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Comparative Analysis: Value at Risk (VaR) with Parametric Method, Monte Carlo Simulation, and Historical Simulation of Mining Companies in Indonesia

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Abstract

This study aims to conduct a comparative analysis between three Value at Risk (VaR) calculation methods, namely the Parametric (Variance-Covariance) method, Monte Carlo Simulation, and Historical Simulation, in measuring market risk in mining companies in Indonesia. The mining industry in Indonesia faces the risk of high commodity price volatility, thus requiring an appropriate approach in measuring potential financial losses. This study uses historical stock data from several major mining companies in Indonesia to analyse the difference in results between the three VaR methods. This study found that the smallest VaR value is owned by PTBA company. Along with the level of stability shows that PTBA company is more stable than other companies. This is inversely proportional to the TINS company which has a large VaR value and high volatility.

Keywords: Value at Risk, Monte Carlo Simulation, Historical Simulation, Parametric Method, Mining Company

1. Introduction

The oil and gas sector in Indonesia has experienced significant dynamism in recent months. Shares of companies in the oil and gas sector have experienced significant price increases. This increase was caused by rising global oil prices fueled by geopolitical tensions in the Middle East. For example, Medco Energy shares have risen in a short period of time. Stocks in the oil and gas sector are generally sensitive to fluctuations in global oil prices. When oil prices rise, oil and gas issuers on the Bursa Efek Indonesia (BEI) tend to gain. This rise in share prices shows confidence that the oil and gas sector is still attractive to investors, especially amid global instability. This shows how external factors, such as global oil prices and geopolitical tensions, play an important role in influencing share prices in the oil and gas sector in Indonesia. The positive sentiment towards rising oil prices is expected to continue to influence the movement of stocks in the sector as long as the oil price trend continues.

Fluctuations in global oil prices have been shown to significantly impact the performance of oil and gas companies. Fluctuations in global oil prices affect Indonesia's economic growth in the short term and contribute to domestic inflation over time (Akhmad et al., 2019). Similarly, global oil price changes have a significant positive effect on Indonesia's inflation rate (Baladraf et al., 2019). These studies emphasize the sensitivity of the oil and gas sector to external factors, reinforcing the need for strategic planning by companies to mitigate risks and seize opportunities amid global dynamics.

The urgency of this research lies in the importance of deeply understanding the relationship between external factors, such as global oil prices and geopolitical tensions, to stock movements in the oil and gas sector in Indonesia. In recent months, changes in the sector have shown that fluctuations in oil prices can have a major impact on the performance of oil and gas companies. Therefore, research on the effect of global oil price volatility on the share prices of oil and gas companies is highly relevant. This research can also provide an overview of the market risks faced by companies in the oil and gas sector, as well as provide guidance for investors and risk managers to prepare more effective mitigation strategies.

The purpose of this study is to analyse the impact of global oil price volatility on the stock performance of oil and gas companies on the Bursa Efek Indonesia (BEI) and understand other external factors that affect stock price movements in this sector. This research is expected to provide benefits in providing investors with a clearer view of the risks and opportunities of investing in the oil and gas sector, as well as helping oil and gas companies to make more informed decisions in the face of changing global dynamics. The results of this study are expected to be a reference for energy policymakers in formulating strategies to respond to geopolitical uncertainty and global commodity prices.

2. Literature Review

2.1. Value at Risk

Value at Risk (VaR) is a method often used to measure market risk in financial portfolios, including in the mining sector. VaR provides an estimate of the maximum potential loss that may occur in a certain period with a certain level of confidence. In this study, VaR is applied to mining companies in Indonesia using three main approaches, namely parametric methods, Monte Carlo simulation, and historical simulation.

2.2. Parametric Method

The parametric, or variance-covariance, method assumes that the distribution of asset returns follows a normal distribution. This method is valued for its simplicity and calculation efficiency, but its normality assumption is often inappropriate in volatile markets such as the mining sector. Some research shows that this method is less accurate in situations with an abnormal distribution of returns, which is often the case for mining companies due to commodity price fluctuations (Jorion, 2007).

2.3. Monte Carlo Simulation

Monte Carlo simulation offers flexibility as it does not rely on the assumption of a normal distribution. This technique generates randomized scenarios to calculate risk but is more computationally intensive. This method is often more accurate in measuring risk in markets with high volatility; however, the results are highly dependent on the distribution assumptions used, and performance may vary (Pritsker, 1997).

