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Comparative Analysis of Hedging Effectiveness in Indonesia's National Electrical Company: An Evaluation of Ordinary Least Square (OLS), General Autoregressive Conditional Heteroskedasticity (GARCH) and Naïve Dollar-Offset Models

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Abstract

This study evaluates the hedging effectiveness of Indonesia's national electrical company, PT PLN (Persero), by comparing Ordinary Least Squares (OLS), Generalized Autoregressive Conditional Heteroskedasticity (GARCH), and Dollar Offset models. Using transaction data from 2018-2023, the analysis shows that the OLS model explains 48.8% of the variance in forward rates, indicating high effectiveness. The GARCH model, while capturing dynamic volatility with an average effectiveness of 4.32%, demonstrates the need for advanced models in volatile conditions. The Dollar Offset method, despite its simplicity, shows a moderate effectiveness of 19.03%. Combining these methods can enhance hedging strategies, providing robust risk management. Future research should expand data sources and periods to further validate findings.

Keywords: exchange rate risk; OLS; GARCH; hedging ratio; hedging effectiveness.

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1. Introduction

In the ever-changing and increasingly complex dynamics of the global economy, currency exchange rate volatility becomes a significant risk for both multinational and domestic companies that engage in foreign exchange transactions. Foreign exchange risk refers to the potential changes in the value of financial transactions, assets, or liabilities due to exchange rate fluctuations (Madura, 2018). This risk can affect corporate value, as empirically demonstrated by Bodnar and Bartov (1994). Exchange rate risk can arise from various sources, including export-import activities, foreign debt, cash flows from overseas operations, and foreign portfolio investments (Adler & Dumas, 1984).

Exposure to exchange rate risk drives corporations to hedge to protect cash flows from the uncertainty of exchange rate volatility. This is particularly crucial for corporations operating in developing countries, which are highly susceptible to exchange rate volatility, especially during crises (Bodnar & Gentry, 1993). To mitigate this exposure, corporations use derivative instruments as hedging tools (Geczy & Schrand, 1997). Furthermore, Aggarwal & Harper (2010) found that domestic companies have foreign exchange risk exposure relatively similar to companies directly involved in international transactions, especially for companies with high market-to-book ratios and financial leverage.

PT PLN (Persero) is a domestic company in Indonesia operating in the electric energy sector. As a state-owned enterprise, PLN serves the national electricity needs. According to research by Aggarwal & Harper (2010), PLN is a local company that sources funding from abroad, resulting in exchange rate exposure similar to that of international companies. This is evidenced by the significant impact of exchange rates on PLN's profit and loss, as illustrated in Figure 2.

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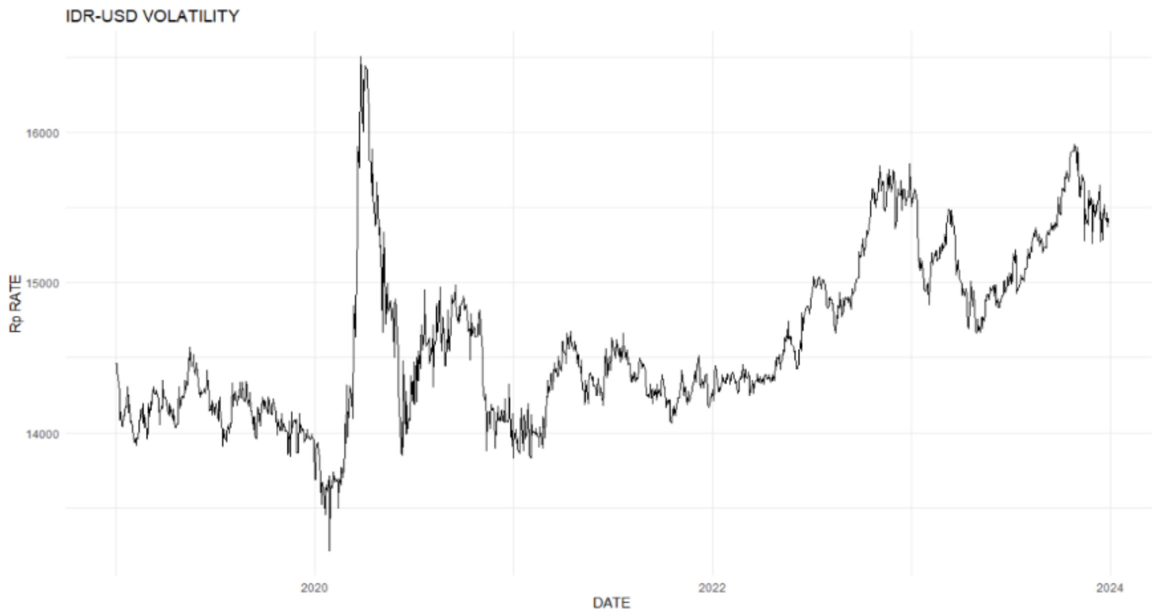

