Estimated Value at Risk in Stock Investments in an Insurance Company using the Extreme Value Theory Method

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Abstract

Stocks as an investment product in the capital market have risks. Therefore, investors must consider the return (yield) and the risk of an investment product. This research uses one of the methods of the Extreme Value Theory (EVT), namely Peaks Over Threshold (POT) with the aim of estimating the value of risk in the General Insurance company for the period 2016-2020. One method that can be used to measure the level of risk in stocks is the calculation of Value. at Risk (VaR). There are several calculation phases in this research, namely, the first is by calculating the return value based on the daily closing stock price of each company then doing descriptive statistical analysis and QQ-Plot to identify the characteristics of the stock return data. Next, determine the threshold value to obtain extreme data and perform data suitability tests with Generalized Pareto Distribution (GPD). Then, estimate the parameters using the maximum likelihood method to calculate the VaR value. Based on the research results, the smallest VaR value with a 99% confidence level is in the range of 4.94% to 5.70%.

Keywords
Return Stocks, Risiko, Extreme Value Theory, Peaks Over Threshold, Value at Risk, Generalized Pareto Distribution

1. Introduction
Investment is an effort to place a number of funds at present in the hope of obtaining future benefits. Stock is one of the investment products that many investors choose, because it is able to provide an attractive rate of return. However, as an investment product in the capital market, of course there is a risk, which must be considered by investors between the return (yield) and the risk of several investment products available in the capital market (Bermudez et al, 2010). How many things to consider in investing include (1) the expected rate of return, (2) the level of risk given (rate of risk), and (3) the availability of funds to be invested (Coles, 2001). Thus, estimating the risks that will be faced is necessary so that readiness arises in facing risks. To measure the level of risk in financial markets, the Value at Risk (VaR) method can be used, which is part of risk management. Investors can use the VaR value as a measure to determine how much the risk target is. Currently, the application of the VaR method is widely applied and is considered a standard method of measuring risk. VaR can be defined as the estimated maximum loss that will be obtained during a certain period of time under normal market conditions at a certain level of confidence (Jorion, 2001; Sukono et al., 2018).
In risk management, incorrect assumptions about the distribution of security returns are often made. For example, practitioners often assume that financial returns are normally distributed, even though this assumption is very doubtful because most financial returns have a heavy tail compared to normal tail, which is the tendency for indications of extreme events compared to normal distribution modeling (Omer et. al, 2011).

One of the risk measurement methods that can detect the existence of extreme values that often appear in stock return data, namely VaR with the Extreme Value Theory (EVT) approach. EVT pays attention to information on extreme events based on the extreme values obtained to form the distribution function of these extreme values. There are two methods that are part of the EVT to identify extreme value movements, namely Block Maxima (BM) and Peaks Over Threshold (POT) (Kotz and Nadarajah, 2002).

Previous research on EVT has been carried out, among others, by Maida Fauziah (2014) by applying the EVT method to analyze risk in shari'ah stock portfolios, Salisa and Agus (2017) use extreme value analysis to estimate the value of risk in stock investment in the banking subsector, Echaust and Just (2020) with their journal entitled Value at Risk Estimation Using GARCH-EVT Approach with Optimal Tail Selection discusses the comparison of the estimated VaR estimation with the optimal distribution tail selection. Baran (2011) entitled A Comparison of EVT and Standard Value at Risk Estimations provides an explanation of claim expectations based on Value at Risk (Chung, M. 2007).

Based on the description above, this research will discuss the Extreme Value Theory method to estimate the risk value of stock investment in insurance companies using the Peaks Over Threshold (POT) method. The aims of this study were to determine the VaR model with the Extreme Value Theory method as a measure of the risk level of insurance company shares

2. Literature review

Extreme Value Theory is a branch of statistics that deals with extreme deviations from the median of their probability distribution. This theory is widely used to predict rare events, which are usually outside the range of available data (Echaust, K. dan Just, M., 2020), (Tripathy, T., & Ahluwalia, E. 2015). Peaks Over Threshold is one of the two main methods of EVT apart from the Block Maxima method. The POT method makes it possible to easily model the tail region of the distribution and obtain closed form expressions for Value at Risk (Echaust, K. and Just, M., 2020). The POT method is an EVT method that identifies extreme values using the threshold (u). The selection of the threshold in this study is 10% of the total data Rydman, M., (2018). Data that exceeds the threshold value will be identified as an extreme value. This method applies the Pick lands-Dalkema-De Hann theorem which states that the higher the threshold, the distribution will follow the Generalized Pareto Distribution (GPD). The cumulative density function (cdf) of GPD is as follows.

