## | RESEARCH ARTICLE

# Value at Risk of Gold Futures Trading During Pandemic Covid-19 with Log-Normal Distribution Assumption Using Monte Carlo Simulation Method

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## | ABSTRACT
Investment provides the potential for great profits, but it does not rule out the possibility of unexpected risks. Risk calculation analysis needs to be carried out so that it can help investors understand the level of risk involved in gold investment. This study discusses the calculation of the highest losses experienced by investors for gold commodity investments in Gold Comex Futures (GC = F) in 2013 - 2023 with the Return value assumed to be distributed Log-Normal. The method used in this study is Monte Carlo Simulation. The results of this study indicate that the Return of the gold price GC = F which is transformed into a log-normal distribution results in an accurate VaR calculation in reflecting investment risk. Longer time periods tend to show higher levels of risk than shorter time periods, due to greater price volatility in the long term. In addition, this study proves that the Covid-19 pandemic has a significant impact on gold futures trading. The results of the VaR model back testing under normal conditions, namely before and after the Covid-19 pandemic, show that accurate VaR can be used, while under abnormal conditions, namely during the pandemic, the VaR model is inaccurate or the VaR model must be reviewed to be used as an investment decision.

## | KEYWORDS
*Value at Risk; investment; log-normal distribution; monte carlo simulation; backtesting; kupiec test*

## | ARTICLE DOI:

## I. INTRODUCTION

Investment is the act or process of allocating funds or resources into various types of assets or financial instruments with the aim of achieving long-term capital growth [1] . Making an investment does promise a large potential profit, but it does not rule out the possibility of an unexpected risk. Risk Management is an important element because it can help the Company identify future losses, operational inefficiencies, and provide a healthier business line. In Risk Management, a risk measurement is carried out. Common tools used to measure risk include standard deviation, beta, Value at Risk, and Conditional Value at Risk or other risk models that can be developed with better results.

VaR is often used to measure the risk value in investment. VaR is a common risk measure used for financial risk management because the concept is simple, easy to calculate, and can be applied directly [2] . The use of Value at Risk is the most recommended option by the Bank of International Settlements (BIS) to measure risk [3] . VaR can help companies manage financial risk by identifying potential losses that may occur. By setting acceptable VaR limits, companies can take preventive measures or manage risks appropriately to minimize their negative impacts. In addition, this method provides important information in making investment decisions. By evaluating the VaR of various investment alternatives, companies can choose a portfolio that has a level of risk that is in accordance with the company's risk tolerance. VaR also helps in determining the optimal position size in an investment portfolio.

Value at Risk measurement can be used to measure the potential loss in an investment in the form of futures commodities. Gold is a promising investment commodity for investors. Generally, investing in gold is considered as an inflation hedge against economic uncertainty. Its value tends to be stable or even increase. However, it is worth investing, of course there are risks that need to be considered. Gold is one of the commodities that involves significant risk. Gold prices can be very volatile in the short term, influenced by factors such as interest rates, exchange rates, and global market conditions. Gold futures prices can be volatile, and investors need to understand well how the futures market works, risk management strategies, and factors that can affect gold prices.

Gold investment can be grouped into 4 types, namely [4]: Physical gold investment (passive), investors only hold physical gold without carrying out active trading activities on the gold market; Physical Trading, investor or traders hold physical gold directly as part of trading transactions; Qirad, gold investment based on sharia principles; Online Trading, the process of buying and selling gold electronically through an online trading platform [4].

In the financial world, the use of Value at Risk (VaR) is widely applied, one of the commonly used VaR measurement methods is the Monte Carlo Simulation Method. The Monte Carlo Simulation Method is a very flexible and powerful method in risk analysis, especially because of its ability to handle complexity, tail risk, and non-linear models without the assumption of a normal distribution. Although it requires more time and computing resources, Monte Carlo provides a more accurate analysis for extreme situations and non-linear relationships than other methods such as Parametric, Historical Simulation, or Variance-Covariance. Its advantages in accuracy often make it superior, although it is more complicated and requires good computing resources in its implementation, but its shortcomings are considered to be still manageable compared to other methods.

The Monte Carlo Simulation method uses a probabilistic approach by conducting simulations by generating random numbers based on the characteristics of the data to be generated, which are then used to estimate the VaR value [5] . In this method, the probability distribution used depends on the characteristics of the random variables modified in the simulation. Monte Carlo simulation is used to model various sources of uncertainty and variations in gold prices. This allows for the inclusion of various variables that affect gold prices, such as volatility, interest rates, and other economic factors. Monte Carlo simulation can handle non-normal distributions well, so that the use of this method can model various possible scenarios.

