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Monte Carlo-Expected Tail Loss for Analyzing Risk of Commodity Futures Based on Holt-Winters Model

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ABSTRACT

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Futures contracts are one of the buying and selling activities based on an agreement on an asset at a price and time that has been agreed upon in advance. Basically, futures are also a derivative market because the underlying assets affect the price of the futures contract. In general, futures have different risks, so risk analysis is needed to improve the effectiveness and efficiency of investment management. In this research, we have the London Metal Exchange (LME) in the metal scope of commodity futures to conduct risk analysis. For commodity price modeling, the Holt-Winters Model is applied so that this research assumes that past data used to predict prices is limited to one period and its seasonal period. Hereafter, Expected Tail Loss (ETL) with the Monte Carlo process is applied to analyze risk measurement through the prediction results of the Holt-Winters model obtained. We took six commodity futures at the LME to implement the method as samples, such as Zinc, Lead, Aluminum, Copper, Nickel, and Tin. Based on the analysis, each commodity has a different average ETL value, where Nickel has the greatest risk with an ETL value of 0.036; which shows that the potential expected loss on the investor's investment assets is 3.6%

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1. Introduction

Futures is a binding agreement between a seller and a buyer to make and receive delivery of an underlying asset commodity on a specified future date with agreed payment terms. In futures contracts, most do not result in delivery of the underlying commodity. Futures contracts are usually regulated by several provisions, such as the month of delivery, such as quantity, quality, location of delivery, and payment terms. [1]. Standardizing futures contract terms is important because it allows traders to focus on the pricing of their variables. Changes caused by commodity price levels make futures contracts considered as commodity price information that is in accordance with that in the market. [2].

In some countries, futures contracts are a special form of forward contracts that are standardized and promised on a particular futures exchange. For example, there is the London Metal Exchange which has many features of futures contracts. Between futures and forward contracts, there is a significant difference where future contracts are legally required to be traded on futures exchange, while forwards are usually created by individual parties operating in the decentralized exchange [3].

As with many other investment instruments, futures contracts also have risks in them. Each futures contract has different risks according to its nature and type. In conducting risk analysis, there are three most important things, namely results that affect community values, uncertainty resulting from probability, and the possibility of both occurring [4]. Futures that have the highest return also have the highest risk, which we know as the concept of high return-high risk [5]. Based on the concept of high return-high risk, if investors want to obtain high return expectations, they will be faced with high levels of uncertainty, so in this case risk management is needed to increase the effectiveness and efficiency of investment management [6].

This paper will discuss the Expected Tail Loss with the Monte Carlo process concerning the analyzed risk measures of commodity futures in the London Metal Exchange (LME) based on Expected Tail Loss (ETL) by iteration using Monte Carlo Simulation. The remainder of the paper is organized as follows. In the next section, we propose the methodology used in this study, which includes the data, stationarity data, estimation of the Holt-Winters model, normality test, Monte Carlo simulation, and estimation of the Expected Tail Loss (ETL). Subsequently, the following section presents the results and discussion. Finally, the last section concludes the study.

2. Research Methods

2.1. Data

In this study, we apply analysis to data in the form of historical daily closing prices of several commodities listed on the London Metal Exchange (LME), namely Zinc Futures (MZNc1), Lead Futures (LEAD), Aluminum Futures (MALTRc1), Copper Futures (MCU), Nickel Futures (NICKEL), and Tin Futures (TIN) from 2 January 2018 to 31 October 2024. All datasets can be downloaded via www.investing.com