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

(Echaust, K. dan Just, M., 2020).

And the probability density function (pdf) for GPD is:

$$g_{\xi,\beta}(x) = \begin{cases} \frac{1}{\beta}\left(1+\frac{\xi}{\beta}x\right)^{-1-\frac{1}{\xi}}, \xi \neq 0 \\ \frac{1}{\beta}\ exp\left(-\frac{x}{\beta}\right) \quad , \quad \xi = 0 \end{cases} \quad (2)$$

where:

$\beta > 0$ and ≥ 0 if $\xi \geq 0$

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

ξ: parameter of form for distribution (shape)

β: parameter of scale

Based on the shape parameter value, the GPD distribution can be divided into three types, namely the exponential distribution if the value $\xi = 0$, the pareto distribution if the value $\xi > 0$; and a type II pareto distribution, if the value $\xi < 0$. Of the three types of distribution, the Pareto distribution has the heaviest tail (heavy tailed) (Cruz, M. 2003). Value at Risk (VaR) is a measure of market risk which can indicate how much the maximum loss of an asset or portfolio of assets is. VaR can also be considered in the context of return (Echaust et al., 2020). VaR is the q-quantile of the distribution of total loss values, the general equation for VaR is as $VaR_q = F^{-1}(q)$. Where F is the cumulative distribution function (cdf) of the total loss value x and u which are the threshold values, then the

Excess Over Threshold (EOT) value is x-u. In this case only conditions with x> u, i.e. positive EOT are considered, where the distribution for EOT is:

$$F_u(y) = P(X - u \le X > u) = \frac{F(y+u) - F(u)}{1 - F(u)} \tag{3}$$

it can be written

$$F(y+u) = [1 - F(u)][F_u(y)] + F(u) \tag{4}$$

$F_u(y)$ in equation (3) will be GPD distributed, so that the following functions will be fulfilled later:

$$F_u(y) = \begin{cases} 1 - \left(1 + \frac{\xi y}{\beta}\right)^{-\frac{1}{\xi}}, & \text{if } \xi \neq 0 \\ 1 - exp\left(-\frac{y}{\beta}\right), & \text{if } \xi = 0 \end{cases} \tag{5}$$

For a 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 amount of data that is above the threshold u. So that equation (5) can be described as follows:

$$\widehat{VaR}_{1-q} = u + \frac{\hat{\beta}}{\hat{\xi}}\left(\left(\frac{n}{N_u}q\right)^{-\xi} - 1\right) \tag{6}$$

where:
$1 - q$: confidence level
u : *threshold*
n : the number of observations
N_u : the number of observations above the threshold

2. Research Methodology

Model simulations are carried out using case study data obtained from open sources. The research method used in this research is to use quantitative methods. Quantitative research methods, namely those used to examine data using sampling techniques, data collection, data analysis aimed at testing the predetermined hypothesis.

3. Results and Discussion

The data and information on company shares used are secondary data from the closing price of Prudential and AXA insurance companies from 2016 to 2020 which were 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 price at the opening on the following day (Kalfin et al., 2019.a; 2019.b).

Table 1 Snippets of Each Company's Daily Return

Date	PRU		AXA	
	Close	Return	Close	Return
1/4/2016	79.839996		24.335	
1/5/2016	79.57	-0.00338	24.345	0.000411
1/6/2016	76.919998	-0.0333	24.255	-0.0037
1/7/2016	73.790001	-0.04069	23.69	-0.02329
1/8/2016	73.050003	-0.01003	23.245	-0.01878
⋮	⋮	⋮	⋮	⋮

1/24/2020	93.519997	-0.02104	24.31	0.006834
1/27/2020	90.349998	-0.0339	23.87	-0.0181
1/28/2020	92	0.018262	24.165	0.012359
1/29/2020	91.910004	-0.00098	24.23	0.00269
1/30/2020	93.110001	0.013056	24.235	0.000206

Based on the table, it can be seen that each return has a different value. Positive values represent returns in the form of profits (profit) and negative values represent returns in the form of losses (loss). To see the condition of the company's stock return, you can see the plot graph in Figure 1.