Figure 1. Local currency (Rupiah) Volatility to USD (Source: finance.yahoo.com)

As an impact of exchange rate risk, hedging becomes an essential tool in PT PLN (Persero)'s risk management strategy. This hedging mechanism aims to reduce financial risk exposure related to exchange rate fluctuations and can be executed through various financial instruments such as futures contracts, options, and swaps. In which according to financial reports, PLN hedged 1.46 billion USD in 2022 and 1.37 billion USD in 2021. This hedging strategy is not straightforward. Transaction costs, counterparty risk, and the complexity in choosing the right instruments are some of the challenges faced by PLN. Additionally, it requires techniques to quantify hedging effectiveness, not only for evaluation purposes and accurate predictions of future exchange rate movements but also to meet the requirements for hedge accounting in financial statements. In addition, in terms of operational characteristics and strategic objectives, state-owned enterprises (SOEs) have different characteristics compared to private companies. Besides aiming for profit, SOEs are expected to contribute socially, drive the economy, and function as economic buffers. This raises questions about the effectiveness of hedging strategies applied by SOEs, as they cannot engage in speculation within hedging activities.

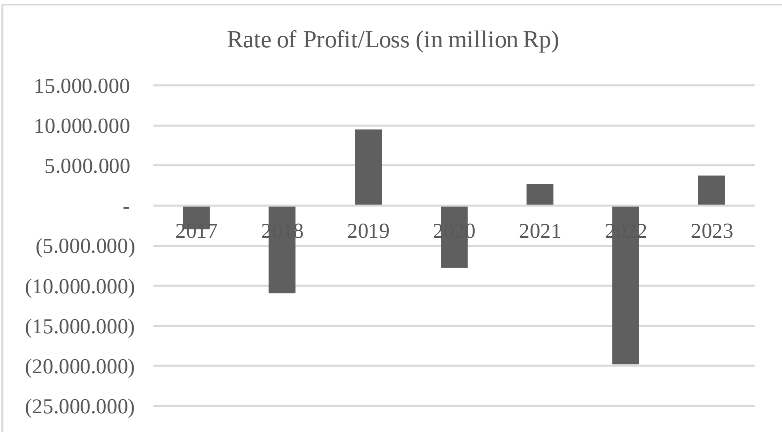

Figure 2. Exchange rate eksposure to PLN (Source: PLN's financial report)

The effectiveness of hedging is crucial to ensure that the strategies employed truly provide the expected protection. The effectiveness of hedging heavily depends on the selection of the appropriate instruments, the use of suitable models, market conditions, and strong risk management policies. Quantifying the effectiveness of hedging, the OLS model provides a simple linear estimate that is useful for data with low variability, while the GARCH model is more suitable for analyzing financial data with high volatility.

2. Literature Review

Hedging effectiveness is crucial to ensure that the strategies employed provide the expected protection. The effectiveness of hedging depends significantly on the selection of appropriate instruments, the use of suitable models, market conditions, and strong risk management policies. The quantification of hedging effectiveness was first introduced by Ederington (1979) using simple regression, Ordinary Least Squares (OLS)/minimum-variance hedge ratio. This method has been widely used due to its computational simplicity and ease of understanding. However, it has two limitations. Firstly, it overlooks the time-varying nature of financial time series; secondly, it calculates a constant hedge ratio.