Log-normal distribution is one of the statistical models often used to describe the price movements of financial assets, including gold futures prices. This model is useful in calculating Value at Risk (VaR) because this distribution takes into account the positive and non-symmetric nature of changes in asset prices. Log-Normal distribution is used on data that cannot be negative because the variables that follow are only positive numbers. This is directly proportional to the movement of gold commodity prices which tend to continue to increase exponentially. VaR result is directly proportional to the confidence level used. It also found that VaR value with the Monte Carlo Simulation method are greater than those with the Historical Simulation method. [5]

In 2021, Yuliah and Leni Triana, in a study entitled "Measurement of Value at Risk in Company Assets with Monte Carlo Simulation" measure Value at Risk (VaR) in the assets of the companies PT Telekomunikasi Indonesia Tbk (TLKM) and PT Bank Mandiri (BMRI) and the portfolios that can be formed by the two assets using the Monte Carlo Simulation Method. This study proves that the portfolio is lower risk than a single asset, this shows that diversification can minimize the risk of investment [6] .

Research entitled "Measurement of Value at Risk (Var) of Optimal Portfolio in State-Owned Enterprises (BUMN) Bank Stock Investment Using the Variance Covariance Method and Monte Carlo Simulation Method" by Noviana Pratiwi in 2020. In her research, she compared the calculation of VaR using the variance-covariance method and the Monte Carlo simulation method, then both models were validated by Back testing with the Kupiec POF-test on individual stocks and portfolios in the period January 23, 2018 - January 23, 2019. Shows that based on the Back testing test, the VaR value of the Portfolio of both methods is not accurate [7] .

This study calculates Value at Risk with Return value assumed to be distributed Log-Normal using Monte Carlo Simulation method. Therefore, based on the background, the author is interested in studying in the final assignment thesis with the topic and raising the title, "Calculation of Value at Risk of Gold Futures Trading with Log-Normal Distribution Assumption Using Monte Carlo Simulation Method"

## II. METHODOLOGY

### Value at Risk (VaR)

VaR aims to answer the question "How high is the loss of an investor during the investment period (t) with a confidence level (1- $\alpha$ )" [8]. So from this question, there are 3 important things that are obtained for measuring VaR, namely loss, investment period (t), and confidence level (1- $\alpha$). The VaR value can be formulated as follows [9] :

$$VaR_{(1-\alpha)} = W_0 R^* \sqrt{t} \quad (1)$$

Where:

| | |
|---|---|
| $VaR_{(1-\alpha)}$ | : VaR confidence level$(1-\alpha)$ |
| $W_0$ | : Initial investment value |
| $R^*$ | : The quantile value of the – $\alpha$th return distribution |
| $\sqrt{t}$ | : Time period |

Monte Carlo Simulation Method for Estimating Value at Risk (VaR) with Return Values Assumed to be Log-Normal Distributed.
Monte Carlo Simulation Method for Estimating Value at Risk (VaR) with Return Values Assumed to be Log-Normal Distributed.
Monte Carlo Simulation to estimate Value at Risk (VaR) is a method used to estimate financial risk using a probabilistic approach, by conducting many random experiments to obtain estimates or simulations of the desired results. VaR estimation using the Monte Carlo Simulation Method shows that asset returns are normally distributed, but single asset returns are not assumed to be linear to portfolio returns. The following are the steps to complete the Monte Carlo Simulation Method for estimating Value at Risk (VaR) with Returns assumed to be Log-Normal distributed [10]: (1) Collecting Closing Price data for trading gold GC=F futures; (2) Count return value based on the closing price data taken; (3) Performing a normality test to return asset value; (4) Asset return data transformation to log-normal distribution; (5) Determining the parameters for asset returns, because the data is assumed to be log-normally distributed, the parameters selected follow the normal distribution parameters, namely $\mu$the mean and $\sigma^2$ standard deviation; (6)Simulating returns, with random return as many as n pieces, so that formed distribution empirical from results Return simulation; (7) VaR confidence level$(1-\alpha)$ after t days, namely with equation (1) (8) Repeat steps 6 to 7 n times, so that various possibilities for estimating VaR are obtained, thus obtaining $VaR_1, VaR_2, \ldots, VaR_n$. (9) Calculate the average of 8 steps to stabilize the VaR value because each simulation produces different results.

Investment Interest, there are still many other factors, including Income Expectation, Risk Perception, and Financial Literacy variables [11].