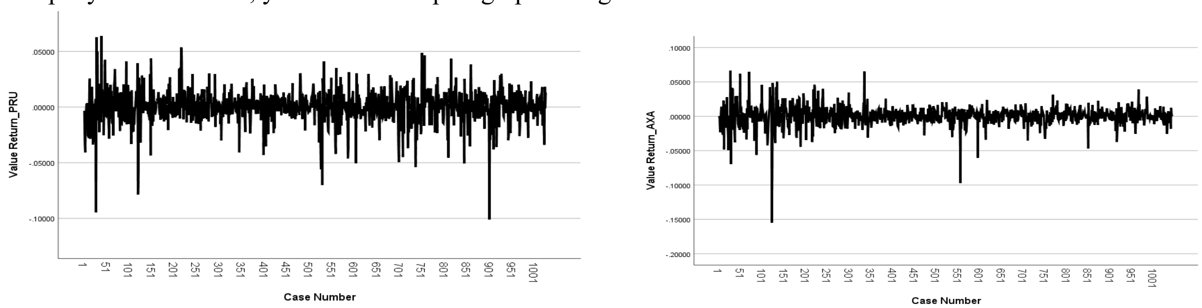


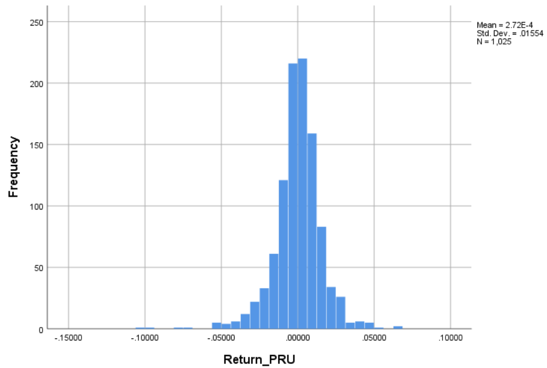
Figure 1. Plot of Company Shares Daily Return

In Figure 2, it can be seen that stock returns in the two companies are very volatile. It can be seen on the graph that in a certain time there is a return that is too high or a return that is too low. So that to find out the general description of the data, descriptive statistical analysis can be carried out.

Table 2 Descriptive Statistics of Company Stock Return Data

Descriptive Statistics		
	PRU	**AXA**
Mean	0.000308084	0.000114919
Standard Deviation	0.015518681	0.015094097
Sample Variance	0.000240829	0.000227832
Kurtosis	5.241241197	15.8031218
Skewness	-0.780666919	-1.451473643
Minimum	-0.100878513	-0.154811715
Maximum	0.063852357	0.066456475

PRU and AXA return data have skewness values which are not equal to zero. PRU has a skewness value of -0.780666919 and an AXA of -0.451473643. A negative skewness value indicates that the distribution is tilted to the right and has a long tail to the left. The kurtosis value of each return data is more than three, PRU has a value of 5.241241197 and AXA has a value of 15.8031218. This shows that the return data tends to have an abnormal distribution. This can also be seen in the histogram, which shows the shape of the histogram is not symmetrical so that it indicates that the data is not normally distributed.



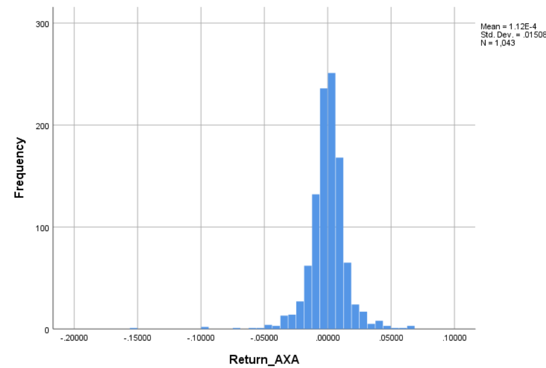
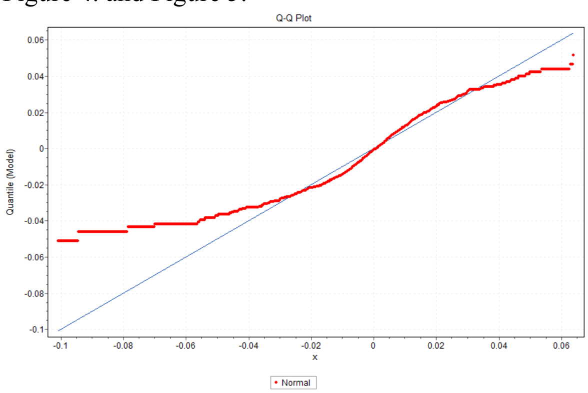


Figure 2. PRU Shares Return Histogram Figure 3. AXA Shares Return Histogram

The identification of tail data and the extreme value of company return data can be seen using the QQ-Plot as in Figure 4. and Figure 5.