Engle (1982) introduced the Autoregressive Conditional Heteroskedasticity (ARCH) model to address heteroscedasticity issues often encountered in econometric analysis. In the ARCH model, the conditional variance changes based on past data information. This model also addresses common issues found in the OLS model, making it more robust for financial data analysis. Bollerslev, T. (1986) introduces the Generalized Autoregressive Conditional Heteroskedasticity (GARCH) model, which extends the ARCH model by including past conditional variances in the current conditional variance equation. This approach improves the ARCH model by providing a more flexible and accurate representation of time-varying volatility in financial time series. Bollerslev's GARCH model better captures the persistence of volatility shocks and offers more robust empirical performance in modeling financial data, making it a valuable tool for econometric analysis of market volatility.

The utilization of GARCH in quantifying hedging effectiveness and hedge ratios is exemplified by Switzer & Park (1995). The study employed the Bivariate GARCH (Generalized Autoregressive Conditional Heteroskedasticity) method to calculate hedging effectiveness and estimate optimal hedge ratios. The Bivariate GARCH regression was used to analyze the changing volatility dynamics of asset and futures prices simultaneously. The data included closing prices of the S&P 500 and Toronto 35 Index as spot prices and daily settlement prices of futures from the New York Stock Exchange and Toronto 35 Index. The GARCH model proved superior in estimating optimal hedge ratios, particularly in volatile market conditions.

A comparative study of the effectiveness of OLS, GARCH, was conducted by Cotter & Hanly (2012). The study found that while the GARCH model provided good hedging performance for symmetric data, the differences were not significant compared to the OLS model. Meanwhile, Wibowo, B (2017) comparing three models, Ordinary Least Squares (OLS), Vector Error Correction Model (VECM), and Threshold-ARCH (TARCH). The study found that the VECM method showed the highest hedging effectiveness, but the difference was not significant compared to OLS. The TARCH method, which is the most complex, provided the lowest hedging effectiveness.

There are many other studies comparing regression methods in calculating hedging effectiveness, showing variations in the most effective model (Kaur & Gupta, 2018; Yang, et al., 2019; Lee & Lee, 2012). These studies generally use publicly available data such as commodities or index prices. Therefore, there is limited information on hedging effectiveness for corporations using corporate transaction data on derivative instruments. This research aims to providing a new perspective on effective regression models for domestic's corporations by conducting a comparative analysis of hedging effectiveness quantification between the Ordinary Least Squares (OLS) regression model, Generalized Autoregressive Conditional Heteroskedasticity (GARCH) and Naïve Dollar-Offset model using derivative transaction data from Indonesia's national electrical company.

3. Data and Methodology

3.1. Data

The data used for analysis in this study comprises both primary and secondary data. The primary data includes derivative transactions from the period 2018 – 2023. From this data, the forward rate is obtained and used as the futures price, the spot rate, and the settlement exchange rate as the closing price. Additional primary data includes PLN's forecast of foreign exchange movements for 2024, in collaboration with Bloomberg. This forecast data is used as a substitute for the settlement exchange rate (JISDOR rate) for derivative contracts in 2023 that have not yet matured. The secondary data consists of JISDOR exchange rates (Jakarta Interbank Spot Dollar Rate) sourced from the Bank Indonesia website. This JISDOR rate data is the same as the settlement rate in the primary data, and its collection aims to cross-check the data.

3.2. Methodology

This research employs a quantitative method by comparing the results of Ordinary Least Squares (OLS) regression analysis and Generalized Autoregressive Conditional Heteroskedasticity (GARCH), benchmarked against the naive method to determine which method is most effective and suitable for the company. The analysis is conducted using R Studio.

