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Estimating the Value-at-Risk (VaR) in stock investment of insurance companies: An application of the extreme value theory

Riaman[a*], Amarulla Octavian[a], Sudradjat Supian[a], Sukono[a] and Jumadil Saputra[b]

[a]*Department of Mathematics, Faculty of Mathematics and Natural Sciences, Universitas Padjadjaran, Sumedang 45363, Indonesia*
[b]*Department of Economics, Faculty of Business, Economics and Social Development, Universiti Malaysia Terengganu, 21030 Kuala Nerus, Terengganu, Malaysia*

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A B S T R A C T

As a capital market investment, stocks have risks that must be managed. Therefore, investors should consider the returns and risks of investment products. This study aims to estimate the risk of insurance companies' loss when investing. The method used to estimate the level of risk is Value at Risk (VaR) based on Extreme Value Theory (EVT). The data used is secondary data in the form of daily stock closing prices from two insurance companies, AXA General Insurance and BRI Insurance, from January 2016 to January 2022. The data were used to estimate the risk value according to the EVT principle. As a result, Insurance AXA General Insurance, with 5.91% liquidity, has the lowest VaR value with a 99% confidence level, while BRI Insurance has 5.04%. We concluded from these results that AXA General Insurance has a lower investment risk. It means that each company has a different risk value. Therefore, investors should know these risk factors when choosing a company.

1. Introduction

Investing is an attempt to invest various funds to generate profits in the future. Several things need to be considered in investing, including the expected return, the level of risk, and the availability of investment funds (Cruz, 2003). Stocks are the investment product of choice for many investors because they offer attractive returns (Riaman et al., 2021). However, stocks as investment products have risks (Dhaene et al., 2012). Therefore, investors must consider the returns and risks of investment products in the capital market (Goetzmann et al., 2014). Therefore, the risk must be assessed to be managed properly (Diop, 2019). The level of capital market risk can be measured using the VaR method. Its value can be used as a benchmark for investors to determine the level of risk. The VaR method is now the standard risk measurement method. It can be defined as estimating the maximum loss obtained over a certain time with a certain confidence level under normal conditions (Jorion, 2001).

In risk management, if we assume that returns are normally distributed, this is a wrong assumption. However, this assumption is questionable (Marimoutou et al., 2009; Megginson, 1997). The return marginal distribution is thicker than the normal marginal distribution. It means there are indications of extreme events analysed by normal distribution modelling. One of the risk measures that can be used to detect the presence of extreme values is the VaR method using the Extreme Value Theory (EVT) approach. EVT is used to form the distribution function of these extreme values. There are two ways to identify the presence of extreme points, namely the block maximum (BM) and the peak over the threshold (POT) (Kotz & Nadarajah, 2000, 2002). Previous research on EVT has been extensive, such as by Fauziah (2014), who applied this technique to risk analysis of Islamic stock portfolios. Zuhara et al. (2012) used the extreme value method to estimate the risk value of equity investment in the banking sector.

* Corresponding author.
E-mail address: riaman@unpad.ac.id (Riaman)

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Echaust and Just (2020) studied Value-at-Risk Estimation Using the GARCH-EVT Approach with Optimal Tail Selection to Estimate VaR using optimal distribution tail selection. Baran and Witzany (2011) compared the EVT and Standard Value-at-Risk Estimates to Explain Expectations Based on Value-at-Risk Claims. Riaman et al. (2022) used Mathematical modelling to estimate the risk of loss for rice farmers due to climate change. Starting from the previous work, the author discusses using the extreme value theory method to estimate the risk value of stock investments in insurance companies in this study. In this study, the authors assessed EVT to determine the risk of loss. The risk of this loss is inherent in the life insurance company. Policyholders can use the results as a benchmark for investment decisions. This study aims to determine the VaR model using the extreme value theory method to measure the risk level of an insurance company's stock and determine the value-at-risk of each insurance company's stock data.

