Syntax Literate: Jurnal Ilmiah Indonesia p–ISSN: 2541-0849
e-ISSN: 2548-1398
Vol. 7, No. 11, November 2022

VALUE AT RISK (VAR) AND EXPECTED SHORTFALL (ES) MEASUREMENTS FOR FOREIGN CURRENCY PORTFOLIO USING EWMA AND GARCH (1,1)

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Abstract

This study assesses the Value at Risk (VaR) and Expected Shortfall (ES) methods in gauging exchange rate risk in PT Telkom Indonesia Tbk, using historical Bank Indonesia closing rates USD/IDR and JPY/IDR from January 2022 - December 2022. Results demonstrate that the ES calculation with Confidence Level (CL) 99%, using the Exponentially Weighted Moving Average (EWMA) and Generalized Autoregressive Conditional Heteroskedasticity (1,1) (GARCH (1,1)) models, provides conservative measures for USD and JPY exposures. These measures, reflecting the highest potential losses, are consistent with management's cautious approach towards currency exchange market risk. Furthermore, based on the ES calculations in this study, it is suggested that PT Telkom Indonesia retains a minimum deposit of 30,000,000,000 IDR, equivalent to roughly 1.007% of its short-term liabilities, which is substantially below the stipulated 25% minimum deposit to efficiently navigate potential foreign exchange risks.

Keywords: Value at Risk, Estimated Shortfall, EWMA, GARCH, Telkom Indonesia, Market Risk.

INTRODUCTION

As Indonesia's largest telecommunications company, PT Telkom Indonesia Tbk operates in multiple currencies and faces market risk, including foreign exchange rate fluctuations (Pristiwantiyasih & Setyawan, 2020). The company's risk management program aims to minimize potential losses resulting from currency and interest rate fluctuations (Settembre-Blundo et al., 2021). Based on the 2022 audited financial report, PT Telkom Indonesia Tbk's total liabilities in foreign currencies amount to IDR 3,899 billion or 3.10% of total liabilities. This shows that transactions in foreign currencies, especially liabilities, are not Telkom's core business considering the small portion (Mburu & Rotich, 2017). However, with the covid pandemic and the anticipation of the economic crisis, it is necessary to mitigate market risk for liabilities in foreign currencies, especially short-term liabilities (Devi et al., 2020).

How to cite:	Firly Armanda, Fatwa Aulia, Jodi Surya Gustanto, Jalil Mujib Tan Ismail, Jonatan Halomoan¬, Dianita Fitriani Pogram, Girindra Chandra Alam, Dewi Hanggraeni (2022) Remodelling Perhitungan Value at Risk (VaR) Studi Kasus Bank XYZ, *(7) 11*, http://dx.doi.org/10.36418/syntax-literate.v7i11.12135
E-ISSN:	2548-1398
Published by:	Ridwan Institute

PT Telkom Indonesia Tbk's market risk management is implemented to minimize the loss of short-term liabilities in foreign currencies, as a result of exchange rate movements (Jatiningtyas & Iradianty, 2016). The form of risk mitigation is in the form of placement of time deposits and hedging for 3-12 months of at least 25% of total short-term liabilities in foreign currency, in anticipation of fluctuations in foreign currency values during this period (Battilossi, 2020).

Total short-term liabilities in foreign currencies of PT Telkom Indonesia Tbk in 2022 which consist of trade payables, other payables, accrued expenses, customer advances, and long-term loans with maturities of less than one year amounting to USD 163, 54 million; JPY 798.45 million; and other foreign currencies equivalent to USD of USD 15.89 million (Damanik et al., 2023). In accordance with the implemented risk management policy, placement of time deposits in foreign currencies is at least 25% of the foreign currency short-term liabilities, namely USD44.85 million and JPY199.61 million.

This study analyzes PT Telkom Indonesia Tbk's foreign currency risk management using Value at Risk (VaR) models, specifically Exponentially Weighted Moving Average (EWMA) and GARCH (1,1), based on Malz (2011) [8] financial risk management framework. PT Telkom's financial strategy prioritizes meeting its short-term liabilities, which comprise a significant percentage of its total liabilities. Researchers used data from the 2022 financial report to assess the company's foreign currency exposure and risk management practices (Chong et al., 2014).