2.2. Stationarity Data

In the first section, we conducted a test to obtain data stationary information. The method or approach that is often used in stationarity testing is by identifying the existence of a unit root. Given time series observational data $Y_1, Y_2, \dots, Y_t, \dots, Y_T$, one of the commonly used stationarity tests is the augmented Dickey-Fuller (ADF) test. The ADF test identifies the existence of a unit root through a mechanism by generating data based on the OLS estimator $\hat{\rho}_n$ of p, obtained by fitting the following equation:

$$Y_t = \rho Y_{t-1} + \sum_{j=1}^{p} a_{j,p} \Delta Y_{t-j} + e_{t,p} \tag{1}$$

to the observed stretch of data. In the above notation, $\Delta Y_t = Y_t - Y_{t-1}$, while the order p is allowed to depend on n, i.e., p is short-hand for $\hat{p}_n$, in a way related to the assumptions imposed on the underlying process. Here $\{e_t\}$ is the residual of the ordered equation based on t which is identical, independent ($i.i.d.$) and has a mean value of zero and variance $0 < \sigma_e^2 < \infty$. While a_i are the estimated coefficient of ΔY [7].

To test H_0 (data is not stationary), Dickey and Fuller initiated the studentized statistic:

$$t_n = \frac{\hat{\rho}_n - 1}{\widehat{Std}(\hat{\rho}_n)} \tag{2}$$

where $\widehat{Std}(\hat{\rho}_n)$ denotes an estimator of the standard deviation of the OLS estimator $\hat{p}_n$ [8].

2.3. Estimation of the Holt-Winters Model

In the next section, we estimate the Holt-Winters model of historical daily closing price for each commodity futures. There are several approaches available for time series data analysis. In this study, we use an exponential smoothing technique to model seasonal time series. The method we use was initially introduced by Holt (1957) and Winters (1960) and is commonly known as the Winters method, where seasonal adjustments are made to the linear trend model. There are two types of adjustments suggested, namely additive and multiplicative [9][10]. The Holt Winters Multiplicative approach is often better than additive, but the opposite is possible, depending on the data condition. In addition, the main structure of the Holt-Winters model consists of three main components commonly referred to as constant/linear (level), trend, and seasonality which are weighted through three smoothing weights (α, β, γ) as constant value. [11].

2.3.1. Model with additive seasonality

This approach assumes that the seasonal time series is considered as an additive expression. In general, the Holt-Winters model with an additive approach is stated as follows:

$$Y_t = L_t + S_t + \varepsilon_t \tag{3}$$

where L_t is a notation for the level or linear trend component; b_t is a notation for the trend component; S_t is a notation for the seasonal adjustment with $S_t = S_{t+s} = S_{t+2s} = \ldots$ for $t = 1,2,\ldots,1-s$, where s is the length of a season in a cycle. The ε_t are identical and independent with mean 0 and variance σ_ε^2 [12].

The modeling steps to obtain optimal model parameters to obtain accurate predictions from actual data Y_t are stated as follows:

1. Update the estimate L_t using:
$$L_t = \alpha(Y_t - S_{t-s}) + (1-\alpha)(L_{t-1} + b_{t-1}) \tag{4}$$
where $0 < \alpha < 1$ and $\alpha$is the smoothing weight of level component.

2. Update the estimate b_t using:
$$b_t = \beta(L_t - L_{t-1}) + (1-\beta)b_{t-1} \tag{5}$$
where $0 < \beta < 1$ and $\beta$is the smoothing weight of trend component.

3. Update the estimate S_t using:
$$S_t = \gamma(Y_t - L_t) + (1-\gamma)S_{t-s} \tag{6}$$
where $0 < \gamma < 1$ and $\gamma$is the smoothing weight of seasonal component.

Get the forecast for m-step-ahead, $Y_{t+m}(t)$, through the following formula:

$$Y_{t+m}(t) = L_t + b_t m + S_{t-s+m} \tag{7}$$

2.3.2. Model with multiplicative seasonality

This approach assumes that the seasonal time series is considered as a multiplicative expression. In general, the Holt-Winters model with a multiplicative approach is stated as follows:

$$Y_t = L_t S_t + \varepsilon_t \tag{8}$$

where L_t is a notation for the level or linear trend component;b_t is a notation for the trend component; S_t is a notation for the seasonal adjustment with $S_t = S_{t+s} = S_{t+2s} = \ldots$ for $t = 1,2,\ldots,1-s$, where s is the length of a season in a cycle. The ε_t are identical and independent with mean 0 and variance σ_ε^2 [12].