**Back testing Accuracy Test**

As the name suggests, back testing refers to the process of testing a trading strategy on relevant historical data before rolling it up to the live market [12]. Back testing is a term used to test the validity of a model/method used in estimating Value at Risk. Back testing functions to show how often a company or investor experiences losses. If the loss is 1% or less, then the selected model is quite good, conversely if the loss is more than or equal to 10%, then the use of the selected model needs to be doubted [13]. The Back testing test is carried out by comparing the Critical Value (CV) with the Likelihood Ratio or also called the Kupiec Test using the Proportional of Failure method, which follows the Chi-Square distribution.$x^2$ with a degree of freedom (df) of 1. The use of the Kupiec Test method in calculating VaR is to find out the potential loss by comparing the daily VaR with the actual Return. The model is said to be invalid if the proportion of the VaR model does not match the Kupiec table. The following are the steps for conducting Backtesting [14][15] :

Determine Hypothesis

$H_0$ : Normal accurate VaR model

$H_1$ : VaR model is not normally accurate

Critical Value follow Chi-Square $x^2$with degrees of freedom (df) of 1.

Test Statistics

Equality Likelihood Ratio as following

$$LR_{POF} = -2ln\left(\frac{1-p^{T-x}p^{x}}{\left[1-\frac{x}{T}\right]^{T-x}\left[\frac{x}{T}\right]^{x}}\right) \quad (2)$$

Where:

$p$: Probability ( $(1-\alpha)$

$T$: Number of Observations

$x$: Failure rate

Critical Area

$H_0$rejected if$LR_{POF} > Chi - Square\ x^2{}_{tabel}$

Interpretation results

If the test results show that $LR_{POF}$ exceeds the critical value, then there is sufficient evidence to reject the null hypothesis, which means the VaR model needs to be revised. Otherwise, there is insufficient evidence to reject the null hypothesis, which indicates that the VaR model is fairly accurate.

## III. RESULTS AND DISCUSSION

### Gold Futures Closing Price Data

In this study, the author uses the Gold Jun 24 gold futures price data with the code GC=F. The data used is the daily gold futures closing price data with the currency in the form of United States Dollar/USD ($) or 1$ or equivalent to the assumption of Rp.16,000. The gold unit in the US is using troy ounces. One troy ounce is equivalent to approximately 31.1035 grams. Data obtained from the website https://finance.yahoo.com with the data collection period at:

The last 10 years span the period from January 1, 2013 – December 31, 2023

The last 5 years period is January 1, 2019 – December 31, 2023

The last 3 years period is January 1, 2021 – December 31, 2023

Plot charts of closing prices from various period ranges can be seen in Figure 1, Figure 2, and Figure 3