2. Literature Review

The following are the research results that discuss the Value-at-Risk Extreme Value Theory (EVT) method. Fernandez (2003) discusses Extreme Value Theory and Value at Risk. Gencay and Selçuk (2004) discuss the theory of extreme and risky value. Relative performance in emerging markets. Brooks et al. (2005) compared extreme value theoretical approaches to determine risk values. Lin and Ko (2009) use GA-based extreme value theory to describe the projected value of a risky portfolio. Learman et al. (2021) used the extreme value theory method and the operational value-at-risk approach to examine the problem of determining travel insurance premiums. Riaman et al. (2021a, 2021b) discuss applying extreme value theory to analyse agricultural risk assessment decision-making.

The basic theories used to solve this problem are risk and return, descriptive statistics, extreme value theory (EVT), inter-quantile plot analysis (QQ plot analysis), maximum likelihood estimation (MLE), and Value at Risk (VaR). An investment is a commitment to a pool of funds or other resources made at that time to generate a series of returns in the future. Investors buy shares in large quantities today in the hope of profiting from a large increase in share price or dividends in the future in return for the time and risk involved in investing (Tandelilin, 2007). There are many types of investments, one of which is stocks. It is proof of capital ownership of a company or limited liability company entitled to dividends and others according to the amount of paid-up capital. Stock exchange prices are determined by market participants and relevant supply and demand in the capital market at a certain time. Yield is one factor that motivates investors to invest because it can clearly represent price changes (Jorion, 2001). The return at time t is denoted by (R_t). Return (R_t) is defined as given in Eq. (1).

$$R_t = \frac{S_t - S_{t-1}}{S_{t-1}} \tag{1}$$

where:

R_t : return on period *t*

S_t : current stock price (period *t*)

S_{t-1} : stock price last period (period $t-1$).

Risk is defined as the probability of economic loss. Assets with a high risk of loss are riskier than assets with a low risk of loss (Megginson, 1997). From this definition, the risk is seen as the opportunity to suffer economic loss. Uncertainty of return is associated with risk. The higher the security risk, the higher the expected return and vice versa. Descriptive statistics include mean, median, quartile, standard deviation, kurtosis, and skewness. Currently, extreme value theory is used to predict rare events which are usually beyond the range of available data (Asimit et al., 2013). Peaks Over the threshold are an easy way to model the tail of a distribution to get a value-at-risk value (Echaust & Jus, 2020). The POT is an EVT method that identifies extreme values using a threshold (u). Chaves-Demoulin suggests choosing a threshold so that the data above the threshold represents about 10% of all data. Data above the threshold are identified as extreme values. This method applies the Pickland-Dalkema de Hann theorem, which states that the higher the threshold, the more the distribution follows the generalised Pareto distribution (GPD). The cumulative density function (cdf) of GPD is given by Eq. (2).

$$G_{\xi,\beta}(x) = \begin{cases} 1-\left(1+\frac{\xi}{\beta}x\right)^{-\frac{1}{\xi}}, & \text{for } \xi \neq 0 \\ 1-exp\left(-\frac{x}{\beta}\right), & \text{for } \xi = 0 \end{cases} \tag{2}$$

(Echaust & Just, 2020).

The probability density function (pdf) of GPD is given by (3):

$$g_{\xi,\beta}(x) = \begin{cases} \frac{1}{\beta}\left(1+\frac{\xi}{\beta}x\right)^{-1-\frac{1}{\xi}}, & for\ \xi \neq 0 \\ \frac{1}{\beta}exp\left(-\frac{x}{\beta}\right), & \xi = 0 \end{cases} \tag{3}$$

$\beta > 0$ and ≥ 0 if $\xi \geq 0$

$0 \leq x \leq -\frac{\beta}{\xi}$ if $\xi < 0$

where:

ξ: the shape parameter of the distribution

β: scale parameters

Based on the shape parameter's value, the GPD distribution can be divided into three types: the exponential distribution for the value $\xi = 0$, the Pareto distribution for the value $\xi > 0$, and the Pareto distribution for type II. increase. The value is $\xi < 0$. Of the three distribution types, the Pareto distribution has the strongest tails (Zuhara et al., 2012). To test the effect of GPD on the data, check the QQ plot (quantile-quantile plot). QQ-Plot is a tool for visually observing a particular distribution. See Baran and Witzany (2011), Quantile-Quantile plots or QQ plots test whether a sample follows a particular distribution. If the QQ plot display forms an approximately straight line, the QQ plot corresponds to the selected distribution. According to Chung et al. (2021), the quantile q of a random variable X is the point that satisfies Eq. (4).

