Available online at http://www.iorajournal.org/index.php/ijgor/index

**International Journal of Global Operations Research**

e-ISSN: 2722-1016
p-ISSN: 2723-1739

Vol. 6, No. 1, pp. 6-12, 2025

# Extreme Risk Analysis on Financial Derivatives in Indonesia Using Extreme Value-at-Risk Based on Generalized Pareto Distribution (GPD)

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**Abstract**

Develop a Value at Risk (VaR) model based on Generalized Pareto Distribution (GPD) to analyze extreme risks in financial derivative portfolios in Indonesia. The GPD approach is chosen because it can describe the tail distribution of price data that exceeds a certain threshold. Price data (in US dollars/USD) of financial derivatives from the Indonesian market are collected from 2011 to 2022 taken from the International Financial Statistics (IMF Data). Furthermore, the data is analyzed to determine the threshold, then the GPD model is applied to extract the tail distribution. The calculation of GPD-based VaR is carried out to provide a more accurate estimate of the potential for extreme losses. This study is expected to contribute to the management of extreme risks in the derivatives market in Indonesia, as well as provide guidance for investors and financial institutions in making more informed investment decisions.

*Keywords:* Extreme risk, financial derivatives, EVT, EVaR, GPD, risk analysis, threshold.

## 1. Introduction

In the face of increasingly rapid economic globalization, risk in financial derivatives trading has become a very important issue. Financial derivatives such as futures, options, and swaps are widely used by various financial institutions for risk hedging and speculation purposes (Embrechts et al, 1997). However, the high volatility and potential for extreme losses of these instruments pose challenges for market players to manage risk.

Extreme risk in this case refers to the potential for very large losses that can occur in a short period of time. Analysis of this extreme risk is important in understanding the potential for large impacts of unexpected price movements on a derivative portfolio (McNeil et al, 2005). One method often used to analyze extreme risk is Value at Risk (VaR), which provides an estimate of the maximum loss that may occur in a certain period with a certain probability.

However, traditional VaR has limitations in handling data with wide tail distributions and non-Gaussian distribution patterns as often occurs in financial market data (Danielsson, 2001). Generalized Pareto Distribution (GPD) is one approach that has emerged as a solution to deal with this problem. GPD is able to describe the behavior of the tail distribution of data distributions that exceed a certain threshold, making it very useful in extreme risk analysis (Kotz & Nadarajah, 2004).

In Indonesia, the use of the GPD method in analyzing extreme risk in financial derivatives is still relatively limited. This study aims to develop a GPD-based VaR model to measure extreme risk in financial derivative portfolios in Indonesia. This approach is expected to provide a more accurate estimate of the potential risk of extreme losses faced by investors in the Indonesian derivatives market.

Zuhara et al (2012) analyzed the risk using the Value at Risk (VaR) method with the Generalized Pareto Distribution (GPD) approach. The study measured the risk of investing in Semen Gresik shares from August 2007 to March 2012. Since financial data often has a heavy-tailed distribution, the GPD approach was chosen to identify extreme values. The data were analyzed using the GARCH model to model the volatility and distribution of the data. The GPD distribution parameters were estimated using the Maximum Likelihood Estimation (MLE) method. In the study, with a 95% confidence level, the minimum possible loss in one day of investment is 3.12% of total assets. If the asset value reaches IDR 1 billion, the minimum potential loss is IDR 31,200,000 in one day out of 20 trading days. The results of the study indicate that the GPD approach is effective in measuring financial risks that are rare but significant. Furthermore, Najamuddin et al (2024) discusses the estimation of Value at Risk (VaR) of non-cyclical consumer sector stocks listed in the LQ45 index using extreme value theory (EVT). The two EVT approaches used are Block Maxima (BM) and Peaks Over Threshold (POT). The BM method divides the data into weekly blocks and takes the maximum value of each block, while the POT method uses a certain threshold to identify extreme values. The estimation parameters are carried out using Maximum Likelihood Estimation (MLE), while the distribution suitability test is carried out using the Kolmogorov-Smirnov and Anderson-Darling tests. The results show that the POT method is more accurate than the BM method in estimating stock risk. The stock with the highest risk is HMSP, while the stock with the lowest risk varies depending on the method used.