VaR has been extensively used in the financial industry to quantify potential losses associated with financial variables, such as foreign exchange rates on Bredin & Hyde (2014) and Kurita (2013) paper. Both EWMA and GARCH (1,1) models have been widely applied to estimate VaR for portfolios with foreign currency exposures (Yasin et al., 2020). These models capture the time-varying nature of financial market volatility, which is particularly relevant for managing foreign currency risk (Yasin et al., 2020). Malz (2011) provides a comprehensive overview of risk management models, including EWMA and GARCH (1,1), and their application in various financial institutions. The present study applies the Exponentially Weighted Moving Average (EWMA) and GARCH (1,1) models to measure the VaR of the foreign currency portfolio of PT Telkom Indonesia Tbk, using the framework discussed in Financial Risk Management Models, History, and Institutions by Malz (2011). The present study concentrates exclusively on these market risks, particularly the potential for default due to foreign exchange rate fluctuations.

Using 2022 financial report data, researchers estimate the VaR of Telkom Indonesia's foreign currency portfolio with EWMA and GARCH (1,1) models. The study provides insights into these models' effectiveness in predicting potential losses and offers valuable information for the company's risk management efforts, benefiting other companies in similar contexts and aiding policymakers in promoting effective risk management practices in the telecommunications industry. Given an annual interest rate of 7% on Telkom Indonesia's IDR 653 billion fixed-term deposit, the potential losses from currency fluctuations, calculated using the most conservative values, only account for about 59.32% of the interest income, indicating that the deposit's earnings could cover the entire foreign exchange risk and still yield a surplus.

Applying EWMA and GARCH (1,1) models to measure the VaR of Telkom Indonesia's foreign currency portfolio, the study compares their performance in capturing foreign currency risk dynamics and offers insights for risk management practitioners in the telecommunication industry. The study concludes that the EWMA with 99% confidence level (CL) is more conservative than the GARCH (1,1) method in calculating VaR and ES for USD exposure. In contrast, for JPY exposure, the GARCH (1,1) method with 99% CL is more conservative than EWMA. The performance of the GARCH (1,1) model for JPY and the EWMA model for USD was determined through the Kupiec statistical test.

Theoretical Model

Value at Risk and Estimated Shortfall

Value at Risk (VaR) and Expected Shortfall (ES) are employed to assess potential losses in investments or portfolios. While both methods focus on quantifying potential losses, their approaches and the information they offer on risk differ. VaR estimates the maximum possible loss a portfolio or investment can incur over a specified time frame and at a certain confidence level. The formula for VaR is:

$$VaR = \mu - (z \times \sigma) \quad \text{.....(1)}$$

where μ is the mean return, z is the z-score corresponding to the chosen confidence level, and σ is the standard deviation of the returns.

ES, alternatively referred to as Conditional Value at Risk (CVaR), calculates the average loss expected in the tail distribution of portfolio returns beyond a specific confidence level. The formula for ES is:

$$ES = -(1 / (1 - \alpha)) \times \int [VaR\_\alpha - \infty]\, x \times f(x)\, dx \quad \text{.....(2)}$$

where α is the chosen confidence level, and f(x) is the probability density function of the returns.

In essence, ES determines the average loss likely to occur in extreme scenarios, surpassing the VaR threshold (Malz, 2011).

Three primary techniques are employed for calculating VaR and ES: historical, parametric, and Monte Carlo simulation methods. The historical method involves deriving calculations based on the historical data of asset or portfolio returns. The first step entails determining the VaR value at the desired confidence level, followed by calculating the average return worse than the obtained VaR value. This average value is known as the Expected Shortfall. The parametric method, on the other hand, presumes that asset or portfolio returns adhere to a specific distribution (e.g., normal). The initial phase involves selecting the appropriate distribution, estimating the statistical parameters (mean, standard deviation), and determining the desired confidence level. Subsequently, the VaR value is determined using the formula mentioned above, and the ES value is calculated according to the chosen distribution. Lastly, the Monte Carlo simulation method utilizes random sampling simulations to generate various scenarios for the returns of owned assets or portfolios. This technique allows for multiple simulations, producing a range of VaR or ES values. These scenarios can then be averaged to yield the final result. Jorion (2009) ; McNeil, Frey & Embrechts (2015).