2.4. Historical Simulation

Historical simulation is a non-parametric method that uses actual historical data to calculate VaR. This method is effective because it does not assume a particular distribution, making it suitable for non-normalized markets. It has been found to be more accurate in capturing market anomalies; however, its main drawback is its reliance on past data, which may not always reflect future market conditions (Hull, 2006).

2.5. Comparison with Previous Literature

Previous research provides a comprehensive comparison of Value at Risk (VaR) methods, focusing on the strengths and weaknesses of different approaches. For instance, a study evaluated three primary methods Historical Simulation, Variance-Covariance (Parametric), and Monte Carlo Simulation to measure VaR on stock portfolios in the Turkish market. The findings suggest that the Monte Carlo method delivers more accurate results in conditions of high market volatility, while Historical Simulation effectively reflects risk distribution using actual data but is less responsive to extreme market events not captured in historical records (Dalbudak et al., 2017).

Historical Simulation is effective in representing actual data, although it struggles to address extreme events. The Variance-Covariance method, despite its computational efficiency, is limited by the assumption of normally distributed returns, which may not align with markets exhibiting heavy tails or significant volatility. Monte Carlo Simulation provides greater flexibility in modeling complex risk scenarios but requires considerable computational resources, making it less practical for certain applications (Linsmeier & Pearson, 1996).

The conclusions from these studies indicate that the selection of an optimal VaR method depends on the characteristics of the data and the specific objectives of the analysis. Monte Carlo Simulation excels in flexibility and adaptability to complex risk structures but demands substantial computational power. In contrast, Historical Simulation is valued for its simplicity and ability to align with actual data, although it has limitations in addressing unexpected market shocks.

3. Materials and Methods

3.1. Materials

The data used in this study are return of asset data per day from oil and gas companies in Indonesia, namely PT Aneka Tambang Tbk (ANTM), PT Medco Energi Internasional Tbk (MEDC), PT Timah Tbk (TINS), and PT Bukit Asam TBK (PTBA). The data used is sourced from the stock page https://www.investing.com. The data used is data in the range of 2014 to 2024 which aims to train datasets for the simulation process.

In this research, it is necessary to process data for further analysis. Data processing uses software assistance in the form of Google Collab (Python Base) and Microsoft Excel. This data processing aims to improve the accuracy of data analysis. Data processing is done in the form of completing missing data to make simulations on the method to be used.

3.2. Methods

Value at Risk (VaR) analysis is a method to predict when bankruptcy occurs. This research analyses the VaR value using several methods, including: parametric method; monte carlo simulation method; and historical value simulation.

3.2.1. Return dan Loss

Return and loss in this study are determined by

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

$$Loss = -Return \tag{2}$$

with:

R_t : Specific time closing prrice return.
P_t : Today's closing price value
P_{t-1}: Closing price value at the time of the previous day-1
t : Time

3.2.2. Parametric Method

The parametric method is a VaR analysis method using descriptive statistics. The use of the parametric method is obtained by the following equation.

$$VaR = \mu + (Z_\alpha \times \sigma) \tag{3}$$

with:

μ : average return
Z_α: Z-value of the confidence level
σ : standard deviation of returns

3.2.3. Monte Carlo Simulation Method

VaR analysis using the monte carlo simulation method is obtained by generating data that is already owned. The assumption of this method is that the data generated is normally distributed. So that the VaR value generated at the 95% and 99% percentiles is normally distributed data. The same aspects as in the parametric method are in equation (3).

3.2.4. Historical Value Simulation Method

VaR analysis using historical simulation is determined by the following aspects.

$$VaR_{1-\alpha} = \mu(R) - R\alpha \tag{4}$$

with:

$VaR_{1-\alpha}$: highest possible loss
$\mu(R)$: average return
$R\alpha$: the highest loss α

3.3. Research Flowchart

The flow of this research can be seen in the following flowchart.

