BAREKENG: Journal of Mathematics and Its Applications
March 2025 Volume xx Issue xx Page xxx–xxx
P-ISSN: 1978-7227 E-ISSN: 2615-3017
https://doi.org/10.30598/barekengxxxxxxxxxxxxx

THE APPLICATION OF LASSO AND RIDGE REGRESSION METHODS IN ANALYZING THE FACTORS INFLUENCING THE USD/IDR EXCHANGE RATE

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Article History:

Received: date month year
Revised: date month year
Accepted: date month year
Published: date month year

Keywords:

LASSO regression;
Multicollinearity;
Ridge regression;
USD/IDR exchange rate.

ABSTRACT

This study aims to analyze the factors influencing the USD/IDR exchange rate by applying the Least Absolute Shrinkage and Selection Operator (LASSO) and ridge regression methods, and to compare the performance of both approaches. The data consist of Indonesian and global macroeconomic indicators from 2010 to 2024, including inflation, interest rates, money supply, foreign exchange reserves, stock indices, and others. The Ordinary Least Squares (OLS) method was initially used as a baseline comparison but revealed multicollinearity among the predictor variables, with 8 out of 15 exhibiting a Variance Inflation Factor (VIF) greater than 10. Consequently, LASSO and ridge regression were selected for their ability to address multicollinearity and regularize regression coefficients. The results show that the LASSO model produces lower Root Mean Squared Error (RMSE) and Mean Absolute Percentage Error (MAPE), along with a higher coefficient of determination (R^2), compared to the ridge model. LASSO also retains fewer significant variables, indicating greater effectiveness in variable selection and improved model interpretability. Simultaneously, there are many variables that influence the USD/IDR exchange rate, but the ones with the largest coefficients are foreign exchange reserves with a negative influence and broad money supply (M2) with a positive influence. Meanwhile, Indonesia's trade balance and narrow money supply (M1) do not have a significant impact. These findings underscore the importance of economic policies aimed at managing foreign exchange reserves and broad money supply (M2) to maintain USD/IDR exchange rate stability. The study is expected to contribute to the formulation of effective monetary and fiscal policies in Indonesia.

How to cite this article:

First author, second author, etc., "TITLE OF ARTICLE", *BAREKENG: J. Math. & App.*, vol. xx, iss. xx, pp. xxx-xxx, Month, Year.

Journal homepage: *https://ojs3.unpatti.ac.id/index.php/barekeng/*
Journal e-mail: *barekeng.math@yahoo.com; barekeng.journal@mail.unpatti.ac.id*

Research Article · Open Access

1. INTRODUCTION

The dominance of the United States Dollar (USD) as a global currency is the result of various strategic decisions and historical conditions. One of the most influential moments occurred in 1971, when President Richard Nixon's administration unilaterally terminated the gold standard policy for the USD in the international monetary system. This decision marked the end of the Bretton Woods system and turned the USD into a fiat currency whose value is determined by market forces rather than gold reserves [1]. In addition, USD dominance was further reinforced during World War II, when the United States served as the primary supplier of weaponry to European countries. In order to purchase arms from the United States, the Allied countries had to convert much of their gold reserves into USD. This process solidified the USD's status as the world's international currency.

According to data from the International Monetary Fund (IMF), approximately 57.3% of global foreign exchange reserves are currently held in USD [2], and over 80% of global trade is conducted in USD, making it the primary benchmark in the international financial system. Due to this dominance, the exchange rate of a currency against the USD serves as an important indicator of a country's economic strength and stability. For Indonesia, the exchange rate of the USD against the Indonesian Rupiah (IDR) is especially vital, as the country heavily relies on commodity exports, foreign debt, and foreign capital flows [3]. Exchange rate fluctuations significantly affect the price of imported goods, public purchasing power, and the current account balance [4]. Thus, movements in the USD/IDR exchange rate have become a central focus for market participants and monetary policymakers.