Exponentially Weighted Moving Average (EWMA)

In VAR estimations, it is usual to assume that logarithmic returns have a normal distribution with mostly a mean of zero. As a result, the volatility must be evaluated as the key factor. There are various ways to determine volatility. The majority are founded on past return information, although implied volatility is an alternative. Data volatility that is not constant is called heteroscedasticity.

One approach to dealing with heteroscedastic data volatility is the Exponentially Weighted Moving Average (EWMA) method. The "RiskMetrics model" - EWMA is an alternate strategy to apply to the return data that considers time-varying volatility developed by J.P. Morgan in 1994 on their RiskMetrics technical document. In EWMA, each observation is provided with a decay factor $\lambda \epsilon$ (0, 1), allowing for the weighting of more recent data over older ones in the volatility calculation. The decay factor is often very nearly, but not precisely, unity. The final volatility estimator is stable as long as the decay factor is smaller than unity. As in RiskMetrics, a value of roughly 0.94 has received strong empirical confirmation for very short time horizons like daily. A decay factor of 0.97 has been suggested for slightly longer time frames, like one month. As the return observations move further into the past, the weights decrease smoothly. More recent data are given more weight and past observations are quickly deemphasized if the decay factor is smaller.

The EWMA estimator according to Morgan (1996) can be written in this form:

$$\sigma_t^2 = \lambda\sigma_{t-1}^2 + (1-\lambda)r_{t-1}^2 \quad (3)$$

σ_t^2 = Variance of return on day t

λ = Decay factor

r_{t-1}^2 = Return on day t-1

For large time series data of *n*, the following formula is used where *m* is *n-1*. The greater the value of *m*, the smaller the value of the decay factor multiplied in past data.

$$\sigma_n^2 = \lambda^m\sigma_{t-m}^2 + (1-\lambda)\Sigma_{i=1}^{m} r_{t-1}^2 \quad (4)$$

After the EWMA model is formed using this formula, the generated variance value (σ) is used to calculate VAR and ES in the VAR parametric formula.

Generalized Autoregressive Conditionally Heteroscedastic (GARCH)

The generalized autoregressive conditionally heteroscedastic (GARCH) model can be seen as a generalization of the EWMA model. It highlights conditional volatility estimation time series rather than profit series (Malz, 2011). This paper use the GARCH (1,1) to estimates the volatility of return in each day. A conditional mean equation in GARCH model can be given by

$$yt = \mu_t + \varepsilon_t = \alpha' x_{t-1} + \varepsilon_t \quad \text{for t = 1…..t} \quad \text{……………..…………………………(5)}$$

where y_t denote the dependent variable analyzsed , μ_t is its conditional mean, x_{t-1} represents the k-dimensional vector of the explanatory variables. Simply, the variable y_t represents the daily return of a financial asset. A conditional variance equation related to the GARCH structure (p, q) can be given by :

$$\varepsilon_t = \eta_t \sigma_t \quad \text{…………………………………………….…………………(6)}$$

$$\sigma_t^2 = \omega + \sum_{i=1}^{p} \beta_i \sigma_{t-1}^2 + \sum_{j=1}^{q} \gamma_j \varepsilon_{t-j}^2 \text{……………………………….…………………(7)}$$

the model is introduced by Bollerslev (1986) , and the paper on ARCH by Engle (1982) this equation is re expressed as :

$$\sigma_t^2 = \omega + \beta(L)\sigma_t^2 + \gamma(L)\varepsilon_t^2 \text{…………………………………….………………(8)}$$

where L is denoting a lag operator. In his book, Malz (2011) explains the equation details the process of updating the estimation of current volatility by incorporating new return information , is:

$$\sigma_t^2 = \omega + \alpha\sigma_{t-1}^2 + \beta r_t^2 \text{………………………………..………………(9)}$$

with an assumption that $\alpha + \beta \leq 1$.