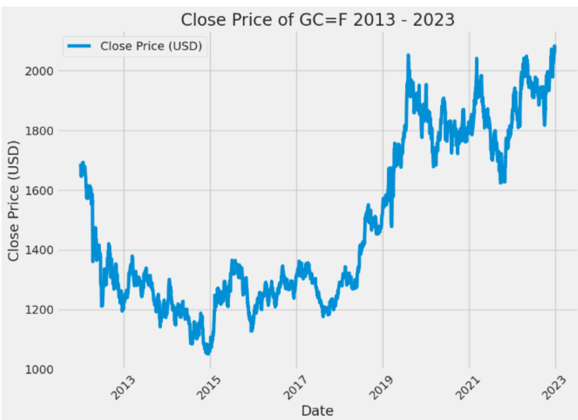


**Figure 1Plot Chart of Closing Price GC=F Year 2013 – 2023**

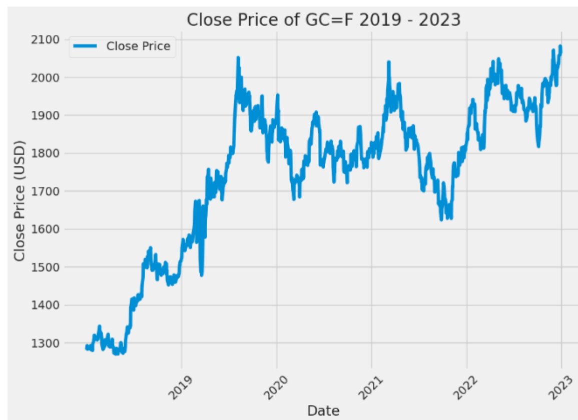


**Figure 2Plot Chart of Closing Price GC=F Year 2019 – 2023**

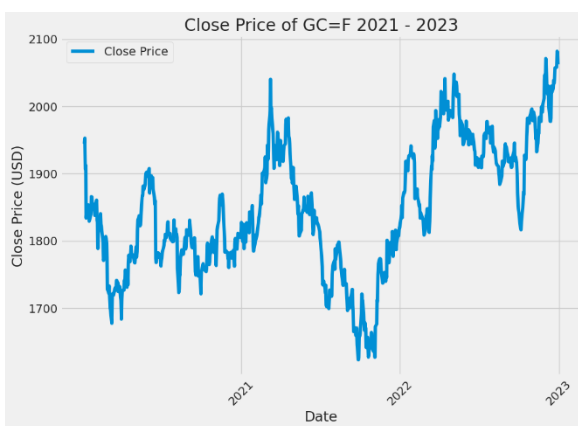


**Figure 3. Plot Chart of Closing Price GC=F Year 2021 – 202 3**

From Figure 1, Figure 2, and Figure 3 which are plot charts of the movement of gold futures commodity prices GC=F with various period ranges. From each period range, the movement of gold futures prices every year and even every month looks fluctuating, in other words, the price of gold is relatively unstable.

Gold Futures Closing Price Return

The return on gold prices is calculated using equation (3), namely

$$R_{it} = \left[\frac{P_{it} - P_{i(t-1)}}{P_{i(t-1)}}\right] \quad (3)$$

After performing the Return calculation, a Return value graph was obtained for Gold Comex Futures (GC=F). Figure 4, Figure 5, Figure 6, show the movement of Return or return of gold futures price GC=F obtained from the calculation of the close price for each period range. From the plot chart, it shows that the movement is fluctuating because the Return moves between -0.10 to 0.6. The Return graph from the daily stock closing price shows that the Return obtained by each stock varies greatly, namely there are very high Returns and very low Returns.