**Table 1**: Research Gap or Content Analysis on Extreme Risk Analysis on Financial Derivatives in Indonesia Using Extreme Value-at-Risk Based on Generalized Pareto Distribution (GPD)

| Authors | Variables | Method | Using the EVaR method | Consider financial derivative data | Comparison with Other Distributions or Models |
|---|---|---|---|---|---|
| Zuhara, Akbar, & Haryono. (2012) | Semen Gresik stock data, Return level, Risk | VaR, GPD, Peaks Over Threshold (POT), Mean Excess Function (MEF) | No | No | Normal Distribution, and GARCH Model |
| Najamuddin, Herdiani, & Jaya. (2024) | LQ45 stock data (HMSP, ICBP, INDF, UNVR) | VaR, Extreme Value Theory (EVT), Block Maxima (BM), Peaks Over Threshold (POT), Maximum Likelihood Estimation (MLE), Kolmogorov-Smirnov, Anderson-Darling | No | No | Generalized Extreme Value (GEV) |

Based on the description above, using the GPD approach is expected to provide a significant contribution in understanding and managing extreme risks in financial derivatives in Indonesia.

## 2. Literature Review

### 2.1. Extreme Value Theory (EVT)

Extreme Value Theory (EVT) is a branch of statistics that focuses on the analysis of extreme values in a dataset, such as the maximum or minimum values of observed variables (Embrechts et al, 1997). This approach aims to model the distribution of rare but high-impact extreme events, such as major damage from natural disasters or financial losses in trade (McNeil et al, 2005).

Identification of extreme values from loss data can be done using two methods. First, the block maxima method, which is a traditional method used to analyze seasonal data. Each block period is determined by its maximum loss. Second, the Peak Over Threshold (POT) method uses data more efficiently by identifying extreme values that are above a certain threshold. Based on this, the POT method will be better used for extreme risks (Embrechts et al, 1997).

### 2.2. Peak Over Threshold (POT)

Peak Over Threshold (POT) is a method in Extreme Value Theory (EVT) that is used to identify extreme values in a dataset by focusing on events that exceed a certain threshold. This approach is more efficient than traditional methods such as block maxima because it only uses data that is above the threshold, which can produce a more accurate estimate of the tail distribution (Embrechts et al, 1997).

In the POT method, a threshold is first set based on the nature of the data. Data exceeding the threshold are identified as extreme values. The advantage of this method is to better estimate the tail distribution without limiting it to certain blocks of data, as is done in the block maxima method (McNeilet al,2005). The POT method can utilize all data more efficiently to estimate extreme risks.

### 2.3. Generalized Pareto Distribution (GPD)

Generalized Pareto Distribution(GPD) is a distribution that is often used to model extreme data, especially in the context of financial risk and insurance. The GPD method is used to estimate the tail distribution of extreme data by focusing on data that is above a threshold. This approach allows for more accurate estimates of the probability of extreme events compared to traditional tail distributions such as Weibull or Exponential (Embrechts et al, 1997).

### 2.4. Extreme Value at Risk(EVaR)

EVaR is a concept that integrates extreme value theory with the Value at Risk (VaR) approach to estimate extreme risk from financial data. The EVaR approach uses the GPD model to estimate the tail distribution of extreme data that exceeds a certain threshold. According to McNeil et al (2005), the EVaR approach is able to provide more accurate and stable estimates for extreme risk compared to conventional VaR, because EVaR is better able to capture tail fluctuations from rare distributions. The EVaR approach using GPD allows for better calculation of tail risk in a financial context, such as stock prices or interest rates (Danielsson, 2001).

## 3. Materials and Methods

### 3.1. Materials

The object used in this study is the loss of financial derivative contracts (in US dollars) in Indonesia taken from the International Financial Statistics annually, from 2011 to 2022. The data records international money flows from financial derivative transactions and employee stock options, including the inflow or outflow of a country's funds due to investment or hedging activities using derivative contracts such as futures, options, or swaps, which are recorded in the financial account of a country's balance of payments. Data analysis and data processing are assisted by Microsoft Excel and Easyfit software.

### 3.2. Methods

#### 3.2.1. Peak Over Threshold (POT)

Peak Over Threshold (POT) identifies extreme values by setting a threshold and ignoring the time of the event. This threshold is the maximum limit or limit of the company's ability to bear operational losses (Coles et al, 2001). In the POT method, the data is sorted from the most significant to the smallest, then the extreme values that are on the threshold are selected as many as the values in Equation (1), and the value $m+1$ becomes the threshold value. The POT approach applies the Picklands-Dalkema-De Hann theorem, which states that the higher the threshold, the distribution will follow the general distribution ($\mu$). Then, the distribution will follow the Generalized Pareto Distribution (GPD) (Mida et al, 2020).

$$m = 10\% \times n \tag{1}$$

$$\mu = m + 1 \tag{2}$$

Where $m$ is the number of data above the threshold, $n$ is the number of observation data, and $\mu$ is the location of the threshold data.