Previous Research

There are several studies that examine the calculation of value at risk on exchange rates as was done by Anjuma and Malik (2020), with the topic "Forecasting risk in the US Dollar exchange rate under volatility shifts". This research examines the movement of the US Dollar exchange rate compared to seven major trading partners based on data from the US Federal Reserve Bank from 1 January 2020 - 07 December 2018. The author believes that "volatility shift" must be considered in estimating volatility because it will affect the estimated var value. By comparing seven models to estimate VAR value, the research performs results that indicate the GARCH-volatility shift model is the most accurate compared to other methods to VAR in Dollar Exchange Rate.

Another research was conducted by Kurita (2013) with the topic "Dynamic characteristics of the daily yen-dollar exchange rate". This research examines the JPY-USD Exchange rate quantitative information on technical trading. Kurita compares some volatility-based models such as GARCH (1,1), FIGARCH, FIAPARCH. The result of this research is that the difference between the highest and lowest value plays a significant part. Also, in order to decide the best model to estimate a VaR based on volatility, one has to pay attention to the skewness as well as the leptokurtosis.

Bredin and Hyde (2014) assessed Various Value-at-Risk (VaR) methodologies using a portfolio centered around the foreign exchange exposure of a small open economy, specifically Ireland. The study employed both parametric and non-parametric Value-at-Risk models for this investigation. Based on advanced evaluation methods, the findings suggested that the Orthogonal GARCH model provided the highest accuracy, while the exponentially weighted moving average (EWMA) model offered a more conservative approach.

Results and Discussion

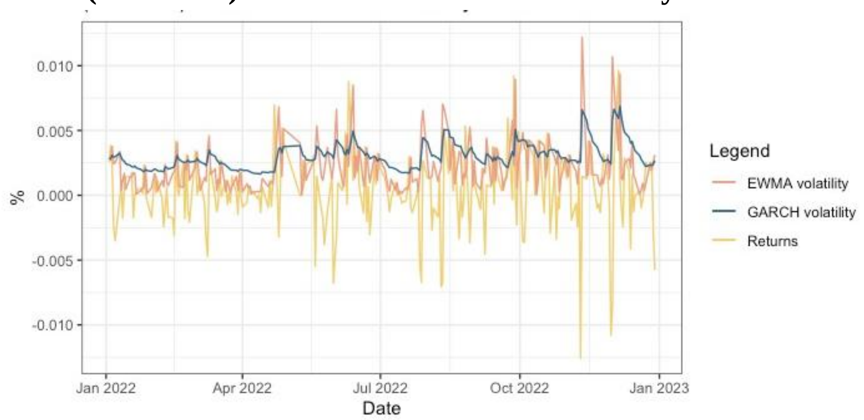
It is suggested in Telkom Indonesia's financial statement that the risk of foreign currency exchange rate fluctuations can be mitigated by the company maintaining fixed deposits and receivables in foreign currencies. These should constitute at least 25% of its total short-term foreign currency-denominated liabilities. The hedging strategy emphasized in the financial statement can offset any potential losses due to currency fluctuations, thereby ensuring the company's financial position's stability. The computation of potential losses for Telkom Indonesia's short-term liabilities due to currency fluctuations was carried out by researchers based on this understanding of the company's financial statement. Valuable insights into potential risks that could impact the company's financial performance can be provided by focusing on short-term liabilities.

A. Volatility Estimates vs Return

The analysis of the risks facing Telkom Indonesia due to foreign currency exchange rate fluctuations was undertaken using 246 observations of the closing prices of USD/IDR and JPY/IDR currency exchanges, as specified in the company's financial statement. This number of observations, covering a span from the start to the end of 2022, aligns with standard practice in banks for such computations. Volatility estimates derived from these observations were subsequently plotted against the returns. This provides a clear illustration of how changes in exchange rates could impact potential losses for the company's short-term liabilities. Graphical representations, including estimates from both GARCH (1,1) and EWMA models, were facilitated to determine the more accurate volatility estimate.