The modeling steps to obtain optimal model parameters to obtain accurate predictions from actual data Y_t are stated as follows:

1. Update the estimate L_t using:

$$L_t = \alpha \frac{Y_t}{S_{t-s}} + (1-\alpha)(L_{t-1} + b_{t-1}) \tag{9}$$

here $0 < \alpha < 1$ and α is the smoothing weight of level component.

2. Update the estimate b_t using:

$$b_t = \beta(L_t - L_{t-1}) + (1-\beta)b_{t-1} \tag{10}$$

where $0 < \beta < 1$ and β is the smoothing weight of trend component.

3. Update the estimate $S_t$using:

$$S_t = \gamma \frac{Y_t}{L_t} + (1-\gamma)S_{t-s} \tag{11}$$

where $0 < \gamma < 1$ and γ is the smoothing weight of seasonal component.

Get the forecast for m -step-ahead, $Y_{t+m}(t)$, through the following formula:

$$Y_{t+m}(t) = (L_t + b_t m)S_{t-s+m} \tag{12}$$

2.4. Normality Test

After successfully obtaining the model, we then tested the normality of the residual model using the Kolmogorov-Smirnov (KS) test. In the KS test, suppose that the sample consists of T independent observations. These observations are sorted $y_1 \leq y_2 \leq \cdots \leq y_T$. For a given mean μ and variance σ^2, the cumulative density function of the normal distribution of y_k is $\Phi\left(\frac{y_k-\mu}{\sigma}\right)$. The KS statistics is provided by:

$$KS(\mu,\sigma) = \max_{1\leq k\leq n}\left\{\frac{k}{n} - \Phi\left(\frac{y_k-\mu}{\sigma}\right), \Phi\left(\frac{y_k-\mu}{\sigma}\right) - \frac{k-1}{n}\right\} \tag{13}$$

In the traditional basic concept, the KS statistic is stated as $KS(\bar{y}, s)$ where $\mu = \bar{y}$ and $\sigma = s$ [13]. This test determines the choice of method in estimating the Expected Tail Loss value. If the model residuals obtained have followed a normal distribution, then the estimation of ETL uses the usual (historical) method. However, if the obtained model residuals do not follow a normal distribution, the ETL estimation must use the modified method.

2.5. Monte Carlo Simulation

Monte Carlo simulation estimates the expected value of a random variable Y, expressed by $E(Y)$, by finding the average value of the results of some independent experiments with the same distribution of these random variables. The simple algorithm in the return simulation using the Monte Carlo simulation method on the portfolio is as follows [14]:

1. Determine the parameter value for the return variable of the assets that make up the portfolio. The distribution and parameters of the return on assets are determined through the distribution of fittings. If the return is not normally distributed, then the installation is carried out based on the generalized lambda distribution.
2. Simulating the return value by generating random returns on assets according to the distribution and parameters obtained in step 1 of n data.
3. Repeat step 2 as many times as m to reflect the different possible return vectors.

Determination of the number of iterations in the Monte-Carlo simulation depends on the expected error percentage. One approach used is the percentage of the error to the mean [15]. The advantage of this approach is that the error percentage is a normalized value. In other words, the value is obtained based on the standard normal approach ($N(0,1)$). Driels and Shien recommend using an average error percentage equal to half the Confidence Interval (CI) value [16]. The average maximum error percentage denoted by ε is expressed as:

$$\varepsilon = Z_{\frac{\alpha}{2}} \frac{100s}{\bar{Y}\sqrt{m}} \tag{14}$$

So, the number of iterations (m) is defined as:

$$m = \left[Z_{\frac{\alpha}{2}} \frac{100s}{\varepsilon \bar{Y}}\right]^2 \tag{15}$$

where m is the number of iterations, Z is the cumulative density function value of the standard normal distribution, s denotes the sample standard deviation, and Y is the sample mean [17].