$$P(X \leq 1) = F_x(q) = p \tag{4}$$

where $F_x(x)$ is the cumulative distribution function (CDF) of X, assuming that the inverse of the cumulative function is Eq. (5):

$$q = F_x^{-1}(p) \tag{5}$$

This function is commonly called the quantile function. Based on the Balkema-de-Hann-Picklands theorem, the estimated tail distribution follows the generalised Pareto distribution (GPD) when the peak-over-threshold method is used to identify extreme values. For parameter estimation, the maximum likelihood estimation (MLE) method was used to obtain equation-like parameter estimates (6):

a. Shape Parameters

$$\hat{\xi} = \frac{n^2 s - \sum_{i=1}^{n} x_i}{\sum_{i=1}^{n} x_i - n\sum_{i=1}^{n} x_i} \tag{6}$$

ξ : Shape Parameters

n : number of extreme data

s : standard deviation of extreme data

x_i : extreme data *i.*

b. Scale Parameter

The probability function of $\xi = 0$ from the probability function GPD is given by the formula (7).

$$L(\beta|x_1, x_2, \ldots, x_n) = \beta^{-n} e^{-\sum_{i=1}^{n}\frac{x_i}{\beta}} \tag{7}$$

The ln likelihood function of the Eq. (7) is as Eq. (8).

$$\ln L(\beta|x_1, x_2, \ldots, x_n) = -n \ln \beta - \frac{1}{\beta}\sum_{i=1}^{n} x_i \tag{8}$$

The estimator for parameter β is obtained as in Eq. (9).

$$\hat{\beta} = \frac{1}{n}\sum_{i=1}^{n} x_i \tag{9}$$

where:

β : scale parameters

n : number of extreme data

x_i : extreme data *i.*

Goodness-of-fit tests are available as Kolmogorov-Smirnov, Anderson Darling, and chi-square tests. These tools help find the best form of the probability distribution of empirical data for each variable. Value-at-Risk (VaR) is a measure of market risk that can indicate the maximum loss of an asset or portfolio of assets. VaR can also be seen in the context of returns (Echaust et al., 2020). VaR is the q percentile of the distribution of total losses. The general formula for VaR is shown in Eq. (10).

$$VaR_q = F^{-1}(q) \tag{10}$$

The value of Excess Over Threshold (EOT) is $y = x - u$. The cumulative distribution function (cdf) of the total loss value *x* and *u,* which is the threshold value for $x > u$, is expressed by $F_u(y)$. The cumulative distribution of y is expressed in Eq. (11):

$$F_u(y) = P(X - u \leq X > u) = \frac{F(y+u)-F(u)}{1-F(u)} \text{; for } 0 < y < x_0 - u \quad (11)$$

or can be expressed as Eq. (12).

$$F(y + u) = [1 - F(u)][F_u(y)] + F(u) \quad (12)$$

$F_u(y)$ in Eq. (11) is *GPD* distribution, so it fulfils a function as seen in Eq. (13).

$$F_u(y) = \begin{cases} 1-\left(1+\frac{\xi y}{\beta}\right)^{-\frac{1}{\xi}}, & \text{jika } \xi \neq 0 \\ 1 - exp\left(-\frac{y}{\beta}\right), & \text{jika } \xi = 0 \end{cases} \quad (13)$$

The very large threshold value, then $F(u)$ will approach $1 - \frac{N_u}{n}$, where n is the number of all data points for the total loss value and N_u is the number of data above the threshold u. So, Eq. (13) can be expressed as Eq. (14):

$$F(u) = 1 - \frac{N_u}{n}\left(1 + \xi\frac{x-u}{\beta}\right)^{-\frac{1}{\xi}} \quad (14)$$

If the probability $q > F(u)$, then *VaR* is calculated by the inverse of Eq. (14). VaR calculation for GPD is as follows (Echaust et al., 2020).

$$\widehat{VaR}_{1-q} = u + \frac{\hat{\beta}}{\hat{\xi}}\left(\left(\frac{n}{N_u}q\right)^{-\xi} - 1\right)$$

where:

$1 - q$: confidence level
u : Threshold
ξ : The shape parameter of the distribution
β : Scale parameters
n : Number of observations
N_u : The number of observations above the threshold