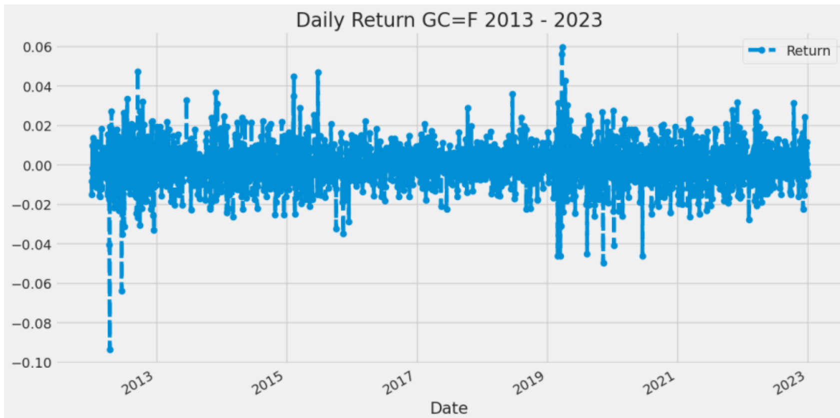


**Figure 4. Daily Return GC=F Year 2013 – 2023**

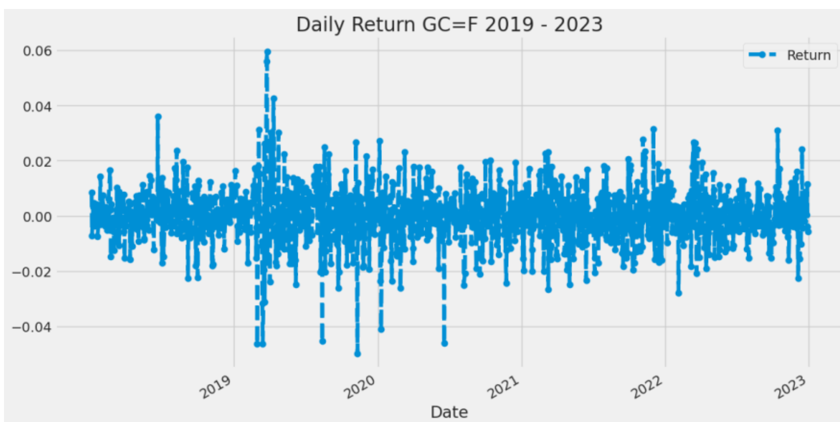


**Figure 5. Daily Return GC=F Year 2019 – 2023**

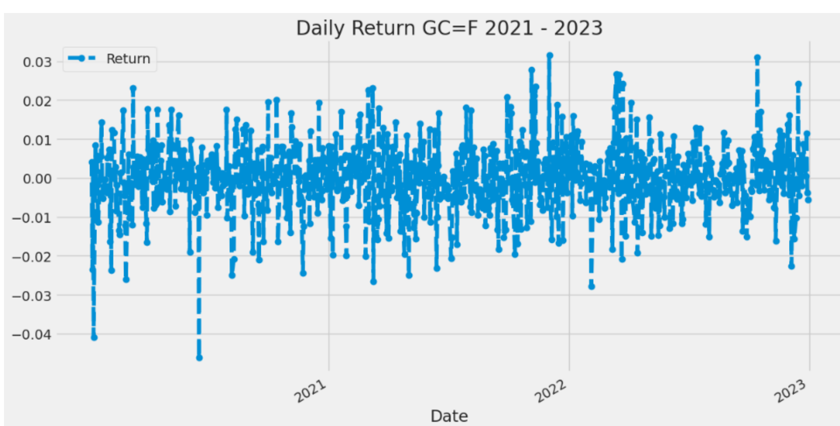


**Figure 6. Daily Return GC=F Year 2021 – 2023**

**Normality Test on Gold Futures Closing Price Returns**

Before calculating VaR, a normality test is performed on the Return of Closing Price of Gold Futures GC=F data using the Kolmogorov-Smirnov test. The normality test is performed to test whether the data is normally distributed or not so that the data can be transformed into a normal distribution. The normality test for gold futures with various data periods is as follows:

Hypothesis

$H_0$ : Data Return price closing gold GC=F futures are normally distributed

$H_1$ : Data Return of closing price of gold futures GC=F is not normally distributed

Significance level alpha = 5%

Criteria

$H_0$rejected if$p - value < \alpha$

Normality Test Calculation and Decision

The last 10 years span the period from January 1, 2013 – December 31, 2023: p-value = 0.000 (REJECT $H_0$)

Last 5 years span period January 1, 2019 – December 31, 2023: p-value = 4.254 (ACCEPTED $H_0$)

Last 3 years span period January 1, 2021 – December 31, 2023: p-value = 2.303 (ACCEPTED $H_0$)

Dealing with Non-Normally Distributed Data

From the normality test, it was found that the last 10-year period in 2013-2023 were not normally distributed. The cause of the data not being normally distributed is due to the presence of outliers which cause the data distribution to skew to the right or left, resulting in the data having extreme values. To overcome data that is not normally distributed, outliers were removed using the SPSS 27 program. The following is a normality test for the GC = F return data after removing outliers:

Hypothesis

$H_0$ : Data Return price closing gold GC=F futures are normally distributed

$H_1$ : Data Return of closing price of gold futures GC=F is not normally distributed

Significance level alpha = 5%

Criteria

$H_0$rejected if$p - value < \alpha$

Normality Test Calculation and Decision

The last 10 years span the period from January 1, 2013 – December 31, 2023: p-value = 0.064 (ACCEPT $H_0$)

Transforming Return Data to Log-Normal Distribution

Data that is already normally distributed can then be transformed to log-normal using Microsoft Excel. The results of the distribution transformation can be seen in the Figure 7, Figure 8 and Figure 9. In Figure 7, Figure 8, and Figure 9, the data from the data transformation to the log-normal distribution shows the movement of Return or return of the gold futures price GC = F obtained from the calculation of the close price for each period range. The plot chart shows that the movement is fluctuating because the Return moves between -0.015 to 0.015. The Return graph shows that the Return value is very fluctuating with extreme value conditions, namely it can be very high and very low.

