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Examining The Relationship Between Money Supply and Banking Credit on Interest Rate Fluctuation

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Abstract

This study examines the relationship between money supply, banking credit, and interest rate fluctuations in Indonesia, an economy characterized by a bank-based financial system. The interaction between monetary policy, money supply, and bank credit plays a critical role in influencing interest rates, which in turn affect the broader economy. Using data from 2010 to 2024, the research applies an econometric approach based on the Autoregressive Distributed Lag (ARDL) model to analyze the short-term and long-term dynamics between these variables. The findings suggest that interest rate fluctuations are significantly influenced by bank credit, while the effects of money supply are less pronounced in the short run. The study contributes to understanding the mechanisms through which monetary policy affects the economy and offers insights for policymakers in Indonesia, particularly in maintaining monetary and financial stability.

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Introduction

The movement of interest rates is influenced by the interaction between money supply and banking credit, not only by changes in the central bank's policy rate. The effectiveness of monetary policy depends on how changes in liquidity affect banks' lending behavior and market interest rates. This mechanism, known as the *lending channel of monetary policy*, plays an important role in maintaining macroeconomic stability, especially in countries with bank-based financial systems like Indonesia.

Several studies show that the transmission of monetary policy is not always stable, and its strength depends on economic conditions. Alpanda, Granziera, and Zubairy (2021) found that monetary policy shocks have stronger effects during economic downturns and weaker effects when interest rates are high. Bosshardt et al. (2024) also showed that monetary tightening in the United States, which increased mortgage rates, reduced credit availability and raised borrowing costs, especially for households with high debt levels. These findings suggest that the relationship between money, credit, and interest rates is dynamic and depends on the business cycle.

In Indonesia, the banking sector plays a key role in transmitting monetary policy. Naiborhu (2020) found that credit growth responds to monetary policy through the lending channel, but the effect depends on banks' capital and liquidity conditions. Large and well-capitalized banks can absorb policy rate increases better than small or less-liquid banks. This means that changes in money supply may affect interest rate fluctuations indirectly through banks' lending capacity.

Other studies also show that unconventional monetary policies have made the transmission process more complex. Basten and Mariathasan (2023) found that negative interest rate policy can weaken the link between policy rates and deposit or lending rates, causing banks to shift their portfolios toward riskier assets. Meanwhile, Hirota (2023) explained that a large increase in money supply can create asset price distortions and weaken the connection between interest rates, credit, and the real economy. These situations show that too much monetary expansion can create instability in financial markets.

Based on these findings, it can be concluded that interest rate fluctuations in Indonesia are not only caused by monetary policy, but also by changes in money supply and bank credit. However, there is still limited empirical research that examines the relationship between these three variables together, especially in developing countries like Indonesia.

Therefore, this study aims to examine the relationship between money supply and banking credit on interest rate fluctuation in Indonesia. The data used in this study include:
(1) Interest rate data as the dependent variable (Y), obtained from the Central Bureau of Statistics (BPS), accessed on September 30, 2025; and
(2) Money supply (M2) and banking credit data as independent variables (X_1 and X_2), obtained from the Indonesian Financial and Economic Statistics (SEKI), Bank Indonesia, accessed on September 29, 2025.

This study uses an econometric approach with a simultaneous system to analyze whether interest rate fluctuations in Indonesia are more influenced by the liquidity effect (*money view*) or by banks' lending behavior (*credit view*). The results are expected to provide useful insights for Bank Indonesia in designing policies to maintain monetary and financial stability. The relationship between monetary policy, banking credit, and interest rates has long been a focal point of economic research, especially in developing economies like Indonesia. Several studies have explored how changes in the money supply can influence interest rates and banking credit behavior. For instance, Syamad and Handoyo (2023) analyzed the effects of money supply on exchange rates in Indonesia using the ARDL model, highlighting how monetary policy interventions impact the economy in both short-term and long-term scenarios. This aligns with the work by Amalia and Suriani (2023), who examined how interest rate policies and liquidity levels affect banking credit risk in Indonesia. Their study indicated that in the short term, policy interest rates and money supply negatively affect bank credit risk, though the long-term effects differ, with money supply showing no significant impact.