To understand the dynamics of the USD/IDR exchange rate, several economic factors may play determining roles. These include inflation, the benchmark interest rate, gross domestic product (GDP) growth, the trade balance, foreign exchange reserves, and the prices of Indonesia's main export commodities such as crude palm oil (CPO) and coal. Additionally, financial indicators such as the broad money supply (M2) and the Jakarta Composite Index (JCI) can also reflect investor sentiment toward Indonesia's economy. Prior studies have shown that economic variables such as inflation, exports, imports, and foreign reserves significantly influence the USD/IDR exchange rate [5]. However, other studies have concluded that while money supply, interest rates, inflation, and imports simultaneously affect the USD/IDR exchange rate, inflation does not have a partial significant effect [6]. These inconsistent findings raise further questions that warrant deeper investigation.

In previous research, the relationship between the exchange rate and these variables has generally been analyzed using linear regression approaches, particularly multiple linear regression [5]. However, multiple linear regression has several limitations, including critical assumptions such as the absence of multicollinearity, that is predictor variables must be mutually uncorrelated [7]. It also assumes homoscedasticity and normally distributed errors. When these assumptions are violated, the model may become invalid and the estimates inefficient [8]. In reality, many economic variables are structurally interrelated. For example, inflation is often correlated with interest rates [9], and the trade balance is closely linked to foreign exchange reserves [10]. These interdependencies lead to multicollinearity, which can undermine the stability of coefficient estimates. Additionally, including too many variables without proper selection can lead to overfitting, where the model fits the training data too closely and performs poorly on unseen data [11].

To overcome these challenges, regularized regression methods have been developed, namely Least Absolute Shrinkage and Selection Operator (LASSO) and ridge regression. LASSO employs a penalty on the absolute values of the regression coefficients, which not only reduces overfitting but also performs automatic variable selection by shrinking some coefficients to zero [12]. Ridge regression adds a penalty on the squared values of the coefficients in its objective function, thereby constraining their magnitude and reducing model variance to handle multicollinearity [12]. As a result, LASSO excels at creating simpler, more interpretable models, while ridge regression provides more stable coefficient estimates in the presence of highly correlated predictors.

LASSO and ridge regression have been widely used in various fields, including data science, finance, bioinformatics, psychology, and public health. However, their application in the context of analyzing the USD/IDR exchange rate remains limited, especially in studies that use a comprehensive set of Indonesia's macroeconomic data. Therefore, it is important to explore the potential of these methods in building more accurate and reliable predictive models for exchange rates.

This research aims to analyze the economic factors that influence the USD/IDR exchange rate using LASSO and ridge regression methods. It also seeks to compare the predictive performance of both models using statistical evaluation metrics such as Root Mean Square Error (RMSE), Mean Absolute Percentage Error (MAPE), and coefficient of determination (R^2). The findings of this study are expected to provide practical contributions for identifying the main drivers of currency fluctuations in Indonesia and to serve as a reference for policymakers and academics in developing regularized econometric models.

2. RESEARCH METHODS

2.1 Data and Research Variable

This study utilizes data consisting of response variables and inde variables, which are secondary data obtained from several official sources such as investing.com, tradingeconomics.com, bloomberg.com, Badan Pusat Statistik (BPS), Bank Indonesia (BI), and Federal Reserve Economic Data (FRED). The data are in monthly frequency, covering the period from January 2010 to December 2024, resulting in 180 observations for each variable. Quarterly data are converted into monthly data by assigning the same value from the corresponding quarter to each month.

The response variable in this study is the USD/IDR exchange rate, while the predictor variables include various macroeconomic indicators that are theoretically expected to influence the exchange rate. The description of each variable is presented in the **Table 1** below:

Table 1. Table of Variable

Variable	Description	Unit
Y	USD/IDR exchange rate	Rupiah
X_1	Monthly inflation rate (M-to-M)	Percent
X_2	Bank Indonesia's interest rate	Percent
X_3	The Federal Reserve's interest rate	Percent
X_4	Indonesia's trade balance	Billion USD
X_5	Foreign exchange reserves	Billion USD
X_6	Export value	Billion USD
X_7	Import value	Billion USD
X_8	Narrow money supply (M1)	Trillion Rupiah
X_9	Broad money supply (M2)	Trillion Rupiah
X_{10}	Jakarta Composite Index (JCI)	Rupiah
X_{11}	Indonesia's external debt	Billion USD
X_{12}	Indonesia's GDP annual growth rate	Percent
X_{13}	Crude oil price	USD
X_{14}	Crude Palm Oil (CPO) price	Ringgit
X_{15}	Coal price	USD

Each predictor variable needs to be standardized beforehand due to the different units of measurement. This is done to ensure that all predictor variables used in this study have a proportional contribution in the model. Consequently, the processes of predictor selection and multicollinearity handling can be carried out optimally and without bias toward variables with larger scales. Standardization is performed using the following formula:

$$z = \frac{x - \bar{x}}{s} \tag{1}$$

where

x : actual value of the predictor variable

$\bar{x}$: mean of the predictor variable

s : standard deviation of the predictor variable.