The OLS model is utilized to estimate the parameters of a linear regression model. This model minimizes the sum of the squared differences between the observed value and the values predicted by the linear model. The OLS model calculated using a mathematical function based on the study by Buyukkara et al. (2021) with the formula:

$$R_f = \alpha + \beta^* \times R_p + \varepsilon \tag{1}$$

Where Rf is the dependent variable (spot rate). α is the intercept constant of the regression, which is assumed to be zero (0) because the realized exchange rate follows the market realization due to the absence of a hedging agreement. β* is the beta of the derivative, measuring the sensitivity of derivative returns to market returns or the slope of the regression between the derivative exchange rate and the market exchange rate. A beta value equal to or greater than 1 indicates perfect hedging. A beta value equal to 0 indicates no hedging activity, while a beta value less than zero (< 0) indicates that hedging activity incurs a loss or is ineffective. β is the independent variable. *Rp* is the independent variable in the form of the agreed-upon derivative exchange rate at the transaction date. ϵ is the error term of the model.

The OLS estimation aims to find the values of α and β that minimize the sum of squared residuals. This method is widely used due to its simplicity and ease of interpretation. However, it assumes that the error term ϵ is normally distributed with a constant variance and that there is no autocorrelation.

The Generalized Autoregressive Conditional Heteroskedasticity (GARCH) model is employed to capture the volatility clustering often observed in financial time series. Unlike the OLS method, which assumes constant variance, the GARCH model allows the variance of the error term to vary over time. This makes it particularly useful for modeling financial returns, which often exhibit periods of high and low volatility.

The GARCH model, as the second comparison, refers to the study by Bollerslev (1986), which extends the ARCH model introduced by Engle (1982). The mathematical functions are as follows:

$$Y_t = \sigma_t \epsilon_t \tag{2}$$

$$\sigma_t^2 = \alpha_0 + \alpha_1 Y_{t-1}^2 \tag{3}$$

$$\sigma_t^2 = \alpha_0 + \alpha_1 Y_{t-1}^2 + \beta_1 \sigma_{t-1}^2 \tag{4}$$

Where Y_t is the dependent variable in the form of returns at time t. This is the value we are trying to predict or explain. σ_t is the conditional standard deviation of Y_t at time t. This indicates the volatility or uncertainty of the variable Y_t at time t. ϵ_t is white noise with a zero mean and constant variance. This part of the model describes the random error component. σ_t^2 is the conditional variance of Y_t at time t. This is the square of the conditional standard deviation (σ_t). α_0 is the intercept or constant in the variance equation. This is the minimum value of the conditional variance that does not depend on the value of Y_{t-1}^2. α_1 is the coefficient that measures the influence of the first lagged squared residual (Y_{t-1}^2) on the conditional variance (σ_t^2). This value indicates how much the variance from the previous period affects the current variance. Y_{t-1}^2 is the squared value of the dependent variable at time t−1. This shows the influence of the previous variance on the current variance. β_1 is the coefficient that measures the influence of the first lagged conditional variance (σ_{t-1}^2) on the conditional variance (σ_t^2). This value indicates how the variance from the previous period affects the current variance. σ_{t-1}^2 is the conditional variance of Y_t at time t−1. This shows the volatility or uncertainty of the variable Y at time t−1, which affects the variance at time t.

The GARCH model is estimated using maximum likelihood estimation (MLE). It is particularly effective in capturing time-varying volatility and is commonly used in risk management and financial econometrics to model asset returns and forecast future volatility.

The Dollar Offset Method is a naïve, non-regression and straightforward approach used to measure the effectiveness of a hedging strategy. This method compares the changes in the value of the hedging instrument to the changes in the value of the hedged item. The equation for the Dollar Offset Ratio is given by:

$$\text{Dollar Offset Ratio} = \frac{\Delta\text{Hedged Item}}{\Delta\text{Hedging Instrument}} \quad (5)$$

Where, ΔHedging Instrument represents the change in value of the hedging instrument. ΔHedged Item represents the change in value of the item being hedged.

The hedging effectiveness can be interpreted based on the Dollar Offset Ratio. A ratio close to 1 indicates a highly effective hedge, meaning that the changes in the value of the hedging instrument closely match the changes in the value of the hedged item. Conversely, a ratio significantly different from 1 suggests less effective hedging.