Similarly, studies such as those by Alpanda, Granziera, and Zubairy (2021) demonstrate the dynamic nature of monetary transmission mechanisms, where the effectiveness of monetary policy can vary depending on the economic cycle. In the context of Indonesia, where the banking sector plays a crucial role in economic stability, understanding the interplay between money supply, banking credit, and interest rates is essential for effective policy formulation (Naiborhu, 2020). These findings suggest that fluctuations in interest rates in Indonesia are not solely driven by central bank policy, but also by changes in liquidity and bank lending behavior.

Method

This study uses secondary data for the period from 2010 to 2024, sourced from Bank Indonesia. The analysis focuses on three main variables: interest rate (IR), money supply (M2), and bank credit (CREDIT). All variables are transformed using natural logarithms to reduce skewness and facilitate interpretation. The transformation allows for easier analysis of elasticities, making the results more meaningful in terms of percentage changes and relationships between the variables. Specifically, the interest rate, money supply, and bank credit are expressed as:

$$LIR = \log(IR),\ D\_LM2 = \log(M2),\ D\_LCREDIT = \log(CREDIT)$$

Following the ADF (Augmented Dickey-Fuller) test for unit roots, variables that were found to be non-stationary at their levels were then differenced to make them stationary. Hence, D_LM2 and D_LCREDIT represent the first differences of the log-transformed variables, ensuring that these variables are now stationary and suitable for inclusion in the ARDL model.

The use of log transformation helps stabilize the variance of the variables, making them more suitable for time series modeling and improving the accuracy of estimates, especially in models like ARDL. By using the log transformation, we can analyze the variables in terms of their percentage changes, which allows for more straightforward interpretation of the dynamic relationships in the model.

Stationarity Test

Before proceeding with further analysis using the ARDL model, the first step is to test the stationarity of each variable used in this study. The Augmented Dickey-Fuller (ADF) test is commonly employed to test for the presence of a unit root in the data, which determines whether the series is stationary or non-stationary. The ADF test can be expressed in the following regression model:

$$\Delta Yt = \alpha + \beta t + \gamma Y_{t-1} + \sum_{i=1}^{p} \delta i\ \Delta Y_{t-1} + \epsilon_t$$

Where:

Y_t is the variable under test (e.g., LIR, M2, and LCREDIT),

ΔY_t is the first difference of the variable Y_t,

α is the constant (intercept),

β is the coefficient for the trend component,

γ is the coefficient for the lagged value Y_{t-1}, representing the previous value of the variable,

$\sum_{i=1}^{p} \delta i \ \Delta Y_{t-1} + \epsilon_t$ represents the lagged differences of the variable,

ϵ_t is the error term.

The null hypothesis of the ADF test is that the series contains a unit root (i.e., the series is non-stationary), and the alternative hypothesis is that the series is stationary (i.e., no unit root). The decision rule is based on the p-value obtained from the test: if the p-value is less than 0.05, the null hypothesis is rejected, indicating that the series is stationary. Conversely, if the p-value is greater than 0.05, the null hypothesis cannot be rejected, implying that the series is non-stationary, and differencing should be performed to make the series stationary.

The procedure in this study begins with the logarithmic transformation of the variables M2, LCREDIT, and IR to reduce skewness and make the variables more linear. After the log transformation, the ADF test is conducted at the first level to check if the data is stationary. If the variables are found to be non-stationary at the first level, differencing is applied to make them stationary, and the ADF test is re-conducted to check if the differenced variables are now stationary. Variables that are stationary will then be used in the ARDL model for further analysis.