Following standardization, the data are modeled using the Ordinary Least Squares (OLS) method, which minimizes the Residual Sum of Squares (RSS) through the following objective function [13]:

$$\min_{\beta} \sum_{i=1}^{n} \left(y_i - \beta_0 - \sum_{j=1}^{p} \beta_j x_{ij} \right)^2 \tag{2}$$

where

y_i : actual value of the response variable at observation i
x_{ij} : value of the j-th predictor for observation i
β_0 : intercept term
β_j : regression coefficient for predictor j
p : number of predictors
n : number of observations.

Subsequently, an assumption test is conducted on the OLS model, particularly to detect multicollinearity. One common method is to calculate the Variance Inflation Factor (VIF) using the following formula [12]:

$$VIF = \frac{1}{1 - R^2} \tag{3}$$

for R^2 calculated using following formula:

$$R^2 = 1 - \frac{\sum_{i=1}^{n}(y_i - \hat{y}_i)^2}{\sum_{i=1}^{n}(y_i - \bar{y})^2} \tag{4}$$

where

$\hat{y}_i$: predicted value of the response variable at observation i
$\bar{y}$: mean of all actual value y_i.

If the VIF > 10, multicollinearity is considered present. To address this issue, LASSO and ridge regression models are applied. In the final stage, the data is returned to its original scale to interpret the estimated regression coefficients.

2.2 Least Absolute Shrinkage and Selection Operator (LASSO) Regression

One of the main objectives of linear regression analysis is to examine how predictor variables influence the response variable. OLS is the most commonly used method, estimating regression coefficients by minimizing the sum of squared residuals between actual and predicted values. This method assumes no heteroskedasticity, no autocorrelation, and no multicollinearity [14].

However, in practice, these assumptions are often violated. A common issue is multicollinearity, where strong linear relationships among predictor variables lead to inflated and unstable variance in the parameter estimates, resulting in reduced prediction accuracy and interpretability.

To address this limitation, regularization techniques such as LASSO regression have been developed. Introduced by Tibshirani in 1996 [15], LASSO selects variables by shrinking the regression coefficients of highly correlated predictors toward zero, thereby automatically identifying the most relevant variables while handling multicollinearity [13]. The LASSO coefficient, $\hat{\beta}_{\lambda}^{L}$, minimizes the following objective function:

$$\min_{\beta} \left\{ \sum_{i=1}^{n} \left(y_i - \beta_0 - \sum_{j=1}^{p} \beta_j x_{ij} \right)^2 + \lambda \sum_{j=1}^{p} |\beta_j| \right\} \tag{5}$$

In the above equation, $\lambda \geq 0$ is regularization parameters. The shrinkage penalty $\sum_{j=1}^{p}|\beta_j|$ in LASSO tends to set some coefficients exactly to zero as λ increases, which facilitates variable selection and leads to a more interpretable model [13].

To determine the optimal value of the tuning parameter λ, rolling window cross-validation is often used, particularly in the context of time series data such as the USD/IDR exchange rate. In this procedure, the data is divided into several sequential segments based on time. The model is repeatedly trained on a fixed-size training window (for example, over T time units), and then validated using data from the next time unit. The training window is then shifted forward step by step (rolled) for each iteration. At each iteration, the model is trained only on the most recent data within the window and tested on the data immediately following it. The prediction error, such as RMSE, is calculated for each iteration and then averaged across all iterations for each candidate value of λ. The optimal λ is the one that yields the lowest average prediction error. This approach provides a reliable method for balancing model complexity and prediction accuracy while helping to prevent overfitting.