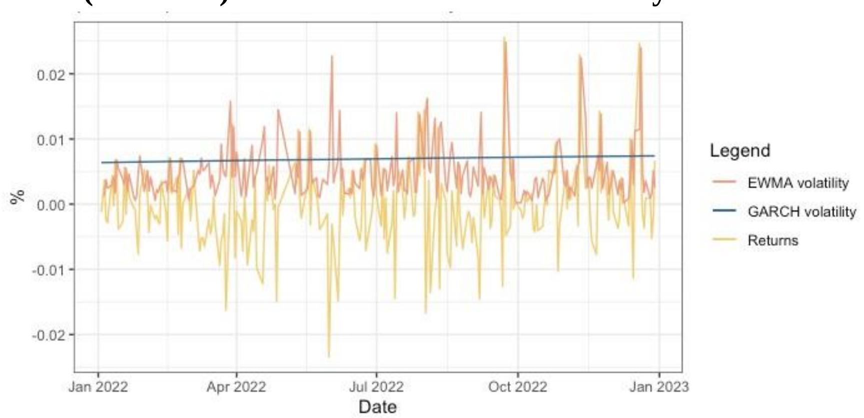
USD/IDR**:** The plot in Figure 1 shows that the GARCH (1,1) model line is volatile and follows the EWMA line closely. This suggests that the volatility of returns is too high, which increases the risk of potential losses for Telkom Indonesia's short-term liabilities. The fact that the GARCH (1,1) line is closely following the EWMA line suggests that both models are providing similar estimates of volatility. This could signify that the GARCH (1,1) model is not adding any extra value in predicting volatility over and above the simpler EWMA model.

Figure 1
(USD/IDR) GARCH and EWMA Volatility vs Return



JPY/IDR**:** The plot in Figure 2 showing the JPY/IDR exchange rate with a GARCH (1,1) model line having a slight upward slope but staying roughly horizontal suggests that the volatility of returns for this pair is not changing dramatically over time. Instead, it is relatively stable, albeit with a slight increasing trend. This means that the level of risk associated with the JPY/IDR exchange rate, as measured by its volatility, is not undergoing drastic fluctuations but might be experiencing a gradual increase.

Figure 2
(JPY/IDR) GARCH and EWMA Volatility vs Returns



B. Kupiec Backtesting

The Kupiec VaR backtesting analysis, a widely employed method for validating VaR estimates, serves to gauge the precision of VaR projections for Telkom Indonesia's short-term foreign currency-denominated liabilities. This is achieved by comparing the frequency of actual losses exceeding VaR predictions with the expected frequency at a given confidence level.

In line with this objective, such an analysis was conducted following the calculation of the VaR coefficients. The results not only inform the selection of risk mitigation measures but also provide insights for refining the company's VaR estimation models.
Furthermore, the Kupiec test assists in identifying the model that best captures the risk dynamics of these liabilities.

***USD/IDR*:** Table 1 presents the results of the Kupiec VaR backtesting for USD/IDR, utilizing both GARCH (1,1) and EWMA models. These results encompass the VaR method, confidence level, accuracy, p-value, likelihood ratio, and the number of errors. For both the GARCH (1,1) and EWMA models at the 90% and 95% confidence levels, the VaR estimates were found to be inaccurate. This is supported by the p-value and likelihood ratio results at these levels, which suggest a low degree of accuracy. Specifically, the p-value for both models at the 90% and 95% confidence levels were 0.032 and 0.014 respectively, with a likelihood ratio of 4.605 and 5.991, and each had one error.

However, at the 99% confidence level, the VaR estimates for both models were accurate, with no errors recorded. This is corroborated by the high p-value of 0.887 and low likelihood ratio of 0.020, suggesting a high level of accuracy for both the GARCH (1,1) and EWMA models at this confidence level.

Based on these results, the VaR coefficients derived from the GARCH (1,1) and EWMA models at the 90% and 95% confidence intervals will be rejected due to their lack of accuracy. The models, however, perform adequately at the 99% confidence level, providing accurate VaR estimates. This indicates that for high confidence levels, both models can be used reliably for risk estimation.