3. Materials and Methods

This study uses secondary data in the form of daily stock closing prices from two insurance companies for January 2016-January 2022 obtained from the website https://finance.yahoo.com/, accessed on May 25, 2022. The data collection method in this study is a non-participant observer, where the researcher only observes the already available data without being part of the data system. The data is used to calculate the estimated risk value based on the Extreme Value Theory method. The research method in this study uses quantitative methods. Quantitative research methods are used to examine samples or populations using sampling techniques, data collection, and statistical data analysis data with the aim of testing predetermined hypotheses (Sukono et al., 2021). The following explains some of the steps in this research as follow:

3.1. Research Planning

This stage is the beginning of the research, which will discuss the outline of the research, the topic of the research problem, to the benefits and objectives of the research. At this stage, the researcher discusses estimating the value of risk in stock investments using the Extreme Value Theory method with the Peak Over Threshold approach.

3.2. Literature Study

This stage is related to collecting material on investment, stock returns, risk, Value at Risk, and the Extreme Value Theory method from various libraries such as guidebooks, journals, previous studies and other literatures related to the issues being discussed.

3.3. Data Collection

The selected data is secondary data in the form of daily closing price data of insurance companies from January 2016 - January 2022 obtained from the website: https://finance.yahoo.com/. The selection of shares at the closing price is because today's closing price is used as a reference for the price at the opening the next day.

3.4. Calculating the value of stock returns

Then calculate each stock's rate of return (return) using Eq. (1).

3.5. Calculating Descriptive Statistics

This stage is related to calculating descriptive statistics from data on closing prices of insurance companies' shares. Descriptive statistical analysis is used to analyse or describe the data that has been collected without the intention of making conclusions. This stage aims to identify a model to determine the presence of a fat distribution tail. If the kurtosis value is more than three, the distribution has a tail heavier than the normal distribution and indicates the presence of extreme data elements.

3.6. Calculating the Threshold

Calculating the threshold is done by sorting the observation data from the largest value to the smallest value. Then count the data that exceeds the threshold u with $n = 10\% \times N$ where N is the total observational data. Data that is in the order of $1\ to\ n$ is extreme data. Determine the threshold u with $u = n + 1$ so that the data in the order of $(n + 1)$ is the limit value of u.

3.7. Identifying the GPD Effect

Testing the effect of GPD on the data can be done by looking at the QQ-plot so that the extreme data forms the GPD distribution. The results of extreme data will be used as material for estimating GPD parameters.

3.7.1. Estimating GPD Parameters with Maximum Likelihood Estimation

Estimating GPD parameters is done by estimating two parameters: the shape parameter in Eq. (6) and the scale parameter in Eq. (9). The two GPD parameters will be used to calculate VaR.

3.7.2. Testing the suitability of the generalised Pareto distribution

The distribution suitability test for the Generalized Pareto Distribution will be carried out using Easyfit software with the Goodness of Fit tools used, namely Kolmogorov-Smirnov, Anderson Darling, and Chi-Squared.

3.7.3. Perform Value at Risk calculations

With the parameter estimation results obtained, it is possible to calculate VaR with a confidence level of 90%, 95%, and 99% using the formula (10).

3.8. Draw a conclusion

From the calculated results of the individual VaR values obtained, it can be concluded that the application of extreme value theory in the measurement of risk in the stocks of individual companies can be concluded.

4. Results and Discussion

This section discusses the stages in estimating the Value at Risk value of the closing stock price of an insurance company using the Extreme Value Theory (EVT) approach, starting with descriptive statistical analysis, determining parameters, determining limit values, and determining Value at Risk. The results of the daily return calculation from each company are calculated using Eq. (1). A snippet of the results of the return calculation can be seen in Table 1. Complete data are presented in Appendix 1 and Appendix 2. Table 1 displays the returns have of kind values, in which an effective cost suggests a go back withinside the shape of income and a terrible cost suggests a go back withinside the shape of a loss. The situation of the company's inventory going back may be visible withinside the graph plot in Fig. 1.