Subsequently, OLS, GARCH and Dollar-offset models are employed to evaluate the effectiveness of hedging strategies. The OLS model provides a straightforward approach to estimate the relationship between spot and forward rates, while the GARCH model accounts for the dynamic nature of volatility in financial time series. Meanwhile, Dollar-offset model provide a benchmark to the non-regression model. By comparing these methods, we aim to determine which provides a more accurate and robust measure of hedging effectiveness. Figure 2 briefly illustrates the research framework.

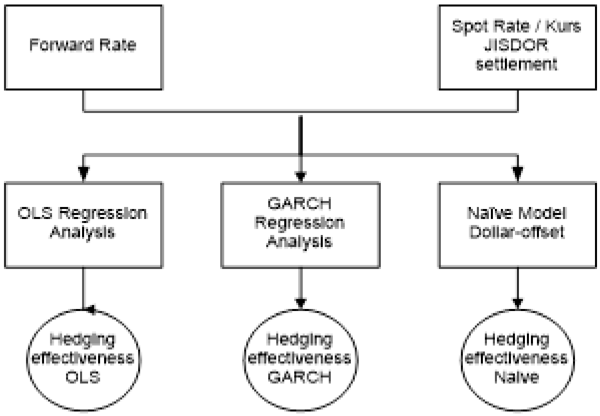

Figure 2. Research Framework

4. Results and Discussion

4.1. Ordinary Least Square (OLS)

The OLS regression analysis reveals that the `Kurs.JISDOR` (Rp) is a significant predictor of the `Forward.Rate` (Rf). The model explains 48.8% of the variance in the `Forward.Rate` ($R^2 = 0.488$), which indicates a moderate fit. The regression coefficient for `Kurs.JISDOR` is 0.672 (95% CI: 0.637, 0.708), suggesting that for every unit increase in `Kurs.JISDOR`, the `Forward.Rate` increases by 0.672 units, holding other factors constant. This coefficient is highly significant ($p < 0.01$).

Table 1. OLS Regression Descriptive Statistic

Description	N	R2	Std. Error	Coeffecient	tStat	Lower bound	Upper Bound
Intercept (Rf)	1457	0.488	369.0	4963.057	18.3	4432.014	5495.101
Kurs JISDOR (Rp)	1457	0.488	369.0	0.672	37.2	0.637	0.708

The intercept of the model is 4,963.057 (95% CI: 4,432.014, 5,494.101), also significant at the 0.01 level. The overall model is significant ($F(1, 1455) = 1387.124$, $p < 0.01$), indicating that the model provides a good fit to the data.

Residual standard error is 368.948, indicating the average distance that the observed values fall from the regression line. The effectiveness of the hedging strategy, as measured by the regression coefficient of the Kurs.JISDOR (Rp), is 0.672. This indicates that the hedging strategy using Kurs.JISDOR (Rp) is effective, as it significantly influences the Forward.Rate (Rf). In summary, the `Kurs.JISDOR` significantly predicts the `Forward.Rate`, and the model provides a reasonable fit to the data.

4.2. Generalized AutoRegressive Conditional Heteroskedasticity (GARCH)

The results of the optimal parameter estimates are summarized in Table 2.

Table 2. Optimal Parameter of GARCH

Parameter	Forward Rate (Rf)	Kurs JISDOR (Rp)
mu	0.000047	0.000009
omega	0.000000	0.000000
alpha1	0.025380	0.156650
beta1	0.966041	0.837564
shape	2.100.007	4.506.760
LogLikelihood	5.989.283	3.828.349
Akaike	-100.155	-63.989
Bayes	-99.943	-63.776
Shibata	-100.156	-63.989
Hannan-Quinn	-100.075	-63.909

The parameters indicate significant volatility dynamics for both series. For the forward rate, the high beta1 value (0.966041) suggests strong persistence in volatility. Similarly, the JISDOR shows substantial volatility persistence with a beta1 value of 0.837564. The GARCH model results indicate that both the forward rate and JISDOR exhibit significant volatility. The parameters alpha1 and beta1 are significant for both series, indicating that past shocks and past conditional variances are relevant in predicting current volatility.