Cointegration Test

To examine the long-run relationships between the variables in the ARDL model, the **Bounds Test** for cointegration is applied. This test is used when the variables are integrated of order 0 (I(0)) or order 1 (I(1)), but not I(2). The general form of the cointegration equation in the ARDL framework is as follows:

$$\Delta Yt = \alpha + \sum_{i=1}^{p} \beta_i \Delta X_{t-1} + \gamma Y_{t-1} + \delta X_{t-1} + \epsilon_t$$

Where:

Y_t is the dependent variable (e.g., LIR),

X_t represents the independent variables (e.g., M2, LCREDIT),

ΔYt and ΔXt are the first differences of the dependent and independent variables respectively,

γ and δ are the coefficients for the lagged level variables Y_{t-1} and X_{t-1}

ϵ_t is the error term.

The Bounds Test assesses the significance of the lagged level terms Y_{t-1} and X_{t-1} to determine whether a long-run relationship exists. The F-statistic is calculated and compared to critical values:

- If the F-statistic is greater than the upper bound, cointegration is present, indicating a long-run relationship.
- If the F-statistic is less than the lower bound, there is no cointegration.
- If the F-statistic falls between the bounds, the result is inconclusive.

This test is crucial for determining whether the variables are cointegrated and whether a long-run relationship exists, allowing further analysis of the short-run and long-run dynamics in the ARDL model.

Lag Optimum

The optimal lag length for the ARDL model is determined using the Akaike Information Criterion (AIC), which balances the goodness of fit with the complexity of the model. The AIC is calculated as:

$$AIC=ln(L)+2k$$

Where L is the likelihood of the model, and k is the number of parameters. The optimal lag length is selected by estimating the ARDL model for different lags and choosing the one with the lowest AIC. This ensures the best fit without overfitting.

To determine the lag length, the ARDL model is estimated for different lag orders, and the AIC values are compared. The lag with the lowest AIC is selected, and the final model is estimated using this optimal lag length.

ARDL Model Specification

This study employs the Autoregressive Distributed Lag (ARDL) model to examine the relationship between interest rate (LIR), money supply (LM2), and bank credit (LCREDIT). The ARDL model is appropriate as it can handle variables with different integration orders (I(0) and I(1)) and allows for the estimation of both short-run and long-run dynamics.

The ARDL model is specified as:

$$LIR_t = \alpha + \sum_{i=1}^{p} \beta_i \, LRI_{t-i} + \sum_{j=0}^{q} \gamma \, \Delta D_j LM2_{t-j} + \sum_{k=0}^{r} \delta k \, \Delta DLCREDITt_{-k} + \varepsilon_t$$

Where:

LIRt is the dependent variable (interest rate), α is the constant term, β_i, γ_j, δ_k are the coefficients of the lagged values of LIR, D_LM2, and D_LCREDIT respectively, ε_t is the error term at time t, *p, q, and r* represent the lag lengths for LIR, D_LM2, and D_LCREDIT, respectively. In this model, D_LM2 and D_LCREDIT represent the first differences of the log-transformed variables LM2 and LCREDIT. These differenced variables are used to ensure stationarity before estimation.

The lag length for each variable is determined using the Akaike Information Criterion (AIC), which results in the optimal lag structure: ARDL(3, 0, 1). This means 3 lags for LIR, 0 lags for D_LM2, and 1 lags for D_LCREDIT.

ARDL Bounds Test for Cointegration

The Bounds Test involves estimating an unrestricted error correction model (ECM) and testing the null hypothesis of no cointegration. This is done by comparing the calculated F-statistic with the critical values from the Bounds Test table. The null hypothesis of no cointegration is rejected if the F-statistic is greater than the upper bound critical value at a given level of significance (typically 5%).

The F-statistic is computed as:

$$F = \frac{SSRrestricted - SSRunrestricted}{SSRunrestricted/(n-k)}$$

Where:

$SSR_{restricted}$ is the sum of squared residuals from the restricted model (without cointegration), $SSR_{unrestricted}$ is the sum of squared residuals from the unrestricted model (with) cointegration), n is the number of observations, k is the number of parameters estimated.

Diagnostic Tests for ARDL Model

Autocorrelation is tested using the Breusch-Godfrey LM Test, which checks whether the residuals are correlated with their own past values. If autocorrelation is present, it suggests that the model has missed some dynamic relationships, leading to inefficient and biased coefficient estimates. A p-value less than 0.05 from this test indicates the presence of autocorrelation, while a p-value greater than 0.05 suggests no significant autocorrelation.