Table 1
Daily return of each company

Date	AXA General Insurance		BRI Insurance	
	Close	Return	Close	Return
1/4/2016	78.23899		23.245	
1/5/2016	79.570023	–0.00338	24.345	0.000411
1/6/2016	76.919998	–0.03334	24.255	–0.00378
⋮	⋮	⋮	⋮	⋮
1/28/2020	92.000003	0.018262	24.165	0.012359
1/29/2020	91.910004	–0.00098	24.230	0.002697
1/30/2020	93.110001	0.013056	24.235	0.000206
⋮	⋮	⋮	⋮	⋮
1/28/2022	91.019992	0.018262	24.165	0.012354
1/29/2022	90.910004	–0.00138	24.233	0.002687
1/30/2022	91.110001	0.021045	24.245	0.001206

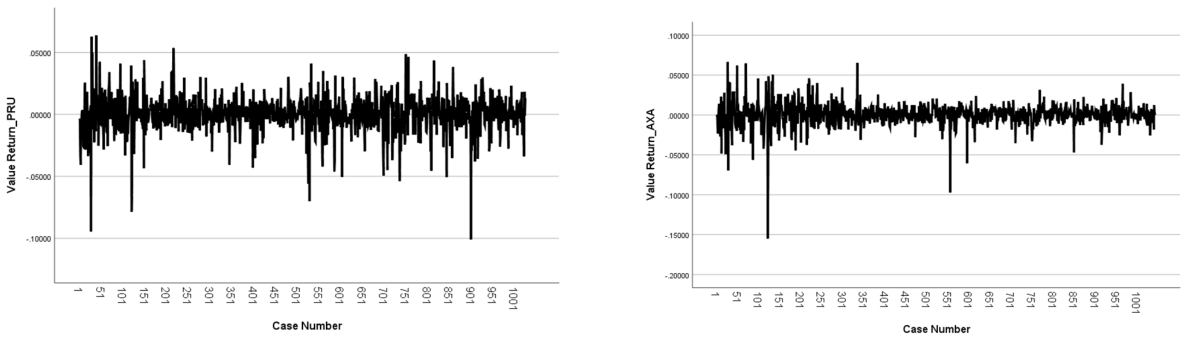

Fig. 1. The plot of company stock daily return

Fig. 1 captures the stock returns of the two highly volatile companies. The graph shows that the return is too high or too low at a certain time. Thus, the data was analysed with descriptive statistics. Descriptive statistics are specifically used to see the presence of extreme elements in the observational data.

Table 2
Descriptive Statistics of Company Stock Return Data

	AXA General Insurance	BRI Insurance
Mean	0.000508093	0.000115129
Standard Deviation	0.016618673	0.015091781
Sample Variance	0.000340854	0.000221092
Kurtosis	5.241241238	15.8031029
Skewness	–0.780661978	–1.451472901
Minimum	–0.100877921	–0.1548113628
Maximum	0.063853529	0.066452768

The skew value of the revenue data for companies *A* and *B* is not zero. AXA General Insurance has a skew value of -0.760876919 and BRI Insurance has a skew value of -0.46794567. A negative skewness value indicates that the distribution is right-skewed and has a long-left tail. Each data return has a kurtosis value greater than 3, A has a value of 5.341269987 and B has a value of 5.8931567. it indicates that return data tend not to be normally distributed. It can also be seen in the histograms in Fig. 2 and Fig. 3. The histogram is not symmetrical, indicating that the data are not normally distributed.

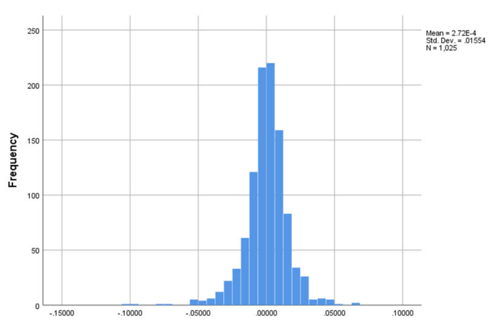

Fig. 2. Histogram Stocks Return *A*

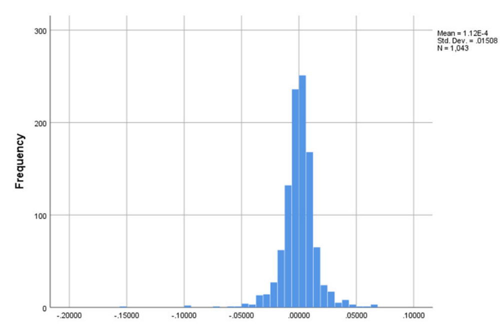

Fig. 3. Histogram Stocks Return *B*

Identification of tailed data and extreme values in company return data can be seen using QQ-Plot as shown in Fig. 4 and Fig. 5.