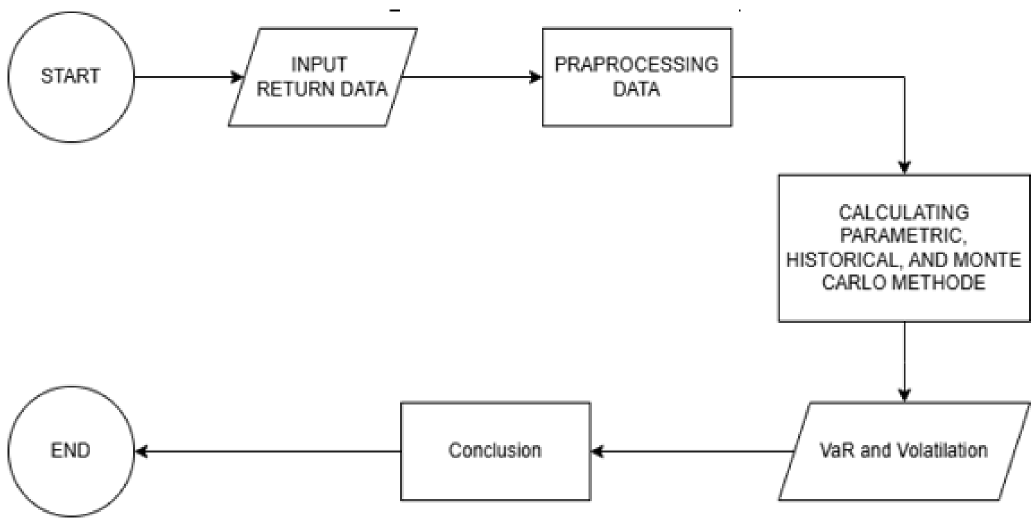

Figure 1: Research flowchart

4. Results and Discussion

This study analyses 4 oil and gas sector companies in Indonesia using parametric methods, monte carlo simulation, and historical simulation. The data used is obtained from secondary data sources, namely on the stockbit.com page.

4.1. Descriptive Statistical Methods

The data obtained is the company's asset return data per day with a range of years 2014 to 2024. This data is processed to obtain the VaR value using the standard deviation value and the average of each company characteristic. The data obtained is processed to obtain descriptive statistics in Table 1.

Table 1: Descriptive statistics of each company

	ANTM	MEDC	TINS	PTBA
Mean	0.002396714119	0.000266400190	0.002519941064	0.000480872146
Volatility	0.669467049394	0.594026631389	1.130497493862	0.269513754195
Variance	0.448186130224	0.352867638800	1.278024583628	0.072637663700
Min	−6.894722513060	−6.877902315832	−6.902742737159	−6.851388406994
Max	6.894774567509	6.892717401618	6.902742737159	6.839812276358
1st Quartile	−0.012270092592	−0.015139912554	−0.012888735913	−0.013015368112
2nd Quartile	0.000000000000	0.000000000000	0.002866512397	0.000000000000
3rd Quartile	0.014528100563	0.017857617400	0.016488453390	0.013638125313
VaR 95%	0.046039478493	0.061317561013	0.059048696501	0.042754750502
VaR 95% (percentage)	4.6%	6.13%	5.9%	4.27%
VaR 99%	0.122495912701	0.127423787513	6.873043541466	0.070752806662
VaR 99% (percentage)	12.24%	12.74%	687.3%	7.07%
Amount of data	3650	3650	3650	3650

Table 1 shows the descriptive statistics of each oil and gas company in the period 2014 to 2024, for the maximum value during this period is the TINS company with an average return of assets of $\mathbf{6.902742737159}$. Then for the minimum value during this period is the TINS company with an average return of assets value of $\mathbf{6.902742737159}$. However, based on the VaR (95%) and VaR (99%) values, the highest VaR value is the company PTBA, meaning that there is $\mathbf{95\%/99\%}$ It is likely that the losses on the portfolio will not exceed that VaR value over a certain period of time. Conversely, there is a $\mathbf{5\%/1\%}$ the likelihood that the loss will exceed that value.

4.2. Historical Simulation Method

The historical simulation method in this study uses a significance level of 95% and 99%, so it is hoped that this study can simultaneously compare the effect of the significance level used in the historical simulation method process. This simulation was carried out 10,000.00 times assuming 252 trading days. The results of the historical simulation method can be seen in Table 2 below.

Table 2: Historical simulation results

	ANTM	MEDC	TINS	PTBA
Mean	0.002397	0.000266	0.002520	0.000481
Volatility	0.669467	0.594027	1.130497	0.269514
VaR (95%)	0.046039	0.061318	0.059049	0.042755
VaR 95% (percentage)	4.6%	6.13%	5.9%	4.27%
VaR (99%)	0.122496	0.127424	6.873044	0.070753
VaR 99% (percentage)	12.24%	12.74%	687.3%	7.07%

Table 2 shows that the volatility value of PTBA is the lowest value, meaning that the dynamics and data simulated tend to be more stable compared to other companies. Based on the value of VaR (95%) and VaR (99%) the highest VaR value is PTBA company. Based on table 4.2. obtained the lowest VaR (95%) value is MEDC and for the VaR (99%) value is TINS.