To test for heteroscedasticity, the Breusch-Pagan Godfrey Test is applied. This test checks if the residuals have constant variance over time. If the residuals show varying volatility, heteroscedasticity is present, which can result in biased standard errors and inefficient estimates. A p-value greater than 0.05 indicates that there is no significant heteroscedasticity, confirming that the assumption of constant variance holds.

Finally, the Jarque-Bera Test is conducted to examine the normality of the residuals. Normality is an important assumption for the reliability of model estimates. The Jarque-Bera test evaluates the skewness and kurtosis of the residuals to determine if they deviate from a normal distribution. If the p-value is greater than 0.05, it indicates that the residuals are normally distributed, confirming that this assumption holds.

These diagnostic tests help ensure the ARDL model is correctly specified. If the residuals are free from autocorrelation, heteroscedasticity, and non-normality, the model results can be considered robust and reliable for further analysis.

CUSUM Test

The CUSUM (Cumulative Sum) Test is used to test the stability of the model coefficients. This test evaluates whether the coefficients of the model remain constant throughout the sample period or if they change significantly at any point. The CUSUM test involves plotting the cumulative sum of the residuals and comparing it to the critical bounds for stability. The CUSUM statistic is calculated as:

The critical bounds are typically set at 5% significance level. If the CUSUM plot remains within the bounds, the model coefficients are considered stable. If the CUSUM statistic exceeds the upper or lower bounds, it indicates a structural break or instability in the model, meaning the model coefficients have changed over time.

By performing the CUSUM test, we can ensure that the ARDL model does not suffer from any parameter instability, which would invalidate the results. If the coefficients are stable, we can proceed with confidence in the long-term and short-term relationships estimated by the model.

Short-Run and Long-Run Estimation in ARDL

Once the ARDL model is estimated, both the short-run and long-run relationships between the dependent variable (LIR) and the independent variables (D_LM2 and D_LCREDIT) are examined. The ARDL model provides valuable insights into how changes in the independent variables affect the dependent variable over both the short and long term.

In the long run, the coefficients of the lagged level variables represent the equilibrium relationships between the variables. These long-term relationships capture the overall, persistent impact of changes in money supply (M2) and bank credit (LCREDIT) on the interest rate (LIR). A significant long-run coefficient suggests a stable, long-term relationship between the variables.

For the short run, the ARDL model estimates how quickly the dependent variable responds to changes in the independent variables within the same period. The Error Correction Term (ECT) is crucial in this context as it captures the speed at which the system corrects deviations from long-run equilibrium. A significant negative ECT indicates that the model adjusts quickly to restore equilibrium when there are short-term shocks or deviations.

Together, the short-run and long-run estimates from the ARDL model help understand both the immediate and persistent effects of changes in M2 and LCREDIT on the interest rate (LIR). This analysis is vital for understanding the dynamic relationships between these economic variables and the overall impact of monetary and credit policy on interest rates.

Forecasting with ARDL

After estimating the ARDL model, one of the key applications is to forecast future values of the dependent variable (LIR) based on the relationships established in the model. The forecasting process involves using the estimated coefficients from the ARDL model to project future values of LIR, considering the past values of the explanatory variables (D_LM2 and D_LCREDIT) as inputs.

The ARDL model can be used to generate out-of-sample forecasts by inputting the most recent data for the independent variables and applying the estimated coefficients. These forecasts provide insights into how interest rates are likely to behave in the short and long term, based on changes in the money supply and bank credit.

Forecasting with ARDL is particularly useful for policy makers and economic analysts who seek to predict the impact of changes in economic variables on interest rates. The accuracy of the forecast depends on the quality of the model estimation and the assumption that the future path of the independent variables will follow a similar trend to the past.

