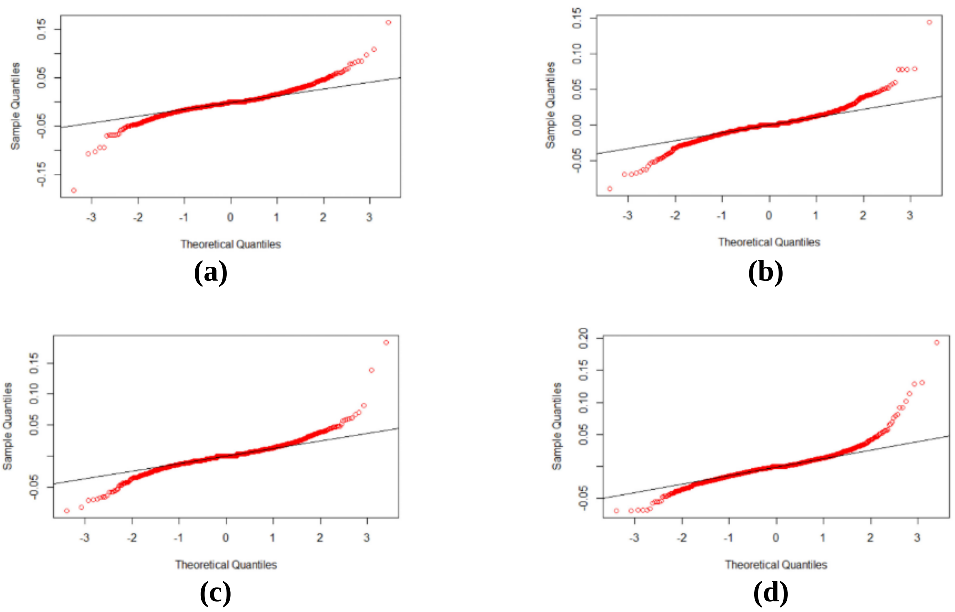


Figure 3. Normality Probability Plot of Stock Returns, (a) HMSP, (b) ICBP, (c) INDF, (d) UNVR

Based on **Figure 3**, it can be seen that the *normality probability plot* of stock *returns* from HMSP, ICBP, INDF, and UNVR has data located outside the standard distribution line, so it is called *heavy tail distribution*. To find out more specifically, the results of testing the distribution of stock *return* data for the four companies are shown in **Table 2** with the following hypothesis:

$H_0: F(x) = F_0(x)$ (Stock *return* data follows normal distribution)
$H_1: F(x) \neq F_0(x)$ (Stock *return* data does not follow a normal distribution)

With the rejection area, namely reject H_0 if $D_{count} > D_{table}$ or *p-value* $< \alpha$.

Table 2. Kolmogorov-Smirnov Test Results Data Normality

Company	HMSP	ICBP	INDF	UNVR
D count	0.11006	0.093404	0.088491	0.091503
D table	0.0355685	0.0355685	0.0355685	0.0355685
P-Value	2.2×10^{-16}	2.2×10^{-16}	2.2×10^{-16}	2.2×10^{-16}
Decision	Reject H_0	Reject H_0	Reject H_0	Reject H_0

Based on **Table 2**, it is known that the stock *return* data of HMSP, ICBP, INDF, and UNVR have a D_{count} value greater than D_{table}, and a *p-value* less than the alpha value of 0.05. Therefore, the decision to reject H_0 is obtained, which means that the stock *return* data of the four companies do not follow the normal distribution.

3.3 Block Maxima

The first EVT approach to deal with extreme values is *Block Maxima*. In this study, weekly blocks are used, namely one block consisting of 5 *return* value data from 5 working days of data. From one block, one extreme value is taken; the extreme value taken is the maximum value of each block. The number of blocks formed is 301 blocks, resulting in 301 extreme data for the BM approach. Modelling stock *returns* with the BM approach includes calculating parameter estimates and testing the suitability of the distribution of the data.

1) *Block Maxima* Parameter Estimation

After obtaining the extreme value population from the BM approach, the next step is to estimate the parameters using 301 extreme value samples that have been obtained previously using the BM approach. The results of parameter estimation using MLE can be seen in **Table 3**.