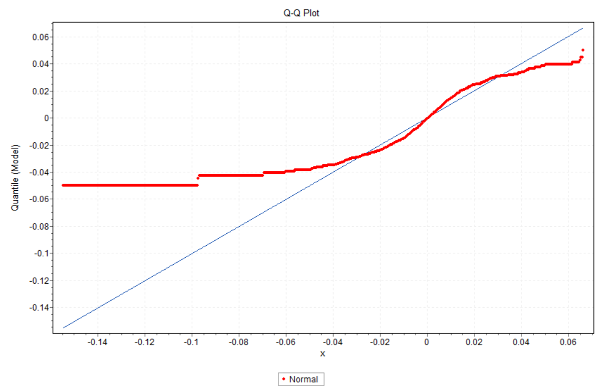


Figure 4. QQ-Plot of PRU Stock Return Data Figure 4. QQ-Plot of AXA Stock Return Data

In both figures, the results are in accordance with the assumptions, namely large data tails or away from the near normal line. Furthermore, extreme data collection will be carried out, by sorting the data from the largest value to the smallest, then taking 10% of the total return data of each company, namely n = 10% x 1,026 = 102.6 ≈ 103, then the first data to the data -103 is the extreme data and the 104th data is the threshold of the PRU return data. Likewise, the calculation for the extreme data and the threshold value for the AXA return data is 1,043 data. The first data to the 104th data is extreme data and the 105th data is the threshold or threshold value. The results of these extreme data are shown in Table 3. and Table 4.

Table 3. Extreme Data of PRU Stock Returns

PRU Extreme Return Data Above Threshold			
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	

Table 4. AXA Shares Return Extreme Data

AXA Extreme Return Data Above Threshold			
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

Based on the results of the QQ-Plot, each company return data in Figure 4. and Figure 5. has a large tail which according to the theory of extreme values, the extreme data from each company in Table 3. and Table 4. are assumed to be in accordance with the Generalized Pareto Distribution. The following is a summary of the results from the extreme data on company returns with the threshold values in Table 5.

Table 5. Threshold Value of Data Return for Each Company

Company name	**The amount of data**	**Extreme Data**	***Threshold***
PRU	1025	103	0.016858
AXA	1043	104	0.014059

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 Table 3 and Table 4, the descriptive statistics for the return data of each company are shown in Table 6.

Table 6. Descriptive Statistics of Extreme Data of Each Company

Descriptive Statistics		
	PRU	**AXA**
Mean	0.026226959	0.025168119
Standard Error	0.000976101	0.0011683
Standard Deviation	0.009906347	0.011914374
Sample Variance	9.81357E-05	0.000141952
Kurtosis	3.148644323	2.890427985
Skewness	1.757761177	1.732772988
Minimum	0.01685772	0.0140625
Maximum	0.063852357	0.066456475
Sum	2.701376787	2.617484401
Count	103	104

Based on the results of the calculation of descriptive statistics in Table 6. The extreme data for each company does not normally distributed, due to the skewness value in not equal 0 and kurtosis not equal 3. The extreme data is assumed, has a GPD distribution. The next step is to test the fit and estimate of the GPD parameters for each distribution of each company return data. The extreme data of each company in Table 3. and Table 4., are assumed to be in accordance with the Generalized Pareto Distribution (GPD), so it is necessary to fit the distribution to the GPD first, to ensure its suitability, so that the initial assumptions are proven and the GPD parameters can be estimated. The distribution fitting process is carried out using the help of Easyfit software. Following are the results of the QQ-Plot with GPD on the extreme PRU return data which can be seen in Figure 5 and Figure 6.