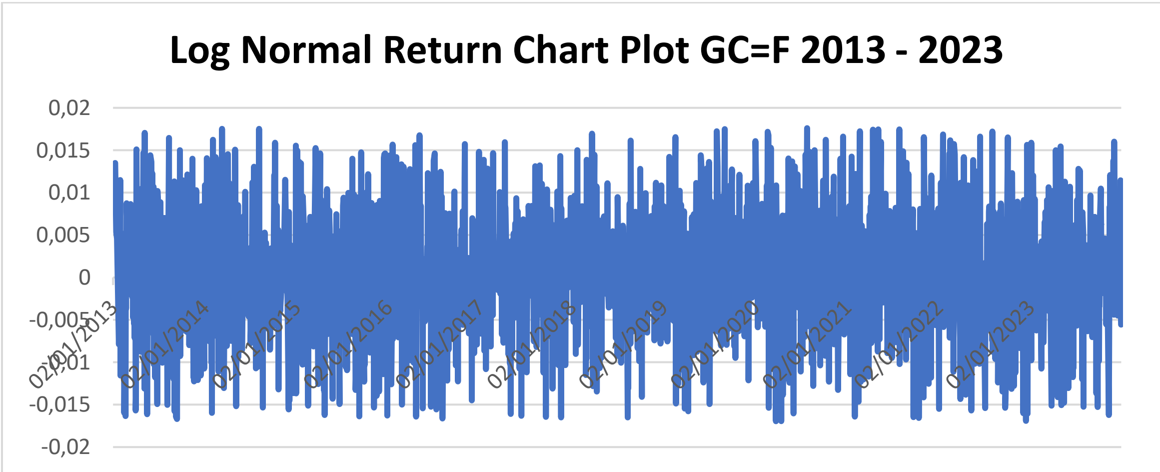


**Figure 7. Plot Chart of GC=F Return Data for 2013 – 2023 Transformed to Log-Normal**

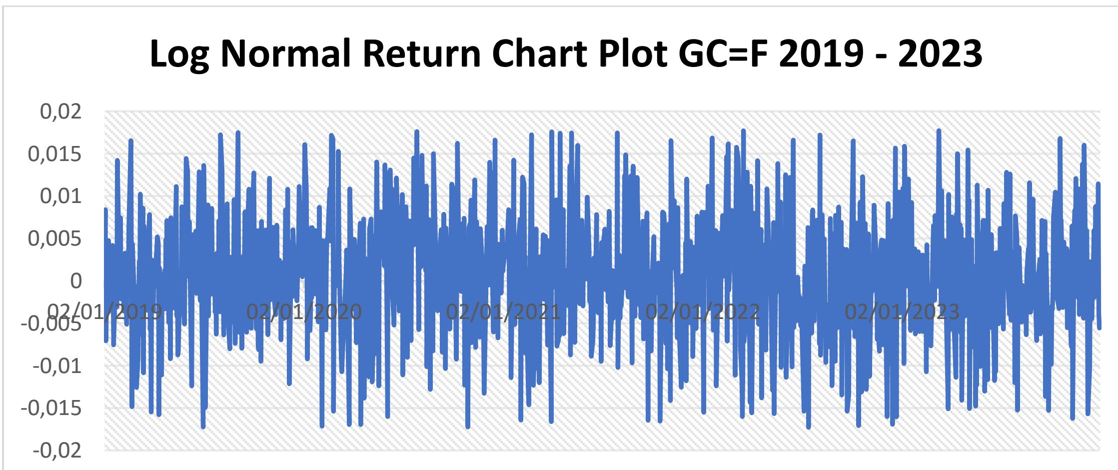


**Figure 8. Plot Chart of GC=F Return Data for 2019 – 2023 Transformed to Log-Normal**

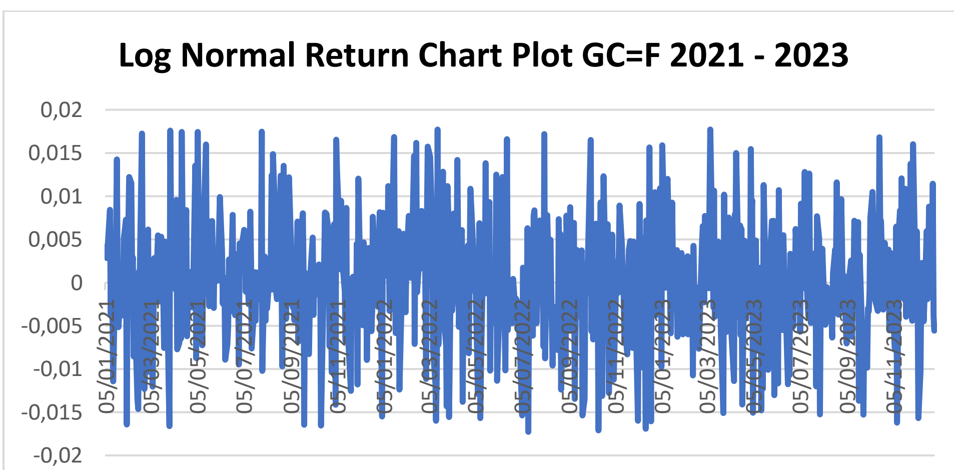


**Figure 9. Plot Chart of GC=F Return Data for 2021 – 2023 Transformed to Log-Normal**

**Determining and Calculating Return Parameters**

Return data is assumed to be distributed log-normally, the parameters determined are the mean ( $\mu$) and standard deviation ( $\sigma$). The following are the results of the parameter calculations:

The last 10 years span the period from January 1, 2013 – December 31, 2023

Mean Log- Return: 0.0005141552572605531

Standard Deviation Log- Return: 0.006879812014892662

The last 5 years period is January 1, 2019 – December 31, 2023

Mean Log- Return: 0.0006560781933044996

Standard Deviation Log- Return: 0.007054326850601427

The last 3 years period is January 1, 2021 – December 31, 2023

Mean Log- Return: 0.0003144000773998833

Standard Deviation Log- Return: 0.007173843249724755

**VaR Calculation Results**

Simulating Return, by taking 1000 random Returns, so that an empirical distribution is formed from the results of the Return simulation. Then the 1-day VaR is calculated with a confidence level of 99%, 95%, 90%. The VaR calculation is carried out 25 times so that 25 possibilities are obtained for the VaR estimate. Furthermore, the VaR value can be stabilized to provide a more consistent risk estimate. The following are the results of the stabilized VaR calculation, in USD ($) currency units with Monte Carlo Simulation, and assuming an initial investment value ( $W_0$) of $100,000,000.

The last 10 years span the period from January 1, 2013 – December 31, 2023

Average VaR Return of GC=F Investment 2023 (10 Years):

Alpha Mean VaR Mean VaR_Pct Mean VaR_USD Mean VaR_Rupiah

0 0.01 -1.530025e+06 -1.530025 $-1,530,025.02 Rp-24,480,400,333.93

1 0.05 -1.090557e+06 -1.090557 $-1,090,557.15 Rp-17,448,914,364.93

2 0.10 -8.293110e+05 -0.829311 $-829,310.97 Rp-13,268,975,584.14

The last 5 years period is January 1, 2019 – December 31, 2023

Average VaR Results of GC=F Investment 2019 - 2023 (5 Years):

Alpha Mean VaR Mean VaR_Pct Mean VaR_USD Mean VaR_Rupiah

0 0.01 -1.574004e+06 -1.574004 $-1,574,004.24 Rp-25,184,067,917.88

1 0.05 -1.096148e+06 -1.096148 $-1,096,148.03 Rp-17,538,368,528.80

2 0.10 -8.402698e+05 -0.840270 $-840,269.80 Rp-13,444,316,776

The last 3 years period is January 1, 2021 – December 31, 2023

Average VaR Results of GC=F Investment 2021 - 2023 (3 Years):

Alpha Mean VaR Mean VaR_Pct Mean VaR_USD Mean VaR_Rupiah

0 0.01 -1.566091e+06 -1.566091 $-1,566,090.96 Rp-25,057,455,413.87

1 0.05 -1.086772e+06 -1.086772 $-1,086,772.13 Rp-17,388,354,018.86

2 0.10 -8.354241e+05 -0.835424 $-835,424.11 Rp-13,366,785,691.63

There is a decrease in Mean VaR from the 10-year period to the last 1 year. This shows that the risk measured by VaR tends to decrease over time, especially in the post-pandemic period. In the pre-pandemic period (2013-2018), the Mean VaR was higher compared to the post-pandemic period (2023). This may indicate that market volatility and the risks faced by GC=F investments were higher before the pandemic. The last 5-year and last 3-year ranges show lower Mean VaR compared to the last 10 years, indicating risk stabilization in a shorter time frame.

**Backtesting Accuracy Test**

After VaR is calculated, an accuracy test (Backtesting) is performed to evaluate whether the VaR model used can actually predict risk accurately. This involves comparing the VaR prediction with the actual loss that occurs. One of the Backtesting methods used is the Kupiec Test (Proportion of Failures Test), which tests whether the number of failures (situations where the actual loss exceeds the predicted VaR) is consistent with the confidence level used.

The last 10 years span the period from January 1, 2013 – December 31, 2023

TABLE 1.

RESULTS OF BACKTESTING LOG NORMAL RETURN GC=F JANUARY 1, 2013 – DECEMBER 31, 2023

| VaR | | Failure Rate | Number of Observations |
|---|---|---|---|
| VaR 99% | -1,530,025.02 | 35 | 2371 |
| VaR 95% | -1,090,557.15 | 135 | 2371 |
| VaR 90% | -829310.97 | 228 | 2371 |

| KUPIEC POF Test | | | |
|---|---|---|---|
| Confidence Level | LR POF Test | Critical Value X^2 | Test |
| 99% | 4.735971234 | 3.84 | REJECT |
| 95% | 2.304221295 | 3.84 | ACCEPT |
| 90% | 0.392569796 | 3.84 | ACCEPT |

Table 1 shows the results of the Back testing Log Normal Return GC=F test for January 1, 2013 – December 31, 2023, where at a confidence level of 99% the VaR model cannot be accepted so it is considered inaccurate based on the Kupiec Test, while at a confidence level of 95% and 90% the VaR model can be accepted so it is considered accurate based on the Kupiec Test.