Table 3. Block Maxima Parameter Estimation

Parameters	HMSP	ICBP	INDF	UNVR
Location ($\hat{\mu}$)	0.01270	0.01142	0.01239	0.01145
Scale ($\hat{\sigma}$)	0.01389	0.00954	0.00983	0.01120
Shape ($\hat{\xi}$)	0.10243	0.15953	0.13435	0.16168

The location parameter estimation result states the location of the data centre point or the peak of the distribution curve. The result of the scale parameter estimation shows the diversity of the data and how far the data is spread from the average value. The shape parameter estimation results show the location of the distribution tail. Based on **Table 3**, UNVR has the most significant shape parameter value, and HMSP has the smallest shape parameter value compared to other companies. The larger the shape parameter value indicates that the chance of extreme values occurring will be greater. If the resulting extreme value is more significant, then the company has the potential to provide greater profits for investors. However, keep in mind that large extreme values can also indicate a higher risk of loss.

2) *Generalized Extreme Value* Distribution Conformance Test

Theoretically, sample data in the form of extreme values taken using the BM approach will follow the GEV distribution. The suitability test was conducted to prove that the 301 extreme data taken using the BM approach had followed the GEV distribution.

Table 4. Generalized Extreme Value Distribution Conformance Test

Company	D_{count}	D_{table}	Decision
HMSP	0.0362	0.0784	Accept H_0
ICBP	0.0366	0.0784	Accept H_0
INDF	0.0344	0.0784	Accept H_0
UNVR	0.0365	0.0784	Accept H_0

Based on **Table 4**, it can be seen that HMSP, ICBP, INDF, and UNVR produce a value of D_{count} which is smaller than D_{table} so that with an alpha of 5%, the decision is obtained that the 301 BM extreme data used have followed the GEV distribution.

3.4 Peaks Over Threshold

Another EVT approach that can be used to identify extreme values in data is the *Peaks Over Threshold* approach. The concept of this approach is to identify extreme values by setting a limit or *threshold*. Data that exceeds the *threshold* value is considered an extreme value. Therefore, the results are obtained as in **Table 5**, namely, there are 150 data above the *threshold value* out of 1505 total data, and the *threshold* value is the value of the 151st order data. Modelling stock *returns* with the POT approach includes calculating parameter estimates and testing the suitability of the data distribution.

Table 5. Threshold Value

	HMSP	ICBP	INDF	UNVR
Threshold (u)	0.02381	0.01719	0.01887	0.01863
Number of Observations (n)	1505	1505	1505	1505
Number of Observations above Threshold (k)	150	150	150	150

1) Parameter Estimation of *Peaks Over Threshold*

After obtaining extreme data from the POT approach, the next step was to estimate parameters using 150 extreme data that had been obtained previously using the POT approach. The results of parameter estimation using MLE can be seen in **Table 6**.

Table 6. Parameter Estimation of Peaks Over Threshold

Parameters	HMSP	ICBP	INDF	UNVR
Scale $(\hat{\sigma})$	0.01450	0.01142	0.01079	0.01257
Shape $(\hat{\xi})$	0.11989	0.14944	0.20482	0.27593

Unlike the GEV distribution, the GPD has only 2 parameters, namely, a scale parameter and a shape parameter. GPD does not have a location parameter because this distribution only describes the extreme tails of a distribution. In the POT approach, the extreme values are sorted from largest to smallest, and the 10% largest values will follow the GPD distribution. Therefore, this distribution only describes the tails. The scale parameter estimation results show the diversity of the data and how far the data is spread from the mean value. The shape parameter estimation results show the characteristics of the distribution shape. Based on **Table 6**, UNVR has the most significant shape parameter value, and HMSP has the smallest shape parameter value compared to other companies. The larger the shape parameter value indicates that the chance of extreme values occurring will be greater. If the resulting extreme value is more significant, then the company has the potential to provide greater profits and greater losses or, in other words, indicates a great risk for investors.

2) Test *Distribution* Fit *Generalized Pareto Distribution*

Theoretically, sample data in the form of extreme values taken using the POT approach will follow the GPD distribution. The distribution suitability test was conducted to prove that the 150 extreme data taken using the POT approach had followed the GPD distribution.

Table 7. Generalized Pareto Distribution Fit Test

Company	AD_{count}	P-value	Decision
HMSP	0.30399	0.70185	Accept H_0
ICBP	0.65878	0.16025	Accept H_0
INDF	0.55673	0.23627	Accept H_0
UNVR	0.61526	0.17072	Accept H_0

Based on **Table 7**, it can be seen that HMSP, ICBP, INDF, and UNVR produce *p-values* more significant than alpha (0.05). Thus, the decision is obtained that the extreme POT data of the four companies used followed the GPD distribution.