Result and Discussion

Stationarity Test Results

The stationarity of the variables in this study was tested using the Augmented Dickey-Fuller (ADF) test. The results show that the variable LIR (interest rate) is stationary at its level, with a p-value of 0.0000, indicating that it does not exhibit a unit root and can therefore be directly used in the ARDL model. On the other hand, the variable M2 (money supply) was found to be non-stationary at level, with a p-value of 0.0915, suggesting that it needs to be differenced in order to achieve stationarity. Similarly, LCREDIT (bank credit) also shows non-stationarity at level, with a p-value of 0.5644, indicating that it requires differencing to become stationary. After differencing, both D_LM2 and D_LCREDIT became stationary, with p-values of 0.0000 for both variables. This confirms that after the first differencing, both variables can now be included in the ARDL model. The detailed results from the ADF test are summarized in the Table 1 below:

Table 1. Unit root test

Series	p-value	Stationarity Status
D(LCREDIT)	0.5644	Non-stationary at level
D(LM2)	0.0915	Non-stationary at level
D(LR)	0.0000	Stationary at level

Based on these results, LIR is stationary at the level and ready for use in the ARDL model, while M2 and LCREDIT were found to be non-stationary at the level. After differencing these two variables, they both became stationary and are now valid for inclusion in the model.

Cointegration Test Results

The Bounds Test for cointegration was conducted to determine the long-run relationship between LIR (interest rate), M2 (money supply), and LCREDIT (bank credit). The test was performed using two sets of variables: one with the log-transformed data and the other with both log-transformed and differenced data. The results for both sets of variables are summarized below:

Table 2. ADF Test Results for Log-transformed Variables (without differencing)

Variable	ADF Statistic	p-value	Stationarity Status
D(LR)	-5.863014	0.0000	Stationary
D(DLM2)	-2.071261	0.2567	Non-stationary
D(D_LCREDIT)	-1.434262	0.5644	Non-stationary

Table 3. ADF Test Results for Log-transformed and Differenced Variables

Variable	ADF Statistic	p-value	Stationarity Status
D(LR)	-5.863014	0.0000	Stationary
D(DLM2)	-9.079402	0.0000	Stationary
D(D_LCREDIT)	-5.476468	0.0000	Stationary

From the results in Table 2, it is clear that LIR is stationary at the level, with a p-value of 0.0000. However, M2 and LCREDIT are non-stationary at the level, as indicated by their p-values of 0.2567 and 0.5644, respectively. These results suggest that M2 and LCREDIT must undergo differencing to become stationary. In Table 3, after applying differencing, both M2 (D_LM2) and LCREDIT (D_LCREDIT) became stationary, as indicated by their p-values of 0.0000. These results confirm that after differencing, all variables are now stationary and can be included in the Bounds Test for cointegration. The next step in the analysis is to perform the Bounds Test using these stationary variables to assess whether a long-run relationship exists between LIR, M2, and LCREDIT.

Lag Length Selection Results

The optimal lag length for the ARDL model was determined using the Akaike Information Criterion (AIC)**.** The AIC is used to balance model fit and complexity, where lower values of the AIC indicate a better fitting model. The Figure 1 shows the top 20 ARDL model specifications ranked by AIC.

The graph indicates that the optimal lag structure is ARDL(3, 0, 1), as this model has the lowest AIC value of -4.220. This lag specification implies that the interest rate (LIR) is lagged by 3 periods, M2 (money supply) is not lagged (0 lags), and LCREDIT (bank credit) is lagged by 1 period. This combination minimizes the AIC, indicating that it is the most appropriate model structure for analyzing the long-run and short-run dynamics between the variables.