2.3 Ridge Regression

Ridge regression, introduced by Hoerl and Kennard, offers an alternative solution to multicollinearity in linear regression models [16]. Ridge regression modifies the OLS method by producing biased estimators with lower variance, improving model stability and prediction accuracy. To prevent overfitting and reduce model complexity, ridge regression includes a regularization term that penalizes large coefficient values in the objective function [17]. The ridge regression coefficient, $\hat{\beta}_\lambda^R$, minimizes the following objective function:

$$\min_{\beta}\left\{\sum_{i=1}^{n}\left(y_i-\beta_0-\sum_{j=1}^{p}\beta_j x_{ij}\right)^2+\lambda\sum_{j=1}^{p}\beta_j^2\right\} \tag{6}$$

The regularization parameter $\lambda \geq 0$ controls the degree of shrinkage: the larger the λ, the smaller the coefficients β_j become, thus reducing model complexity and mitigating overfitting. Unlike LASSO which tends to set some coefficients exactly to zero, ridge regression retains all predictors in the model, making it suitable when the predictors are highly correlated [18]. The optimal value of λ in ridge regression is typically selected using rolling window cross-validation, similar to LASSO. This method ensures a balance between model bias and variance.

2.4 Model Evaluation

Model performance is assessed using the following evaluation metrics:

2.4.1 Root Mean Square Error (RMSE)

RMSE is a metric used to quantify the average squared error between predicted and actual values. It is calculated by taking the square root of the mean squared differences between predicted and observed values. Lower RMSE values indicate better model performance in terms of accuracy [19]. The formula for RMSE is as follows:

$$RMSE=\sqrt{\frac{1}{n}\sum_{i=1}^{n}(y_i-\hat{y}_i)^2}\,. \tag{7}$$

2.4.2 Mean Absolute Percentage Error (MAPE)

MAPE measures the average absolute percentage error between predicted and actual values. It is useful for interpreting the relative accuracy of model estimates. A lower MAPE value indicates that the predicted values closely approximate the actual observations [20]. The MAPE method can be calculated using the following formula:

$$MAPE=\frac{1}{n}\sum_{i=1}^{n}\left|\frac{y_i-\hat{y}_i}{y_i}\right|\times 100\%. \tag{8}$$

2.4.3 Coefficient of Determination (R^2)

Coefficient of determination represents the proportion of variance in the response variable that can be explained by the predictor variables in a regression model. A higher R^2 value suggests stronger explanatory power, while a lower value indicates limited ability of the model to capture underlying patterns [21]. For calculate R^2 use **Equation (4)**.

3. RESULTS AND DISCUSSION

3.1 Multicollinearity Analysis Using the Variance Inflation Factor (VIF)

From an economic perspective, the USD/IDR exchange rate is a multidimensional issue influenced by many interrelated factors. Before building the LASSO and ridge regression models, a preliminary analysis was carried out to detect the possibility of multicollinearity between predictor variables. In this study, the multicollinearity test was conducted using the VIF method based on **Equation (3)**. A VIF value greater than 10 indicates the presence of multicollinearity among variables. The VIF values for all predictor variables used in this study can be seen in **Table 2**.

Table 2. VIF Value for All Predictor Variables

Variable	VIF Value
X_1	1.20
X_2	2.87
X_3	10.30
X_4	28.68
X_5	8.94
X_6	146.85
X_7	80.53
X_8	547.66
X_9	769.48
X_{10}	18.53
X_{11}	71.54
X_{12}	3.07
X_{13}	4.37
X_{14}	7.61
X_{15}	3.97

The VIF test results show that there are eight predictor variables that have a high correlation level with VIF > 10, namely X_3, X_4, X_6, X_7, X_8, X_9, X_{10}, dan X_{11}. This condition can create difficulties in modeling using ordinary linear regression. Therefore, in the next modeling stage, regression methods that can handle multicollinearity and perform regularization were used, namely the LASSO and ridge regression methods. These methods are used with the aim of producing a more stable and interpretable model in identifying factors that influence the USD/IDR exchange rate. In the modeling process of both methods, the λ parameter was optimized using the minimum RMSE value.

3.2 LASSO Regression Results

The LASSO regression modeling process was carried out using RStudio software by setting set.seed(123). A rolling window cross-validation process was then carried out to obtain the best λ value, which was then used in building the LASSO model.