Table 1
Kupiec Backtesting USD/IDR

VaR Volatility Estimate Used	Confidence Level	Accuracy	p-value	Likelihood Ratio	Number of Errors
GARCH (1,1)	90	Not Accurate	0.032	4.605	1
EWMA	90	Not Accurate	0.032	4.605	1
GARCH (1,1)	95	Not Accurate	0.014	5.991	1
EWMA	95	Not Accurate	0.014	5.991	1
GARCH (1,1)	99	Accurate	0.887	0.020	0

EWMA	99	Accurate	0.887	0.020	0

***JPY/IDR*:** Table 2 provides the Kupiec VaR backtesting results for JPY/IDR, including the VaR method, confidence level, accuracy, p-value, likelihood ratio, and the number of failures for both GARCH (1,1) and EWMA models. For all confidence levels - 90%, 95%, and 99% - both the GARCH (1,1) and EWMA models returned accurate VaR estimates. No failures were recorded across these levels for either model, reinforcing their accuracy. The p-value and likelihood ratio results for all confidence levels further suggest a high degree of accuracy.

These results imply that the GARCH (1,1) and EWMA models perform effectively in estimating VaR for JPY/IDR across all examined confidence levels. This reliability suggests that both models can be utilized confidently for foreign exchange risk assessment involving the Japanese Yen and Indonesian Rupiah.

Table 2
Kupiec Backtesting JPY/IDR

VaR Volatility Estimate Used	***Confidence Level***	***Accuracy***	***p-value***	***Likelihood Ratio***	***Number of Errors***
GARCH (1,1)	90	Accurate	0.646	0.211	0
EWMA	90	Accurate	0.646	0.211	0
GARCH (1,1)	95	Accurate	0.749	0.103	0
EWMA	95	Accurate	0.749	0.103	0
GARCH (1,1)	99	Accurate	0.887	0.020	0
EWMA	99	Accurate	0.887	0.020	0

C. Value-at-Risk (VaR) and Expected Shortfall (ES)

Upon obtaining accurate VaR coefficients from the Kupiec backtesting, the computation of VaR and ES values for the short-term liabilities ensued. This was done to translate the findings of the backtesting into practical risk measures that can be used in real-world risk management.

The provided data revealed that for JPY/IDR, VaR and ES were calculated at three distinct confidence levels: 90%, 95%, and 99%. The decision to use these multiple confidence levels stems from the Kupiec backtesting results, which indicated that both GARCH (1,1) and EWMA models provided accurate VaR estimates across all these levels for JPY/IDR.

Conversely, for USD/IDR, VaR and ES measures were only computed at the 99% confidence level. This was determined by the Kupiec backtesting results, which suggested that accurate VaR estimates for USD/IDR were only obtained at the 99% confidence level using both GARCH (1,1) and EWMA models.

Therefore, the choice of confidence levels for each currency pair directly reflects the findings from the Kupiec backtesting, tailoring the risk measurement approach to the demonstrated accuracy of the models at different confidence levels. This approach ensures a more accurate and reliable estimation of potential losses, enhancing the effectiveness of risk management efforts.

***USD/IDR*:** The given data in Table 3 presents the USD/IDR rate, which is computed based on Telkom Indonesia's total short-term liabilities, 163,540,000 USD. This rate plays a pivotal role for the company as it provides a critical benchmark to assess its foreign exchange risk exposure to the US dollar.

It is important to note that currency exchange rates are subject to fluctuations due to a myriad of factors including economic indicators, geopolitical events, and market sentiment. In this context, a strengthening US dollar against the Indonesian Rupiah would mean a higher value of liabilities when converted back to Rupiah. This would in turn lead to higher repayment obligations for Telkom Indonesia, potentially causing financial losses if not properly managed.

In the data provided, potential losses are expressed in Indonesian Rupiah at the 99% confidence level for both GARCH (1,1) and EWMA models. The VaR (Value-at-Risk) and ES (Expected Shortfall) under both methodologies provide different perspectives on the potential losses.

For the GARCH (1,1) model, the VaR is -15,029,203,960 IDR, and the ES is -21,613,694,523 IDR. This means that, with 99% confidence, the maximum expected loss over the given time period would not exceed these amounts. It is important to note that while VaR provides an estimate of potential losses, ES gives an estimate of the expected loss given that the VaR threshold is breached.

For the EWMA model, the VaR is -17,573,009,841 IDR, and the ES is -24,908,396,063 IDR. These values are higher than those obtained from the GARCH (1,1) model, indicating a potentially greater risk according to this model.