4.3. Monte Carlo Simulation Method

The Monte Carlo simulation method in the study also uses 95% and 99% significance levels. This simulation was carried out 10,000.00 times assuming 252 trading days. Assuming that the return of asset data of each company is normally distributed, the results of the Monte Carlo simulation method can be seen in Table 3 below.

Table 3: Monte Carlo Simulation results

	ANTM	MEDC	TINS	PTBA
Mean	0.002397	0.000266	0.002520	0.000481
Volatility	0.669467	0.594027	1.130497	0.269514
VaR (95%)	16.871787364495905	15.465776490725396	29.348499457630684	7.067363183710358
VaR 95% (percentage)	1687.17%	1546.57%	2934.84%	7067.36%
VaR (99%)	24.265506561139585	21.782983594423932	41.61768640183418	9.965378271951408
VaR 99% (percentage)	2426.55%	2178.29%	4161.76%	996.53%

Table 3 shows that the volatility value of PTBA is the lowest value, meaning that the dynamics and data simulated tend to be more stable compared to other companies. Based on the value of VaR (95%) and VaR (99%) the highest VaR value is PTBA company. Based on table 4.2. obtained VaR (95%) and VaR (99%) value is TINS.

4.4. Influence and Simulation of VaR values

Suppose a person invests 1,000,000.00 in some of these companies with a significance level of 95% or 99%, then what will happen is

Table 4: VaR analysis results

Invest (1,000,000 IDR)	VaR (95%) Descriptive Statistics	VaR (99%) Descriptive Statistics	VaR (95%) Historical Simulation	VaR (99%) Historical Simulation	VaR (95%) Monte Carlo Simulation	VaR (99%) Monte Carlo Simulation
ANTM	4.6%	12.24%	4.6%	12.24%	1687.17%	2426.55%
VaR ANTM (IDR)	46,000	122,400	46,000	122,400	16,871,700	24,265,500
MEDC	6.13%	12.74%	6.13%	12.74%	1546.57%	2178.29%
VaR MEDC (IDR)	61,300	127,400	61,300	127,400	15,465,700	21,782,900
TINS	5.9%	687.3%	5.9%	687.3%	2934.84%	4161.76%
VaR TINS (IDR)	59,000	6,873,000	59,000	6,873,000	29,348,400	41,617,600
PTBA	4.27%	7.07%	4.27%	7.07%	7067.36%	996.53%
VaR PTBA (IDR)	42,700	70,700	42,700	70,700	70,673,600	9,965,300

Table 4 shows that the VaR value in historical simulation is the same as descriptive statistics. While for monte carlo simulation tends to show a number that is not small. In the VaR analysis, the values in the currency row (IDR) show that the VaR of its portfolio for one day with a confidence level of 95% and the result is IDR 100,000, this means that the company estimates that there is a 95% chance that the largest loss that may occur in one day will not exceed IDR 100,000. Conversely, there is a 5% chance that the loss will be greater than that amount.

This shows that the value of PTBA company is the smallest possible loss in the monte carlo simulation. The value shown from the monte carlo simulation for PTBA company is 9,965,300 IDR. This shows that the value of PTBA company is the smallest value in monte carlo simulation. The resulting value of the monte carlo simulation for PTBA company is 42,700 IDR.

This shows that the value of PTBA company is the smallest value in monte carlo simulation. The resulting value of the monte carlo simulation for PTBA company is 0.269514. This shows that PTBA is more stable in its return income. This is inversely proportional to the company TINS which has a volatility of 1.130497 which makes TINS company will experience fluctuations in its return income.

5. Conclusion

The analysis results indicate that the values from descriptive statistical analysis align with the outcomes of historical simulations conducted 10,000.00 times using 252 trading days for companies ANTM, MEDC, TINS, and PTBA. In terms of Value at Risk (VaR), PTBA has the smallest value in the Monte Carlo simulation, which is 996.53%, while the results from historical simulations and descriptive statistics show a value of 4.27%. On the other hand, the highest VaR value based on descriptive statistical analysis is achieved by MEDC with 6.13%, whereas the highest VaR value in the Monte Carlo simulation is found in TINS with 4,161.76%.

In terms of volatility, PTBA has the smallest volatility with a value of 0.269514, reflecting relative stability compared to the other companies. Conversely, TINS shows the highest volatility with a value of 1.130497, indicating a higher level of fluctuation. These findings provide a clear picture of the differences in risk and levels of uncertainty among the analyzed companies, whether from the perspective of historical simulations, Monte Carlo simulations, or descriptive statistical approaches.

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