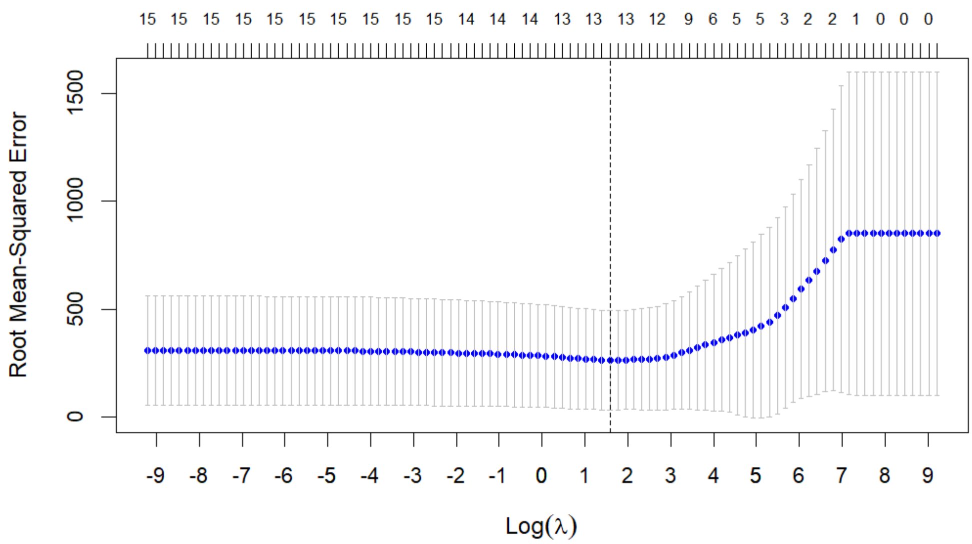

Figure 1. Cross Validation of λ Regularization Parameters in LASSO Regression

Figure 1 shows the relationship between the value of the parameter λ and the RMSE value for LASSO regression. The blue dots represent the average RMSE for each λ value, while the gray vertical lines at each blue dot indicate the standard error. It can be seen that as $\log(\lambda)$ increases, the RMSE tends to increase due to the stronger regularization effect, which may lead to a simpler model and the elimination of some variables. The dashed vertical line on the graph indicates the optimal λ value, which is the λ with the minimum RMSE. The model with this λ is the most accurate and has good predictive performance.

From the results obtained, the best λ value for the LASSO regression model is 4.86 with an RMSE of 422.62. This relatively high RMSE is due to the fact that the value is on the same scale as the response variable (Y). Thus, to assess whether this model is good, the RMSE value will later be compared with the ridge regression model, which uses the same scale for the response variable. From the total of 15 predictor variables, the LASSO model automatically removed two variables, namely X_4 and X_8, due to their insignificant contributions to the prediction results. Therefore, only 13 variables were used in the model. This shows that the LASSO method not only improves predictive accuracy but also performs variable selection automatically. As a result, the model produced is more efficient, stable, and easier to interpret without sacrificing predictive ability.

3.3 Ridge Regression Results

The ridge regression modeling process was carried out using RStudio software by setting set.seed(123). A rolling window cross-validation process was then carried out to obtain the best λ value, which was then used in building the ridge model.