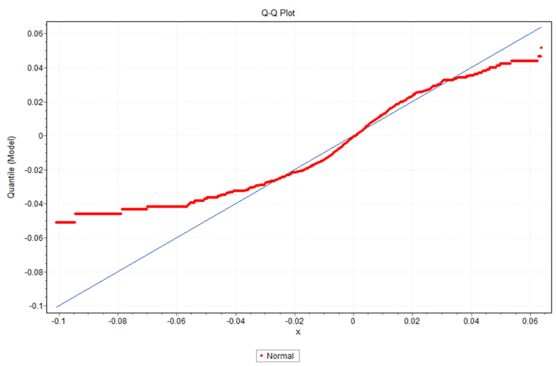

Fig. 4. QQ-Plot of Stock Return Data A

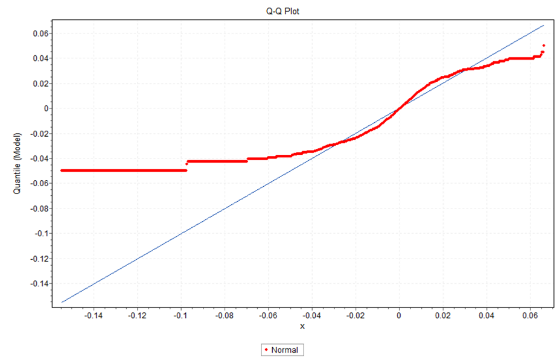

Fig. 5. QQ-Plot of Stock Return Data B

In both figures, the results are consistent with the desired assumption that the data have large tails or are not close to normal lines. Extremum data is 10% of total sales data for each company *n*=10%x1,026=102.6 about 103, data with extreme values up to the 103rd data, and the 104th data represents the return data threshold, AXA General Insurance. Based on this, there is a large data tail in the return data for each company in Fig. 4 and Fig. 5. According to extreme value theory, the extreme value data for each company in Tables 1 and 2 are assumed to follow a Generalized Pareto Distribution (GPD). will be Below is a summary of the company's extreme return data results using the threshold of
in Table 3.

Table 3
Threshold data return value of each company

Company	Number of Data	Extreme Data	*Threshold*
AXA General Insurance	1125	112	0,0168345
BRI Insurance	1143	114	0,0142351

The characteristics of extreme data in the form of descriptive statistics are needed in determining the form of the Generalized Pareto Distribution (GPD) distribution so that from Tables 1 and 2, descriptive statistics of the return data of each company are obtained with the help of MS software. Excel is shown in Table 4.

Table 4
Descriptive statistics of extreme data for each company

	AXA General Insurance	BRI Insurance
Mean	0.026222325	0.025168119
Standard Error	0.000972367	0.0011683
Standard Deviation	0.009903215	0.011914374
Sample Variance	8.81612E-05	0.000141952
Kurtosis	3.448641235	2.890427985
Skewness	1.248791129	1.732772988
Minimum	0.016862347	0.0140625
Maximum	0.063858976	0.066456475
Sum	2.701374567	2.617484401
Total	112	114

Table 4 shows the extreme data of each company are not normally distributed, the skewness value is not equal *to* 0, and kurtosis is not equal to 3. The extreme data are assumed to be distributed in GPD. The next step is to test the suitability of the distribution and calculate the estimated GPD parameters for each distribution of each company's return data. The results of the VaR calculation of each company are in Table 5. illustrate the estimated loss value of each company's return at each confidence level.