#### 3.2.2. Generalized Pareto Distribution (GPD)

Baran (2011) defines GPD as the limit of the distribution of scaled excesses above the threshold value. Suppose that $X$ is a random variable of daily losses with 2 GPD parameters, the GPD distribution function of $X$ is in equation (3),

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

where, if $\xi > 0$ then $\beta > 0$ and $x \geq 0$. And if $\xi < 0$ then $0 \leq x \leq -\frac{\beta}{\xi}$. With $\xi$: shape parameters and $\beta$: scale parameters.

There are three types of distributions in GPD that are distinguished based on the value of their shape parameters ($\xi$), namely exponential distribution if $\xi = 0$, Pareto distribution type I if $\xi > 0$, and Pareto distribution type II if $\xi < 0$. The GPD distribution function has properties that describe extreme values. These properties can be identified based on the value of $\xi$ (shape parameter). This can be interpreted that, if the value of $\xi$ is greater, the GPD has a fatter tail, so the chance of extreme values occurring is also greater.

#### 3.2.2.1. GPD Fit Test

Extreme data taken above the threshold value (threshold) in this study tested its suitability to GPD using EasyFit tools Goodness of Fit software. According to Arwindy (2014), EasyFit is software specifically designed to facilitate the analysis of data probability in simulation. This tool helps in selecting the best distribution according to the given data, using various goodness of fit test methods such as Kolmogorov-Smirnov, Anderson-Darling, and Chi-Squared. These tools make it possible to find the most suitable form of probability distribution for each variable in the simulation.

#### 3.2.2.2. GPD Parameter Estimate

In this study, the MLE of the GPD parameters is not closed form. To obtain a closed form equation, the Easyfit software is continued. The following is equation (4) of the shape parameter and equation (5) of the scale parameter of the obtained parameter estimates,

$$\hat{\xi} = \frac{n^2 s - \sum_{i=1}^{n} z_i}{\sum_{i=1}^{n} x_i - n\sum_{i=1}^{n} z_i} \tag{4}$$

$$\hat{\beta} = \frac{1}{n}\sum_{i=1}^{n} z_i \tag{5}$$

where $\hat{\hat{\xi}}$ is the estimate of the shape parameter, $n$ is the number of extreme data, $s$ is the standard deviation of the extreme data, $z_i$ is the i-th extreme data, and $\hat{\beta}$ is the estimate of the scale parameter.

### 3.2.3. Extreme Value at Risk (EVaR)

Suppose $X$ the random variables and the conditional distribution function ($F_u$) of the profit and loss above the threshold ($\mu$) are defined in equation (6),

$$F_u(y) = P[X - \mu \leq y | X > \mu] = \frac{F(x) - F(\mu)}{1 - F(\mu)} \tag{6}$$

for $0 \leq y \leq X_f - \mu$, where $X_f$ is the rightmost point of F. And $X_f = Sup\{x \in R: F(x) < 1\} \leq \infty$ with $y = x - \mu$ is the gain over $\mu$.

Based on the Pickands Dalkema-deHaan theorem, the distribution function $F(x)$ is obtained in equation (7),

$$F(x) = (1 - F(\mu))G_{\xi,\beta}(x - \mu) + F(\mu) \tag{7}$$

for $x > \mu$, estimate the value $\mu$ to find the quantile corresponding to $\mu$ the distribution in equation (8),

$$\hat{F}(\mu) = \frac{n - N_\mu}{n} \tag{8}$$

where $n$ is the data sample size, and $N_u$ is the number of losses above the threshold $\mu$. The tail estimator of $F(x)$ for $x > \mu$ is found in equation (9),

$$\hat{F}(x) = 1 - \frac{N_\mu}{n}(1 + \frac{\xi(x - \mu)}{\beta})^{-\frac{1}{\xi}} \tag{9}$$

Value at Risk (VaR) is defined as the expected value of the maximum loss of the value of an asset or stock in a certain period and at a certain level of confidence. According to Baran et al. (2011), for the probability $p > (\mu)$, the quantile function estimate can calculate the potential loss (EVaR) with the GPD distribution using equation (10),

$$EVaR_p = \mu + \frac{\beta}{\xi}\left\{\left[\frac{n}{N_\mu}(1 - p)\right]^{-\xi} - 1\right\} \tag{10}$$

Where:
$\mu$: Threshold
β: Scale parameter
ξ: Shape parameter
$n$: Number of observation data

$N_\mu$: Number of data above the threshold
$p$: Confidence level.

## 4. Results and Discussion

### 4.1. Data Implementation

In this study, data on financial derivative contract losses (in US dollars) in Indonesia were used, taken from the International Financial Statistics on an annual basis, from 2011 to 2022. The data in table 4.1 records international money flows from financial derivative transactions and employee stock options, including the inflow or outflow of a country's funds due to investment or hedging activities using derivative contracts such as futures, options, or swaps, which are recorded in a country's balance of payments financial account.