Table 3. The Hedge Ratio and Effectiveness Value of GARCH

Metric	Value
Average Hedge Ratio (GARCH)	0.170837739681683
Average Hedging Effectiveness	0.0432462555939639

The average hedge ratio of approximately 0.171 suggests that for every unit of exposure in the JISDOR rate, 0.171 units should be hedged using the forward rate to minimize risk. However, the average hedging effectiveness is relatively low at 0.043, indicating limited efficiency in reducing volatility through hedging with the forward rate.

4.3. Dollar-offset

The effectiveness of the hedging strategy was evaluated using the Dollar Offset Method. The results are summarized in the Table 4.

Table 4. The Effectiveness of the Hedging Strategy using the Dollar Offset Method

Methods	Valye
Average Hedge Ratio of Dollar	0.3416
Average Hedging Effectiveness (Dollar-Offset)	19.030%

The Average Dollar-Offset Ratio of 0.3416 indicates that the change in value of the hedging instrument is approximately 34.16% of the change in value of the hedged item. Ideally, an effective hedge would have a Dollar Offset Ratio close to 1, suggesting that the changes in value between the hedging instrument and the hedged item are closely matched. A ratio significantly lower than 1, as observed here, suggests that the hedge is not fully effective in offsetting the changes in value of the hedged item.

The Hedging Effectiveness of 19.03% indicates the percentage reduction in risk due to the hedging strategy. A higher percentage would imply greater effectiveness in hedging. In this case, the effectiveness is relatively low, suggesting that the hedging strategy has only marginally reduced the risk.

4.4. Discussion

The analysis demonstrates that both the OLS and GARCH models offer insights into the effectiveness of hedging strategies. The OLS model, while straightforward, shows a significant relationship between the forward rate and Kurs JISDOR, with a substantial portion of the variance explained by the model. However, it does not account for time-varying volatility, which is crucial in financial markets.

The GARCH model, on the other hand, provides a dynamic view of volatility and better captures the risk dynamics over time. Despite its lower average hedge ratio, the GARCH model's hedging effectiveness is more nuanced, reflecting the complexities of financial time series.

Comparatively, the Dollar Offset Method, with its higher effectiveness ratio, indicates that it might be a more suitable approach for measuring hedging effectiveness in this context. However, its simplicity also means it may overlook some dynamic aspects of financial markets that GARCH can capture.

5. Conclusion

The analysis of hedging effectiveness using Ordinary Least Squares (OLS), Generalized Autoregressive Conditional Heteroskedasticity (GARCH), and the Dollar Offset Method has provided comprehensive insights into the performance of different hedging strategies for Indonesia's National Electrical Company.

The OLS model indicated a significant relationship between the forward rate and Kurs JISDOR, with an R^2 value of 0.488. This suggests that nearly half of the variability in the dependent variable can be explained by the independent variables, indicating a high level of hedging effectiveness. The GARCH model effectively captured the time-varying volatility in the financial time series, highlighting the significant influence of past shocks and variances on current volatility. Despite a relatively low average hedge ratio of 0.1708, the model demonstrated the importance of accounting for dynamic volatility in risk management, with an average hedging effectiveness of 4.32%. The Dollar Offset Method showed a higher average effectiveness ratio of 19.03%, suggesting that it provides a more effective hedge in this context compared to the GARCH model. The OLS model's hedging effectiveness of 48.8% was the highest, indicating that it might be the most suitable approach for this data set.

The Dollar Offset Method, while simple and effective, may overlook the intricacies of financial market behaviors that the GARCH model captures. Combining both methods could enhance the robustness of hedging strategies. The findings suggest that while simpler methods like the Dollar Offset can be effective, more sophisticated models such as GARCH should be considered for a comprehensive understanding and management of financial risks. The high R^2 value from the OLS model suggests its strong potential for effective hedging in this specific context.

Future research could Expand the source of data from more corporate in the same industries and data set from diverse economic conditions and longer time periods could provide further insights into the effectiveness of different hedging strategies.

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