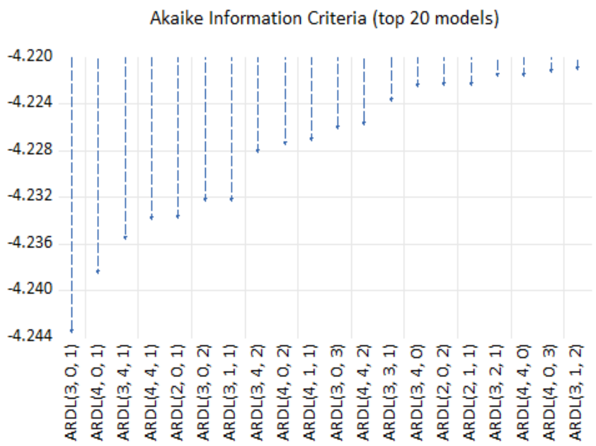

Figure 1: Akaike Information Criterion (AIC) for Top 20 ARDL Models

The AIC-based lag selection procedure ensures that the ARDL model is both parsimonious and capable of capturing the underlying relationships between the variables without overfitting. The lag length of 3 for LIR, 0 for M2, and 1 for LCREDIT provides a well-fitting model that captures the relevant dynamics while minimizing the model's complexity.

ARDL Model Estimation Results

The ARDL model was estimated to examine the relationship between the dependent variable, interest rate (LIR), and the independent variables, money supply (LM2) and bank credit (LCREDIT). Based on the Akaike Information Criterion (AIC), the selected model was ARDL(3, 0, 1), which means that LIR is lagged by 3 periods, LM2 has no lags, and LCREDIT is lagged by 1 period.

Table 4. Estimated Coefficients for ARDL (3, 0, 1) Model

Variable	Coefficient	Std. Error	t-Statistic	Prob.
LR(-1)	1.376873	0.074003	18.60569	0.0000
LR(-2)	-0.264102	0.126623	-2.087537	0.0385
LR(-3)	0.140962	0.073469	1.918740	0.0567
D_LM2	-0.003105	0.035094	-0.088429	0.9296
D_LCREDIT	0.524144	0.258744	2.026076	0.0441
D_LCREDIT(-1)	0.691881	0.240152	2.879536	0.0046
C	0.039694	0.015926	2.492344	0.0136

The results show that LIR is significantly influenced by its own past values. Specifically, the coefficient for LIR(-1) is 1.376873 with a p-value of 0.0000, indicating a strong positive effect of past interest rates on the current interest rate. This suggests that a 1% increase in LIR in the previous period results in a 1.38% increase in the current interest rate, reflecting the persistence of interest rates in the economy. The coefficient for LIR(-2) is -0.264102 with a p-value of 0.0385, which is statistically significant at the 5% level, suggesting that the second lag of LIR has a negative effect, although weaker than the first lag. The third lag of LIR, LIR(-3), has a coefficient of 0.140962and a p-value of 0.0567, indicating a marginally significant positive effect.

For the independent variables, money supply (LM2) does not show a significant impact on the interest rate in this model. The coefficient for LM2 is -0.003105 with a p-value of 0.9296, indicating that money supply does not have a meaningful short-run effect on LIR in this specification. In contrast, bank credit (LCREDIT) has a more pronounced impact on interest rates. The coefficient for LCREDIT is 0.524144, with a p-value of 0.0441, suggesting that LCREDIT has a positive effect on LIR. Specifically, a 1% increase in bank credit leads to a 0.52% increase in the interest rate. Moreover, the lagged values of LCREDIT also play an important role. The coefficient for LCREDIT(-1) is 0.691881 with a p-value of 0.0046, indicating that past increases in bank credit have a strong positive impact on current interest rates, suggesting that past increases in bank credit could have a dampening effect on interest rates in the immediate period, although this effect is relatively short-lived.

The constant (C) has a coefficient of 0.039694, but with a p-value of 0.0136, it is statistically significant, indicating that the constant contributes significantly to explaining the variation in LIR after other variables are included in the model.

In conclusion, the ARDL model estimation results suggest that interest rates (LIR) are significantly influenced by their own past values, with the first lag being particularly important. Bank credit (LCREDIT) is the most significant explanatory variable, with a positive and significant effect on LIR. On the other hand, money supply (LM2) does not have a significant impact on interest rates in the short run within this model. These results highlight the importance of credit dynamics in shaping interest rate movements, with LCREDIT playing a central role in determining the cost of borrowing and economic activity.