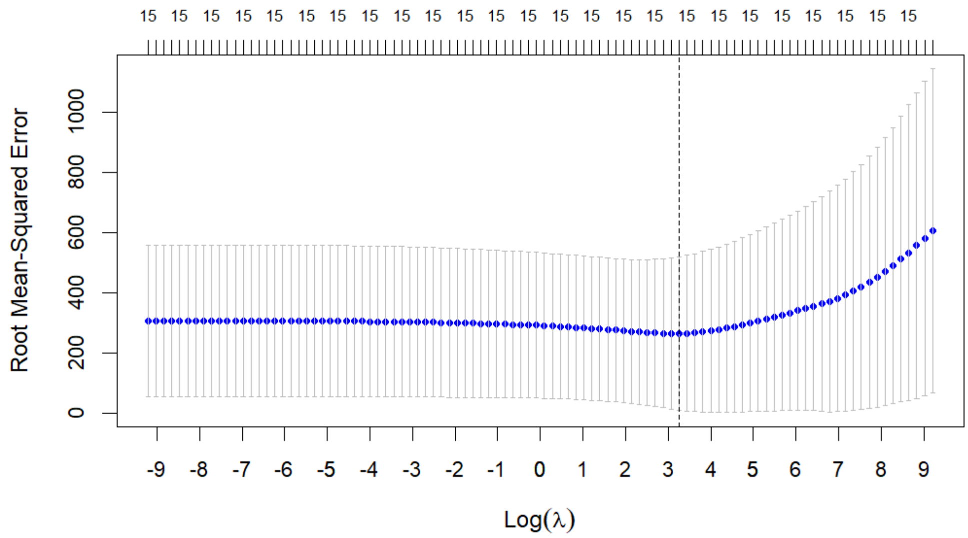

Figure 2. Cross Validation of λ Regularization Parameters in Ridge Regression

Figure 2 shows the relationship between the value of the parameter λ and the RMSE value for ridge regression. The blue dots represent the average RMSE for each λ value, while the gray vertical lines at each blue dot indicate the standard error. It can be seen that as $\log(\lambda)$ increases, the RMSE tends to increase due to the stronger regularization effect. The dashed vertical line on the graph indicates the optimal λ value, which is the λ with the minimum RMSE. Similar to the LASSO regression modeling, the model with this λ is the most accurate and has good predictive performance.

According to the analysis, the optimal λ value for ridge regression was 25.95, with an RMSE of 433.12. Unlike LASSO, which can eliminate variables by shrinking coefficients to zero, ridge regression merely shrinks the coefficients proportionally without removing any variables from the model. This leads to more stable parameter estimation, although it does not perform explicit variable selection.

3.4 Regression Coefficients and Evaluation Metrics

To find out the extent to which macroeconomic factors influence the USD/IDR exchange rate, this study used penalized regression methods. Two methods were applied, namely ridge and LASSO regression. Ridge regression retains all variables in the model by reducing the size of the coefficients to address multicollinearity. Meanwhile, LASSO not only shrinks the coefficients but also removes variables that have little effect. As a result, the LASSO model is more concise and only focuses on variables that are truly relevant in explaining the USD/IDR exchange rate dynamics.

Table 3. Coefficient Values for Each Variable

Variable	Description	LASSO	Ridge
Intercept	-	1.29×10^4	1.29×10^4
X_1	Monthly inflation rate (M-to-M)	-7.83×10^1	-8.64×10^1
X_2	Bank Indonesia's interest rate	3.16×10^2	3.29×10^2
X_3	The Federal Reserve's interest rate	-3.46×10^2	-3.33×10^2
X_4	Indonesia's trade balance	-	9.85×10^0
X_5	Foreign exchange reserves	-6.11×10^2	-5.85×10^2
X_6	Export value	-9.36×10^1	-1.18×10^2
X_7	Import value	-1.11×10^1	-1.11×10^1
X_8	Narrow money supply (M1)	-	4.39×10^2
X_9	Broad money supply (M2)	1.91×10^3	1.25×10^3
X_{10}	Jakarta Composite Index (JCI)	3.20×10^2	4.33×10^2
X_{11}	Indonesia's external debt	1.02×10^3	1.08×10^3
X_{12}	Indonesia's GDP annual growth rate	1.37×10^2	1.14×10^2
X_{13}	Crude oil price	-3.56×10^2	-3.94×10^2
X_{14}	Crude Palm Oil (CPO) price	-2.15×10^2	-1.94×10^2
X_{15}	Coal price	7.27×10^1	8.96×10^1

Table 3 shows that the LASSO model eliminated variables such as Indonesia's trade balance and M1 money supply due to their limited contribution, whereas ridge regression retained all variables with more moderate coefficients. Several variables including the Bank Indonesia's interest rate, the Federal Reserve's interest rate, foreign exchange reserves, M2 money supply, JCI, Indonesia's external debt, Indonesia's GDP annual growth rate, crude oil prices, and CPO prices exhibited large coefficients in both models, indicating a significant influence on the USD/IDR exchange rate. Meanwhile, variables such as inflation, the Federal Reserve's interest rate, foreign exchange reserves, export value, import value, crude oil prices, and CPO prices consistently demonstrated negative effects on the exchange rate across both models. The consistency in coefficient direction between the two methods reinforces the reliability of the relationships among variables and strengthens the interpretation of the most influential economic factors.