2.6. Estimation of the Expected Tail Loss

In the first step, we estimate the Value at Risk (VaR). VaR is defined as the estimated value of an asset's loss, where the market movement does not exceed a predetermined probability. [18]. The VaR value can be obtained by estimating the value of the quantiles α, denoted $y_{t,\alpha}$ from a known distribution [19]. In general, the calculation of VaR value is stated as follows:

$$P\left(\frac{P_{t+h} + P_t}{P_t} < y_{t,\alpha}\right) = \alpha \tag{16}$$

$$VaR_{t,\alpha} = -y_{t,\alpha} \tag{17}$$

where P_t is the price at time t -th, h is the time period, and $\alpha$is the confidence level of threshold.

Considering the shortcomings of the VaR method, especially in extreme cases, namely not verifying the principle of diversification, and especially because it is not successful in modelling phenomena that are considered extraordinary [20]. Therefore, another alternative, further analysis of VaR, has been developed to correct the shortcomings presented by VaR, commonly known as Expected Tail Loss (ETL) or Conditional VaR (CVaR), defined as the expected loss outside the VaR limit [21].

Let Y is a random variable representing the risk a particular portfolio, and $VaR_\alpha(Y) = \pi_\alpha$ is a value that indicates the magnitude of risk of a random variable (or asset) Y with a level of confidence $(1-\alpha)100\%$. In general, the conditional VaR, denoted $ETL_\alpha(Y)$, value is expressed as follows: [22]:

$$\begin{aligned} ETL_\alpha^t(Y) &= E[Y|Y > \pi_\alpha] \\ &= \frac{1}{(1 - F(\pi_\alpha))} \int_{\pi_\alpha}^{\infty} y \cdot f(y)\, dy \\ &= \pi_\alpha + \frac{\left(\int_{\pi_\alpha}^{\infty} (x - \pi_\alpha) f(y)\, dy\right)}{(1-\alpha)} \\ &= VaR_\alpha(Y) + e(\pi_\alpha) \end{aligned} \tag{18}$$

There are cases where the data is not normally distributed because it has an excess of skewness and kurtosis. Therefore, Cornish-Fisher developed a "modification" method to estimate VaR and ETL for the case. The method is stated as follows [23][24]:

$$F_{CF}^{-1}(\alpha) = \phi^{-1}(\alpha) + \frac{\varsigma}{6}([|\phi^{-1}(\alpha)|]^2 - 1) + \frac{(k-3)}{24}\left([|\phi^{-1}(\alpha)|]^3 - 3\phi^{-1}(\alpha)\right) - \frac{\varsigma^2}{36}\left(2[|\phi^{-1}(\alpha)|]^3 - 5\phi^{-1}(\alpha)\right) \tag{19}$$

So that:

$$ETL_\alpha^2(X) = -\hat{\mu}_t +_t \frac{\hat{\sigma}_t}{\alpha\sqrt{2\pi}} e^{\frac{\left(F_{CF}^{-1}(\alpha)\right)}{2}} \tag{20}$$

where $\hat{\mu}_t$, $\hat{\sigma}_t$ denote the expectation and standard deviation of the data at t-th time period, respectively, F_{CF}^{-1} indicates the quantile value at α from the distribution of z_t, $\phi^{-1}(\alpha)$ indicates the quantile value at α from the standard normal distribution, and ς, k denote the skewness and kurtosis of $\hat{z}_t$, respectively, where $\hat{z}_t = \frac{y_t - \hat{\mu}_t}{\hat{\sigma}_t}$.

3. Results and Discussion

This section used the return of closing price data of commodity futures to estimate the Expected Tail Loss (ETL). First, find the Holt-Winters model of price data of commodity futures and then estimate the Expected Tail Loss that depends on the distribution of the Holt-Winters residuals, using historical if normally distributed and modified if otherwise.