3.5 Estimated Value at Risk

After obtaining parameter estimates and testing the suitability of the BM and POT distributions, it is possible to predict stock risk using VaR. The known values are substituted into **Equation (7)** for BM and **Equation (8)** for POT. The estimated risk value can be seen in **Table 8**.

Table 8. Value at Risk Estimation

Company	Value at Risk Estimation	
	Block Maxima	**Peaks Over Threshold**
HMSP	-0.01473	-0.03429
ICBP	-0.00872	-0.02678
INDF	-0.00937	-0.02645
UNVR	-0.01055	-0.02973

The VaR estimation results in **Table 8** above show that using the BM approach with a confidence level of 95%, an investor who invests his funds of Rp1,000,000,000 in HMSP shares with an estimated risk of -0.01473 will experience a loss of Rp14,730,000. The estimated loss is obtained by multiplying the investment amount by the estimated risk. Likewise, if an investor invests Rp1,000,000,000 in ICBP with a risk estimate of -0.00872, the investor will experience a loss of Rp8,720,000. If investing in INDF with a risk estimate of -0.00937, the investor will experience a loss of Rp9,370,000, and if investing in UNVR with a risk estimate of -0.01055, the investor will experience a loss of Rp10,550,000. Then, using the POT approach on HMSP shares with an estimated risk of -0.03429, the investor will experience a loss of Rp34,290,000. The same applies if an investor invests Rp1,000,000,000 in ICBP with an estimated risk of -0.02678; the investor will experience a loss of Rp26,780,000. If investing in INDF with an estimated risk of -0.02645, the investor will experience a loss of Rp26,450,000. If investing in UNVR with an estimated risk of -0.02973, the investor will experience a loss of Rp29,730,000.

3.6 Comparison of the Two Extreme Value Theory Approaches

After estimating the stock risk of the four companies using the BM and POT approaches, the next step is *backtesting* to determine the accuracy of the stock risk that has been obtained. The results of risk estimation *backtesting* can be seen in **Table 9** and **Table 10**.

Table 9. Block Maxima Risk Estimation Backtesting Results

Company	HMSP	ICBP	INDF	UNVR
Amount of data	1505	1505	1505	1505
Number of *failures*	276	315	351	352
α	0.05	0.05	0.05	0.05
Z_{stat}	23.743	28.356	32.614	32.732
Chi-square	3.831	3.831	3.831	3.831
Conclusion	Invalid	Invalid	Invalid	Invalid

Table 10. Backtesting Results of Peaks Over Threshold Risk Estimation

Company	**HMSP**	**ICBP**	**INDF**	**UNVR**
Amount of data	1505	1505	1505	1505
Number of *failures*	65	60	77	55
$\boldsymbol{\alpha}$	0.05	0.05	0.05	0.05
$\boldsymbol{Z_{stat}}$	-1.212	-1.804	0.207	-2.395
Chi-square	3.831	3.831	3.831	3.831
Conclusion	Valid	Valid	Valid	Valid

Based on the results of *backtesting the* risk estimation of the two approaches in Table 9 and Table 10, it can be seen that the *backtesting* results with the BM approach of the four companies have values Z_{stat}, which is greater than the *chi-square value*, and this indicates that the VaR estimation with the BM approach produces an invalid value. Conversely, *backtesting* with the POT approach of the four companies has a value smaller than the chi-square value. Z_{stat} is smaller than the *chi-square value*, and this indicates that the VaR estimation with the POT approach produces a valid value. Therefore, in this study, the POT approach produces a more accurate value than the BM approach in estimating the VaR value.

4. CONCLUSIONS

Based on the calculation of data for the period February 01, 2017 to January 31, 2023, VaR with BM obtained the estimated risk of HMSP, ICBP, INDF, and UNVR stocks -0.01473, -0.00872, -0.00937, and -0.01055, respectively. Meanwhile, with POT, the estimated stock risks for HMSP, ICBP, INDF, and UNVR are -0.03429, -0.02678, -0.02645, and -0.02973, respectively. Based on both approaches, the risk level in HMSP is the highest. A high level of risk indicates that investors will experience more losses when investing in the company. The risk level in ICBP is the lowest based on the calculation of VaR with BM, and in INDF, it is the lowest based on the calculation of VaR with POT. A low level of risk indicates that investors will experience fewer losses when investing in these companies. *Backtesting* between the two *Extreme Value Theory* approaches, namely BM and POT in estimating VaR values, shows that the POT approach is more accurate than the BM approach.

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