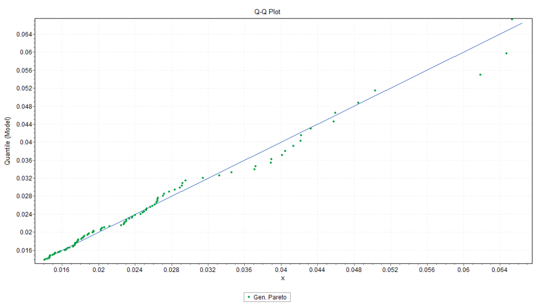


Figure 5. QQ-Plot of Extreme AXA Return Data with GPD

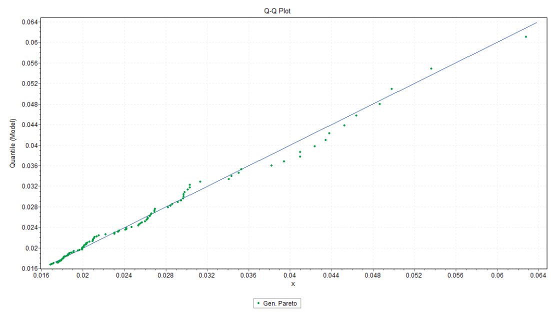


Figure 6. QQ-Plot of PRU Extreme Return Data with GPD

The results of the PRU return extreme fit distribution data with QQ-Plot to the GPD distribution in Figure 5. and Figure 6. provide an overview of the data compatibility with the GPD distribution because the QQ-Plot approaches the approximate line of the GPD distribution. In addition to the QQ-Plot, the compatibility test with the GPD distribution was also carried out with goodness of fit, namely the Kolmogorov-Smirnov, Anderson Darling, and Chi-Squared tests to determine the distribution test results with GPD. Following are the results of these three tests with the help of Easyfit Software in Table 7 and Table 8.

Table 7. Goodness of Fit Extreme Data Return PRU with GPD

Gen. Pareto [#22]					
Kolmogorov-Smirnov					
Sample Size Statistic P-Value Rank	103 0.06236 0.79455 1				
α	0.2	0.1	0.05	0.02	0.01
Critical Value	0.10573	0.12051	0.13381	0.14957	0.16051
Reject?	No	No	No	No	No
Anderson-Darling					
Sample Size Statistic Rank	103 0.45015 3				
α	0.2	0.1	0.05	0.02	0.01
Critical Value	1.3749	1.9286	2.5018	3.2892	3.9074
Reject?	No	No	No	No	No
Chi-Squared					
Deg. of freedom Statistic P-Value Rank	6 5.5532 0.47505 6				
α	0.2	0.1	0.05	0.02	0.01
Critical Value	8.5581	10.645	12.592	15.033	16.812
Reject?	No	No	No	No	No

Table 8. Goodness of Fit Extreme Data Return AXA with GPD

Gen. Pareto [#22]					
Kolmogorov-Smirnov					
Sample Size Statistic P-Value Rank	104 0.04681 0.96859 1				
α	0.2	0.1	0.05	0.02	0.01
Critical Value	0.10522	0.11993	0.13316	0.14885	0.15974
Reject?	No	No	No	No	No
Anderson-Darling					
Sample Size Statistic Rank	104 0.38247 1				
α	0.2	0.1	0.05	0.02	0.01
Critical Value	1.3749	1.9286	2.5018	3.2892	3.9074
Reject?	No	No	No	No	No
Chi-Squared					
Deg. of freedom Statistic P-Value Rank	6 4.2689 0.64034 2				
α	0.2	0.1	0.05	0.02	0.01
Critical Value	8.5581	10.645	12.592	15.033	16.812
Reject?	No	No	No	No	No

From the results of the goodness of fit of the extreme data returns, it can be concluded that the extreme return data is in accordance with the GPD distribution, so that it can be continued to estimate its parameters. The following is the form parameter for the PRU and AXA respectively stock return extreme data $\hat{\xi} = -0{,}3740105379$ and $\hat{\xi} = -0{,}4682788807$ and estimated value for β respectively $\hat{\beta} = 0{,}02606329126$ and $\hat{\beta} = 0{,}02516811538$. The result of the calculation of form parameters with a value of $\xi < 0$ provides an explanation that the GPD distribution of the extreme PRU stock return data obtained is GPD type II. In the distribution function if the value $\xi < 0$ then the x domain that satisfies the distribution is $0 \leq x \leq -\frac{\beta}{\xi}$ where β is the scale parameter. VaR describes the value of the risk of loss that may occur, to calculate it requires the threshold value and the amount of extreme data on stock returns from Table 5, as well as the estimated scale and shape parameters. The calculation results are presented in the Table 9.

Table 9. VaR Calculation Results by Company

Company name	*VaR*		
	q=90%	*q*=95%	*q*=99%
PRU	0.01693398182	0.03283050275	0.05712269755
AXA	0.01398645527	0.02890353385	0.04949648525

The result of VaR calculation illustrates the estimated loss value of each company return at each level of confidence. The VaR value at the PRU company, for example, is 0.05712269755 means that with a confidence level of 99%, the maximum possible loss in the next 1 day is 5.71% of the current asset.