3.1. Statistics Estimation of Futures Price

Statistics estimation summarize daily closing price data for commodity metal futures on the London Metal Exchange (LME) for Zinc, Lead, Aluminum, Copper, Nickel, and Tin, including the number of observations, basic location statistics such as mean, median, minimum, and maximum, and basic variety statistics such as standard deviation, skewness, and kurtosis. Statistics on commodity futures prices are given in **Table 1**.

Table 1. Statistics value of the daily closing price of commodity metal futures

Commodity	Zinc	Lead	Aluminum	Copper	Nickel	Tin
Sample	950	950	948	950	950	950
Mean	2627	2054	1977	6843	14550	20656
Median	2584	2025	1906	6395	13922	19314
Minimum	1815	1598	1426	4608	10678	13165
Maximum	3580	2669	2957	10557	20410	36798
Standard Deviation	380.3312	221.5964	303.0919	1322.723	2360.744	4914.292
Skewness	0.1703488	0.5208408	0.779647	1.115487	0.5338214	1.547965
Kurtosis	-0.3819262	-0.05420627	0.359816	0.1884386	-0.7798046	1.716502

Table 1 shows that each Commodity has different statistics, which shows that the data conditions are quite diverse before the modeling process is carried out.

3.2. The Result of Stationarity Test

The stationarity of data for each commodity was tested using the ADF test. The significance of the stationary test based on ADF is presented in **Table 2**.

Table 2. Stationary test results of the daily closing price of commodity metal futures

Commodities	Zinc	Lead	Aluminum	Copper	Nickel	Tin
Dickey-Fuller Statistic	-1.6658	-2.2145	0.39768	-1.5553	-2.1037	0.40514
P-Value	0.7198	0.4875	>0.9900	0.7666	0.5344	>0.9900

The Augmented Dickey-Fuller test has an alternative hypothesis that data is stationary. Referring to **Table 2**, it is found that all data on closing prices of commodity futures are not stationary because they have a p-value above 5%. Therefore, it is assumed that all that data contains trend, seasonality, or both elements, so that the Holt-Winters model is considered to be able to be used to model the actual data that exists.

3.3. Estimation of the Holt-Winters Model

The data in the form of historical daily closing prices for each commodity metal futures is modeled using Holt-Winters. Under normal circumstances, the amount of data available is only five for each week, which refers to the number of trading days; so, the length of the seasonal data is assumed to be five. Let α, β, γ denote the smoothing parameters for updating the mean level, trend, and seasonal index respectively, the estimation results of smoothing weight parameters are shown in **Table 3**.

Table 3. Estimation results of smoothing weight parameters

Commodities	Zinc	Lead	Aluminum	Copper	Nickel	Tin
α	0.9462934	0.9929290	0.9757433	0.9387490	0.9916444	0.9987155
$\boldsymbol{\beta}$	0.0001129	0.0001000	0.0048527	0.0041865	0.0026866	0.0079639
γ	0.0001251	0.002191	0.0001844	0.0001000	0.0065530	0.0001002
Seasonal Effect	Additive	Additive	Additive	Additive	Additive	Additive

1. Holt-Winters model for commodity future price of Zinc:

$$F_{t+m} = L_t + b_t m + S_{t-s+m}$$

where

$L_t = 0.9462934\left(Y_t - S_{t-s}\right) + 0.0537066\left(L_{t-1} + b_{t-1}\right)$
$b_t = 0.0001129015\left(L_t - L_{t-1}\right) + 0.9998870985\, b_{t-1}$
$S_t = 0.0001251316\left(Y_t - L_t\right) + 0.9998748684\, S_{t-s}$