**Table 2**: Derivative contract loss data (USD) in Indonesia

| Year | Derivative Contract Losses (USD) |
|---|---|
| 2011 | $693,512,538,438,497.00 |
| 2012 | $129,872,398,954,718.00 |
| 2015 | $199,612,990,736,721.00 |
| 2017 | $127,765,321,829,887.00 |
| 2018 | $336,057,001,827,809.00 |
| 2019 | $186,398,605,011,477.00 |
| 2020 | $177,273,419,245,962.00 |
| 2021 | $332,708,199,367,186.00 |
| 2022 | $483,601,012,417,738.00 |

### 4.2. Variable Identification

For data analysis, the variables identified in this study are year, derivative contract losses, and international fund flows.

### 4.3. Parameter Formation Generalized Pareto Distribution(GPD)

In the EVaR approach using the GPD distribution, the parameters obtained through analysis using Easyfit with $k$ are -0.35804, the number of observations or random number1000 data, data above the threshold ($N_\mu$) is 100, and the threshold ($\mu$) is 56,117,187,622.76. Table 4.2 shows the GPD parameters,

**Table 3**: Generalized Pareto Distribution (GPD) Parameters

| Parameter | Parameter Values |
|---|---|
| Scale Parameter (β) | 2,423,700,000.00 |
| Shape Parameter (ξ) | 0.358404 |
| Data above Threshold ($N_\mu$) | 100 |

The Scale Parameter (β) describes how spread out or large the data fluctuations are above the threshold, the Shape Parameter (ξ) describes the tail of the distribution, namely how far the extreme data deviates from the threshold value. The ξ value of 0.358404 indicates that the loss data follows a thick distribution tail. Then from a total of 1000 data, 100 data are above the threshold ($N_\mu$).
With value $\xi \neq 0$ The GPD distribution function $X$ is obtained from equation (12),

$$g(x) = \frac{1}{2.423.700.000,00}\left(1 + \frac{0,358404}{2.423.700.000,00}x\right)^{-1-\frac{1}{0,358404}} \tag{12}$$

### 4.4. Calculation Extreme Value at Risk(EVaR)

Used method Extreme Value Theory (EVT) with the Generalized Pareto Distribution (GPD) approach to estimate the risk of extreme losses in financial derivative contracts. With a threshold ($\mu$) of 56,117,187,622.76 to capture the extreme behavior of the loss data, the GPD parameter, and the confidence level ($p$) indicate the probability of estimating extreme losses will not exceed a certain value.

The Extreme Value at Risk (EVaR) value is calculated using the formula in equation (11) to calculate the extreme loss value based on the GPD distribution parameters. The higher the confidence level ($p$), the EVaR value will increase because the probability of the extreme event being considered becomes smaller. In other words, estimating the risk in a more extreme scenario. With confidence levels of 90%, 95%, and 99%, the results of the EVaR calculation for various levels of confidence are obtained in table 4.3,

**Table 4**: EVaR calculation results

| Confidence level (p) | EVaR (USD) |
|---|---|
| 90% | $505,617,187,622,760.00 |
| 95% | $696,298,731,790,542.00 |
| 99% | $1,372,468,418,333,350.00 |

At the 90% confidence level, the EVaR of $505,617,187,622,760.00 indicates that there is a 10% chance that the derivatives contract loss will exceed that amount. In other words, the maximum reasonable risk of loss at this level is half a trillion US dollars. At the 95% confidence level, the EVaR increases to $696,298,731,790,542.00. This means that there is a 5% chance that the loss will exceed that amount. The increase in the EVaR value at higher confidence levels indicates that the potential for loss is greater. At the 99% confidence level, the EVaR value reaches $1,372,468,418,333,350.00, which means that there is only a 1% chance that the extreme loss will exceed this amount. This value indicates that in the extreme scenario (the highest risk), the loss could reach $1.3 trillion.

## 5. Conclussion

Based on the analysis of extreme loss risk in financial derivative contracts using the Extreme Value at Risk (EVaR) approach with the Generalized Pareto Distribution (GPD), it was found that the potential loss increased significantly as the confidence level increased, with an EVaR value of $1.3 trillion at a 99% confidence level. This shows that extreme losses have a small probability but a very large impact, so serious attention is needed in risk management. Therefore, it is recommended that financial institutions implement more effective risk mitigation strategies, such as portfolio diversification, hedging, and the use of risk models that consider extreme data, while regulators need to increase supervision of derivative transactions to minimize the potential for systemic losses in the financial market.

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