The last 5 years period is January 1, 2019 – December 31, 2023

TABLE 2.

LOG BACKTESTING RESULTS – NORMAL RETURN GC=F JANUARY 1, 2019 – DECEMBER 31, 2023

| VaR | | Failure Rate | Number of Observations |
|---|---|---|---|
| VaR 99% | -1574004.24 | 18 | 1161 |
| VaR 95% | -1096148.03 | 75 | 1161 |
| VaR 90% | -840269.8 | 115 | 1161 |

| KUPIEC POF Test | | | |
|---|---|---|---|
| Confidence Level | LR POF Test | Critical Value X^2 | Test |
| 99% | 3.041769673 | 3.84 | ACCEPT |
| 95% | 4.789341044 | 3.84 | REJECT |
| 90% | 1.16E-02 | 3.84 | ACCEPT |

Table 2 shows the results of the Back testing Log Normal Return GC=F test for January 1, 2019 – December 31, 2023, where at the 99% and 90% confidence levels the VaR model is acceptable so it is considered accurate based on the Kupiec Test, while at the 95% confidence level the VaR model is unacceptable so it is considered inaccurate based on the Kupiec Test.

In the back testing results for the last 5 years (January 1, 2019 – December 31, 2023), the VaR model is considered accurate at the 90% and 99% confidence levels. However, this model is considered inaccurate at the 95% confidence level, this incident has occurred in [11] . This may be due to the characteristics of the return distribution that do not match the model assumptions at the 95% confidence level. At this level of confidence, the frequency of losses exceeding the VaR value is more frequent than at the 99% confidence level, but not as frequent as at the 90% confidence level. This incident becomes more prominent and causes the model to be inaccurate at the 95% confidence level.

In addition, this can occur due to sensitivity to anomalies. At the 95% confidence level, there may be some anomalies or outliers that occur frequently enough to interfere with the accuracy of the model at this level. If the model cannot properly capture the frequency of anomaly occurrences, then the model will fail the Kupiec test.

The last 3 years period is January 1, 2021 – December 31, 2023

TABLE 3.

RESULTS OF BACKTESTING LOG NORMAL RETURN GC=F JANUARY 1, 2021 – DECEMBER 31, 2023

| VaR | | Failure Rate | Number of Observations |
|---|---|---|---|
| VaR 99% | -1566090.96 | 13 | 704 |
| VaR 95% | -1086772.13 | 52 | 704 |
| VaR 90% | -835424.11 | 78 | 704 |

| KUPIEC POF Test | | | |
|---|---|---|---|
| Confidence Level | LR POF Test | Critical Value X^2 | Test |
| 99% | 4.077983256 | 3.84 | REJECT |
| 95% | 7.406142345 | 3.84 | REJECT |
| 90% | 8.84E-01 | 3.84 | ACCEPT |

Table 3 shows the results of the Back testing Log Normal Return GC=F test for January 1, 2021 – December 31, 2023, where at a 90% confidence level the VaR model is acceptable so it is considered accurate based on the Kupiec Test, while at a 99% and 95% confidence level the VaR model is unacceptable so it is considered inaccurate based on the Kupiec Test.

In the back testing results for the last 3 years (January 1, 2021 – December 31, 2023), the VaR model is considered accurate at the 90% confidence level because it is able to capture more frequent events well. However, at the 95% and 99% confidence levels, the model fails to capture less frequent extreme events, possibly due to anomalies, changes in volatility, or return distributions that do not match model assumptions. This suggests that the VaR model may need to be adjusted or improved to more accurately capture events at higher confidence levels.

## IV. CONCLUSION

The conclusion of this study is that investment risk can be measured using a measurement tool for investment loss risk in gold futures trading using Value at Risk. The analysis shows that the Covid-19 pandemic has caused significant changes in the potential for losses in gold futures trading, which is reflected in the decrease in Mean VaR after the pandemic. The back testing accuracy test shows that under normal conditions, namely before and after the Covid-19 pandemic, it shows that accurate VaR can be used, while under abnormal conditions, namely during the pandemic, the VaR model is inaccurate or the VaR model must be reviewed.

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