2. Holt-Winters model for commodity future price of Lead:

$$F_{t+m} = L_t + b_t m + S_{t-s+m}$$

where

$$L_t = 0.992929022(Y_t - S_{t-s}) + 0.007070978(L_{t-1} + b_{t-1})$$
$$b_t = 0.0001000191(L_t - L_{t-1}) + 0.9998999809 b_{t-1}$$
$$S_t = 0.002190593(Y_t - L_t) + 0.997809407 S_{t-s}$$

3. Holt-Winters model for commodity future price of Aluminum:

$$F_{t+m} = L_t + b_t m + S_{t-s+m}$$

where

$$L_t = 0.9757433(Y_t - S_{t-s}) + 0.0242567(L_{t-1} + b_{t-1})$$
$$b_t = 0.004852679(L_t - L_{t-1}) + 0.995147321 b_{t-1}$$
$$S_t = 0.0001844311(Y_t - L_t) + 0.9998156689 S_{t-s}$$

4. Holt-Winters model for commodity future price of Copper:

$$F_{t+m} = L_t + b_t m + S_{t-s+m}$$

where

$$L_t = 0.938749(Y_t - S_{t-s}) + 0.061251(L_{t-1} + b_{t-1})$$
$$b_t = 0.004186541(L_t - L_{t-1}) + 0.995813459 b_{t-1}$$
$$S_t = 0.0001000032(Y_t - L_t) + 0.9998999968 S_{t-s}$$

5. Holt-Winters model for commodity future price of Nickel:

$$F_{t+m} = L_t + b_t m + S_{t-s+m}$$

where

$$L_t = 0.9916444(Y_t - S_{t-s}) + 0.0083556(L_{t-1} + b_{t-1})$$
$$b_t = 0.002686596(L_t - L_{t-1}) + 0.997313404 b_{t-1}$$
$$S_t = 0.006553036(Y_t - L_t) + 0.993446964 S_{t-s}$$

6. Holt-Winters model for commodity future price of Tin:

$$F_{t+m} = L_t + b_t m + S_{t-s+m}$$

where

$$L_t = 0.9987155(Y_t - S_{t-s}) + 0.0012845(L_{t-1} + b_{t-1})$$
$$b_t = 0.007963877(L_t - L_{t-1}) + 0.992036123 b_{t-1}$$
$$S_t = 0.0001001989(Y_t - L_t) + 0.9998998011 S_{t-s}$$

Based on the result above, it is known that the estimate of α parameter for each commodity model is greater than the other parameters, i.e., β and γ, indicating that the level (linear component) element or mean is the most dominant of all elements. In addition, the trend and seasonal parameters of each commodity model have relatively very small values (>1%), which means the possibility of the weight of trend and seasonal elements are tiny. However, this is not a problem because the main purpose of this study is to estimate and analyze the risk of the price return based on VaR value which is calculated from the predicted results of the Holt-Winters model.

3.4. The Result of Normality Test

When we estimate the Expected Tail Loss (ETL) value, we must first find out whether the residual model obtained is normally distributed or not. Using the distribution suitability test, Kolmogorov-Smirnov, the p-value results are given in **Table 4**.

Table 4. Significance of the Kolmogorov-Smirnov normality test

Commodities	Zinc	Lead	Aluminum	Copper	Nickel	Tin
Statistic	0.484063	0.4618515	0.4623335	0.5061002	0.5139569	0.5719293
p-value	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000

In this test, we use a significance level of 5%. Based on **Table 4**, the level of significance or commonly called p-value obtained for each commodity is very small (less than 5%), which in this case can be decided to reject the null hypothesis (data is normally distributed). Thus, these results conclude that all residual distributions of the model for each commodity are not normally distributed.