Table 5
Calculation Results of VaR

Company	VaR		
	$q = 90\%$	$q = 95\%$	$q = 99\%$
AXA General Insurance	0.01693398182	0.03283050275	0.05712269755
BRI Insurance	0.01398645527	0.02890353385	0.04949648525

AXA General Insurance has a VaR value of 0.05712269755, indicating that at the 99% confidence level, the maximum possible loss the next day is 5.91% of liquid assets. BRI Insurance's stock has a VaR of 0.04949648525, which at the 99%

confidence level indicates that the maximum possible loss the next day is 5.04% of liquid assets. If your current assets are IDR 1,000,000,000, your maximum loss is IDR 49,400,000.00. Similarly, we can also understand VaR with 90% and 95% confidence levels. It represents his one-day-ahead return estimates for each company. Of the two insurers surveyed from January 2016 to January 2022, AXA General Insurance has the lowest risk.

5. Conclusion

On the basis of the findings, this study concluded that the return is based on the negative skewness value and the kurtosis value that exceeds the normal distribution limit. Skewness is the degree of asymmetry or distance of symmetry of a distribution. Skewness is defined as the slope of the data distribution. An asymmetric distribution will have unequal mean, median, and mode so that the distribution will be concentrated on one side, and the curve will be skewed. The measure of the slope of the curve is the degree or measure of the asymmetry of a data distribution. It indicates that the returns are very limited. With the extreme value, the VaR value can be estimated using the extreme value theory method. Using the EVT method to estimate value-at-risk by identifying extremes based on Peak Over Threshold, the lowest GPD-based VaR value for BRI Insurance is 5.04%. AXA General Insurance holds 5.91% of liquid assets at a 99% confidence level. Therefore, BRI Insurance has a smaller risk compared to AXA General Insurance.

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Appendix

Appendix 1
Return Extreme Data above Threshold for AXA General Insurance

Return Extreme Data above Threshold for AXA General Insurance			
0.063852	0.029471	0.023038	0.018864
0.062759	0.029202	0.022199	0.018708
0.053634	0.028636	0.021538	0.018623
0.049811	0.0285	0.021342	0.018623
0.048679	0.028244	0.02116	0.018588
0.046389	0.026974	0.021092	0.018571
0.045236	0.026943	0.021017	0.01848
0.043795	0.026942	0.021013	0.018262
0.043426	0.026638	0.021008	0.018194
0.042375	0.026544	0.020961	0.018188
0.040977	0.026445	0.020653	0.018136
0.040969	0.026265	0.020423	0.01812
0.039443	0.026245	0.02035	0.018013
0.038208	0.026142	0.020328	0.017962
0.035319	0.026009	0.02023	0.017935
0.035076	0.02573	0.020132	0.017926
0.034372	0.025539	0.020105	0.017837
0.03412	0.02543	0.020079	0.017665
0.031353	0.02538	0.019994	0.017657
0.030325	0.024705	0.019961	0.017644
0.030317	0.024223	0.019918	0.017533
0.030127	0.024182	0.019914	0.017163
0.02981	0.024088	0.019689	0.017109
0.029731	0.02348	0.019524	0.016957
0.029714	0.023395	0.019115	0.016858
0.029673	0.023047	0.019084	

Appendix 2
Return Extreme Data above Threshold for BRI Insurance

Return Extreme Data above Threshold for BRI Insurance			
0.066456	0.027759	0.020623	0.017201
0.065333	0.0272	0.020404	0.01682
0.064687	0.027069	0.020303	0.016617
0.061856	0.026511	0.020231	0.016524
0.050304	0.02648	0.019479	0.016489
0.048461	0.026452	0.019443	0.016408
0.045957	0.026346	0.019366	0.016329
0.045767	0.026175	0.018937	0.015807
0.043233	0.025868	0.018894	0.015752
0.042175	0.025678	0.018785	0.015617
0.042112	0.025282	0.018461	0.015251
0.041344	0.025233	0.018409	0.015219
0.04046	0.024978	0.018316	0.0152
0.040102	0.024851	0.018246	0.015129
0.038938	0.024623	0.018137	0.014988
0.038893	0.02398	0.017797	0.01469
0.037209	0.02373	0.017768	0.01467
0.037122	0.023681	0.017695	0.014665
0.034576	0.023375	0.017668	0.014663
0.03321	0.023026	0.017618	0.014613
0.031421	0.023025	0.017457	0.014586
0.029539	0.022886	0.017451	0.014577
0.029199	0.022792	0.017448	0.014338
0.029136	0.022778	0.017407	0.014115
0.02894	0.022477	0.017245	0.014085
0.028383	0.021174	0.017238	0.014063