4. Conclusions

Based on the results of the discussion in the previous chapter, it can be concluded that, seen from the characteristics of the return data based on the amount of skewness which is negative and kurtosis that exceeds the normal distribution, it indicates that the return data is heavy-tailed, that is, there is an extreme value so that the Extreme Value Theory method can be used to VaR calculation. Estimating the risk value using the EVT method by identifying the extreme value based on the Peak Over Threshold, the smallest VaR-GPD value is in the AXA company at 4.94% while PRU is 5.71% of current assets with a 99% confidence level.

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References

Anita, R. (2013). Identification of Climate Change with Generalized Extreme Value (GEV) Distribution Approach. Journal of Physics.: Conf. Ser. 423 012026

Baran, J. and Witzany, J. (2011). A Comparison of EVT and Standard VaR Estimations. *SSRN eJournals* (Online). *Czech Science Foundation grant no*. 402/09/0732

Bermudez, P., and Kotz, S. (2010). Parameter estimation of the generalized Pareto distribution-Part II. *Journal of Statistical Planning and Inference*, vol. 140, no. 6, pp. 1374-1397.

Chung, M. (2007). Quantile-Quantile Plot. *Online Journals*, 1-3. Retrieved from

Coles, S. (2001) An Introduction to Statistical Modeling of Extreme Values. London: Springer.

Cruz, M. (2003). *Modelling, Measuring and Hedging Operational Risk.* New York: John Wiley & Sons.

Echaust, K. and Just, M. (2020). Value at Risk Estimation Using the GARCH-EVT Approach with Optimal Tail Selection. *Mathematics*, *8*(1), p.114.

https://finance.yahoo.com/ (diakses pada tangal 25 September 2020).

Jindrová, P. and Pacáková, V. (2019). Natural Catostrophe Models for Insurance Risk Management. Wseas Transactions on Bussiness and Economics.

Jorion, P. (2001). *Value at Risk : The New Benchmark for Managing Financial Risk, 3nd.* New York: McGraw-Hill Companies.

Kalfin, Sukono and Carnia, E. (2019.a). Optimization of the mean-absolute deviation portfolio investment in some mining stocks using the singular covariance matrix method. *IOP Conf. Series: Journal of Physics: Conf. Series*, 1315 (2019) 012002.

Kalfin, Sukono, and Carnia, E. (2019.b). Portfolio Optimization of the Mean-Absolute Deviation Model of Some Stocks using the Singular Covariance Matrix. International Journal of Recent Technology and Engineering (IJRTE), Volume-8 Issue-3, September 2019, 7818-7822.

Kotz, S. and Nadarajah. S. (2002). *Extreme Value Distribution (Theory and Application).* London: Imperia College Press.

Omer L. Gebizlioglua, Birdal, and Kantar. Y.M. (2011). Comparison of certain value-at-risk estimation methods for the two-parameter Weibull loss distribution. Journal of Computational and Applied Mathematics journal homepage: www.elsevier.com/locate/cam

Pribadi, D.M., Sukono, Riaman. (2019). Robust model of the combination of expectations and conditional valueat-risk from paddy farming risk management based on climate variability, International Journal of Innovation, Creativity and Change.

Rockafellar R., Tyrrell, and Uryasev, S. (2002). Conditional value-at-risk for general loss distributions. Journal of Banking & Finance 26 (2002) 1443–1471. http://www.elsevier.com/locate/econbase

Rydman, M., (2018). Application of the Peaks-Over-Threshold Method on Insurance Data.

Sukono, Kartiwa, A., Subartini, B., Hidayat, Y., and Bon, A.T. (2018). Estimation of Conditional Value-at-Risk under Assets Liability Model with Non Constant Volatility. *Proceedings of the International Conference on Industrial Engineering and Operations Management,* Bandung, Indonesia, March 6-8, 2018, 2726-2733.

Tripathy, T., & Ahluwalia, E. (2015). "Day Long Effect of Liquidity on Stock Return: An Empirical Investigation in a Day of Political and Economic Importance in India". International Journal of Economics and Finance, 7(10). https://doi.org/10.5539/ijef.v7n10p204 Undang- Undang Nomor 8 Tahun 1995 Tentang Pasar Modal. (1995). Retrieved from http://www.jdih. kemenkeu. go.id/fulltext /1995/8TAHUN~1995UU.htm

William, M.L. (1997). *Corporate Finance Theory,* 1st edition, Addison-Wesley Educational Publisher Inc, 1997.

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