Table 4. Comparison of Model Evaluations Values

Model	RMSE	MAPE (%)	R^2
LASSO	422.62	2.62173	0.96667
Ridge	433.12	2.65762	0.96499

In this study, the best model was determined based on the smallest RMSE value as the main indicator of predictive accuracy. The evaluation results in **Table 4** show that the LASSO regression model has a lower RMSE compared to ridge regression. In addition, it also has a lower MAPE and a higher R^2 value. These results indicate that the LASSO model is better at capturing data patterns and provides more accurate predictions. The LASSO model is also more efficient because it only includes the most influential variables in the model.

$$\hat{Y} = 1.29 \times 10^4 - (7.83 \times 10^1)X_1 + (3.16 \times 10^2)X_2 - (3.46 \times 10^2)X_3 - (6.11 \times 10^2)X_5 - (9.36 \times 10^1)X_6 - (1.11 \times 10^1)X_7 + (1.91 \times 10^3)X_9 + (3.20 \times 10^2)X_{10} + (1.02 \times 10^3)X_{11} + (1.37 \times 10^2)X_{12} - (3.56 \times 10^2)X_{13} - (2.15 \times 10^2)X_{14} + (7.27 \times 10^1)X_{15} \quad (9)$$

Equation (9) presents the best model derived from the LASSO regression method, which retained only variables with significant contributions to the USD/IDR exchange rate, while eliminating Indonesia's trade balance and M1 money supply through coefficient shrinkage to zero. The remaining variables in the model include inflation, Bank Indonesia's interest rate, the Federal Reserve's interest rate, foreign exchange reserves, export value, import value, M2 money supply, JCI, Indonesia's external debt, Indonesia's GDP annual growth rate, and commodity prices such as crude oil, CPO, and coal. Most of these variables have negative coefficients, indicating that increases in their values tend to reduce the USD/IDR exchange rate. With a simpler model structure and higher predictive accuracy, the LASSO regression model proves to be the most suitable approach for analyzing the dynamics of the USD/IDR exchange rate in this study.

4. CONCLUSION

This study clearly demonstrates that the application of penalized regression methods, particularly LASSO and ridge regression, is a relevant and effective approach in identifying and analyzing the factors that influence the USD/IDR exchange rate. In the context of multicollinearity issues, the use of these two methods allows the construction of more stable and interpretable predictive models compared to conventional regression techniques. Based on the analysis results over the observation period, several conclusions can be drawn as follows:

a. The LASSO regression model shows better performance compared to ridge regression in terms of predictive accuracy, as indicated by lower RMSE and MAPE values, as well as a higher R^2 value. This suggests that the LASSO regression method is more effective in performing variable selection and reducing model complexity while maintaining accuracy.

b. The LASSO regression results indicate that increases in the inflation rate, the Federal Reserve's interest rate, foreign exchange reserves, export and import values, crude oil prices, and CPO prices simultaneously contribute to a depreciation of the USD/IDR exchange rate, with foreign exchange reserves having the largest coefficient.

c. The LASSO regression results also show that increases in Bank Indonesia's interest rate, M2 money supply, JCI, Indonesia's external debt, Indonesia's GDP annual growth rate, and coal prices simultaneously lead to an appreciation of the USD/IDR exchange rate, with M2 money supply having the largest coefficient.

d. Indonesia's trade balance and M1 money supply do not have a significant effect on the USD/IDR exchange rate, as indicated by the LASSO regression results.

The implications of these findings are particularly important for fiscal and monetary policymakers in formulating strategic policies to maintain the stability of the USD/IDR exchange rate and to prevent economic volatility. By integrating modern statistical approaches into economic analysis, this study opens avenues for the development of more accurate and adaptive predictive models in response to global economic dynamics. These results are expected to serve as a valuable reference for economic policymakers and market participants in understanding the dynamics of the USD/IDR exchange rate and in formulating more targeted policies.

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