Table 3
USD/IDR VAR & ES

Confidence Level	***VaR GARCH (1,1)***	***ES GARCH (1,1)***	***VaR EWMA***	***ES EWMA***
99%	-15,029,203,960	-21,613,694,523	-17,573,009,841	-24,908,396,063

JPY/IDR: the provided data in Table 4, the JPY/IDR rate is computed based on Telkom Indonesia's total short-term liabilities in JPY, 798,450,000 JPY. This rate offers a significant benchmark for the company to assess its foreign exchange risk exposure to the Japanese yen.

Similar to the USD/IDR analysis, a strengthening Japanese yen against the Indonesian Rupiah would lead to higher repayment obligations for Telkom Indonesia when these liabilities are converted back to the local currency. This could potentially lead to financial losses if the company doesn't have an effective risk management strategy in place.

The potential losses are denoted in Indonesian Rupiah at three confidence levels: 90%, 95%, and 99%. For each of these confidence levels, the Value-at-Risk (VaR) and Expected Shortfall (ES) are calculated using two methodologies: GARCH (1,1) and Exponentially Weighted Moving Average (EWMA).

At the 90% confidence level, the GARCH (1,1) model estimates a VaR of -911,927,393 IDR and an ES of -1,302,288,224 IDR, while the EWMA model projects a VaR of -321,553,350 IDR and an ES of -715,112,045 IDR. This indicates that the GARCH (1,1) model foresees a higher risk of loss at this confidence level compared to the EWMA model.

A similar pattern is observed at the 95% and 99% confidence levels. The GARCH (1,1) model consistently estimates a higher VaR and ES compared to the EWMA model. At the 99% confidence level, for example, the VaR for the GARCH (1,1) model is -1,640,025,172 IDR compared to -568,343,442 IDR for the EWMA model.

This discrepancy between the two models suggests that they capture different aspects of the market risk. The GARCH (1,1) model, which accommodates volatility clustering and leverage effects, might be capturing more potential for extreme events in the JPY/IDR exchange rate, while the EWMA model, which assigns a decreasing weight to older data, might be more sensitive to recent changes in volatility.

Table 4
JPY/IDR VAR & ES

Confidence Level	***VaR GARCH (1,1)***	***ES GARCH (1,1)***	***VaR EWMA***	***ES EWMA***
90%	-911,927,393	-1,302,288,224	-321,553,350	-715,112,045
95%	-1,165,105,378	-1,451,651,092	-407,368,497	-819,297,224
99%	-1,640,025,172	-2,205,458,957	-568,343,442	-1,006,773,784

The potential losses due to currency fluctuations were estimated using the most conservative values from the provided tables. These values are -24,908,396,063 IDR (ES-EWMA@99CL for USD/IDR) and -2,205,458,957 IDR (ES GARCH@99CL for JPY/IDR), resulting in a total potential loss of 27,113,855,020 IDR.

Concurrently, according to the financial report, Telkom Indonesia holds 653,000,000,000 IDR in fixed short-term deposits. These deposits can serve as a contingency fund to offset any potential losses from the fluctuations of their foreign currency-denominated short-term liabilities.

In this context, the potential losses constitute merely about 0.0042% of the total contingency funds available. This suggests that Telkom Indonesia's strategy, as stipulated in their financial report, of maintaining fixed deposits and receivables in foreign currencies equal to at least 25% of their total short-term foreign currency liabilities, could be more conservative than necessary given the actual risks posed by currency fluctuations, even in the worst-case scenarios.

Conclusion

This study concludes that the Kupiec statistical test validates the effective performance of the Expected Shortfall (ES) calculation using the GARCH (1,1) model at a 99% Confidence Level (CL) for JPY exposure. For USD exposure, the ES using the Exponentially Weighted Moving Average (EWMA) model at a 99% CL was found to be more effective.

The ES calculation using the EWMA model at 99% CL provides a more conservative measurement of exchange rate risk for USD exposure, with an IDR of 24,908,396,063. Similarly, for JPY exposure, the ES calculation using the GARCH (1,1) model at a 99% CL offers a more conservative risk measurement, with an IDR of 2,205,458,957.

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