3.5. Monte Carlo – Expected Tail Loss

The results of the previous process show that all return data are not normally distributed, so the simulation process for estimating the Expected Tail Loss (ETL) value is carried out based on the generalized lambda distribution. The value of ETL calculated from return for each commodity based on the Holt-Winters model is estimated using Rstudio, especially with "PerformanceAnalytics" packages. Referring to the Holt-Winters modeling results, the model used to predict commodity futures prices has seasonal effect with additive properties. The seasonal effect in the additive model means that the seasonality has a fixed impact, so that the seasonal pattern will remain uniform even though the data has a trend, which better reflects the volatility of commodity futures prices. In addition, when the seasonal effect is considered in the model, the ETL results obtained can vary depending on the particular season so that they are not biased. Ignoring the seasonal effect can lead to underestimation or overestimation of the risk in calculating ETL because the model does not capture seasonal differences in the error distribution. Hereafter, the simulation process is carried out to capture all possible estimated values, from the smallest to the largest, and their average. The dissimilarity of the values obtained results in the emergence of an acceptable range of results, known as the Confidence Interval (CI). The simulation process that has been carried out and has resulted in the estimated value of ETL is stated in **Table 5**.

Table 5. The Result of Monte Carlo Simulation Process For ETL

Commodity	Mean Return	Standard Deviation Return	Number of Simulation	95% CI for ETL	
				Lower	Upper
Zinc	-0.000065688	0.01306081	60747474	0.02896632	0.02959407
Lead	-0.000168489	0.01257540	85598920	0.02867434	0.02938175
Aluminum	0.000330451	0.01205135	20437580	0.02560743	0.02628983
Copper	0.000298815	0.01182279	24054960	0.02721389	0.02799636
Nickel	0.000490599	0.01662229	17640040	0.03555993	0.03643655
Tin	0.000590669	0.01257359	69631000	0.03002281	0.03104553

Based on **Table 5**, the CI range length for each commodity's ETL is obtained differently. Therefore, we cannot directly interpret the level of risk for each commodity and compare it.

3.6. Mean Expected Tail Loss

The final discussion is about the mean value of Monte Carlo simulation of Expected Tail Loss (ETL), which we can assume as ETL value. With ETL value, we can analyze what commodity has the greater risk. The estimation results of the ETL value for each commodity are given in **Table 6**.

Table 6. Estimation results of Expected Tail Loss (ETL)

Commodities	Zinc	Lead	Aluminum	Copper	Nickel	Tin
$ETL_{5\%}$ (%)	0.0292802	0.02902804	0.02594863	0.02760512	0.03599824	0.03053417

Based on **Table 6**, we obtain ETL values with relatively small variations, but they are different from each other. The commodity with the largest ETL value is Tin, making it have the most significant risk with an ETL value of 0.036. The interpretation of this result is that the potential loss expected to be borne by the investor is 3.6%. Assume a sum of funds worth USD 100 is purchased for Nickel Commodities with an investment objective of 48 days (5% of 1000 days). In this case, the investment period with a 95% confidence level can bear the expected loss by the investor is USD 3.6. Basically, the interpretation for each commodity applies the same as nickel for other commodities, so we can also estimate the loss value for other commodities.

4. Conclusions

The following are the conclusions obtained from the results of this research regarding the Holt-Winters model concerning analyzing risk measures of commodity futures in the London Metal Exchange (LME) based on Expected Tail Loss (ETL). All closing price data for future commodities used in this study, namely Zinc, Lead, Aluminum, Copper, Nickel, and Tin, are not stationary, so it can be suspected that the data does not meet the assumptions because it contains trends, seasonality, or both. The estimation results of the Holt-Winters model show that all commodities have the same seasonal effect, namely additives, with different smoothing constants (alpha, beta, gamma) for each commodity model. The residuals of the Holt-Winters model obtained from all commodities are not normally distributed, so the Monte Carlo simulation based on generalized lambda distribution and the estimation of Expected Tail Loss (ETL) is obtained using the modified approach. The average ETL estimate for each commodity produces varying values. Futures of Nickel has the greatest ETL value, and Futures of Aluminum have the lowest ETL value. Thus, based on the analysis of risk measures using ETL, commodity futures of Nickel have the highest risk; in contrast, Commodity futures of Aluminum has the minimum risk as an investment.

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