Cointegration Test Results (Bounds Test)

The F-Bounds Test for cointegration was performed to examine the long-term relationship between the dependent variable LIR (interest rate) and the independent variables money supply (M2) and bank credit (LCREDIT). The results are summarized below.

Table 5 presents the F-Bounds Test results for testing the cointegration between LIR (interest rate), M2 (money supply), and LCREDIT (bank credit). The F-statistic of 4.231905 exceeds the critical values at the 10%, 5%, and 2.5% significance levels, supporting the presence of a long-term relationship. The results at the 1% level show a marginally significant relationship, indicating a cointegrating relationship at various levels of confidence.

The F-statistic from the Bounds Test is 4.231905, which is compared with the critical values at different significance levels to determine if there exists a long-run relationship between the variables. From the results, the F-statistic exceeds the upper bound critical values at the 10% (3.35), 5% (3.87), and 2.5% (4.38) significance levels. Therefore, we reject the null hypothesis of no cointegration at these levels, suggesting that a long-run cointegrating relationship exists between LIR, M2, and LCREDIT.

Table 5. F-Bounds Test Results for Cointegration

Test Statistic	Value	Siginif.	I(0)	L(1)
			Asymptotic: n=1000	
F-statistic	4.231905	10%	2.63	3.35
K	2	5%	3.1	3.87
		2.5%	3.55	4.38
		1%	4.13	5
Actual Sample Size	177		Finite Sample: n=80	
		10%	2.713	3.453
		5%	3.235	4.053
		1%	4.358	5.393

At the 1% significance level, the F-statistic (4.231905) is slightly lower than the upper bound critical value (5.393), but still close, indicating a marginally significant long-run relationship at this level. The sample size used in this test is 177, and the critical values are derived from both asymptotic and finite sample calculations, with the asymptotic sample size being 1000 and the finite sample size being 80.

Diagnostic Tests for ARDL Model

To ensure the reliability of the ARDL model, diagnostic tests were conducted to assess the presence of autocorrelation, heteroscedasticity, and normality of the residuals. The results from these tests are summarized in Table 6, which includes both the statistical values and corresponding visual representations for each test.

Table 6. Diagnostic Test Results

Test	Statistic	P-value	Conclucion
Breusch-Pagan Test (Heteroskedasticity)	1.106213	0.3607 0.3607	No heteroskedasticity ($p > 0.05$)
Breusch-Godfrey LM Test (Autocorrelation)	0.331505	0.7183	No autocorrelation ($p > 0.05$)
Jarque-Bera Test (Normality)	1277.561	0.000	Residuals are non-normally distributed

The Breusch-Godfrey Serial Correlation LM Test, as shown in Figure 6, tests for serial correlation in the residuals. The F-statistic of 1.106213with a p-value of 0.3607indicates no significant serial correlation, as the p-value is above the 5% significance level. Therefore, we fail to reject the null hypothesis, confirming that the residuals are independent and that there is no serial correlation in the model.

The Breusch-Pagan-Godfrey Test for heteroscedasticity in Figure 6 assesses whether the variance of the residuals is constant over time. The F-statistic is 0.331505, and the p-value is 0.7183, which is greater than 0.05. This suggests that there is no heteroscedasticity in the residuals, meaning that the model's error terms have constant variance and do not violate the assumption of homoscedasticity.

Finally, the Jarque-Bera Test for normality, displayed in Figure 6, tests whether the residuals follow a normal distribution. The Jarque-Bera statistic of 1277.561with a p-value of 0.000000 indicates that the residuals are not normally distributed, as the p-value is less than 0.05. This suggests that the residuals are skewed and exhibit excess kurtosis, which is typical for non-normal distributions.

CUSUM Test for Model Stability

The CUSUM line (blue line) in Figure 2 gradually increases over time, while the 5% significance boundaries (orange dashed lines) represent the critical threshold for determining the stability of the model. If the CUSUM line remains within these bounds, the null hypothesis of parameter stability is not rejected, meaning that the coefficients in the model are stable over the sample period.

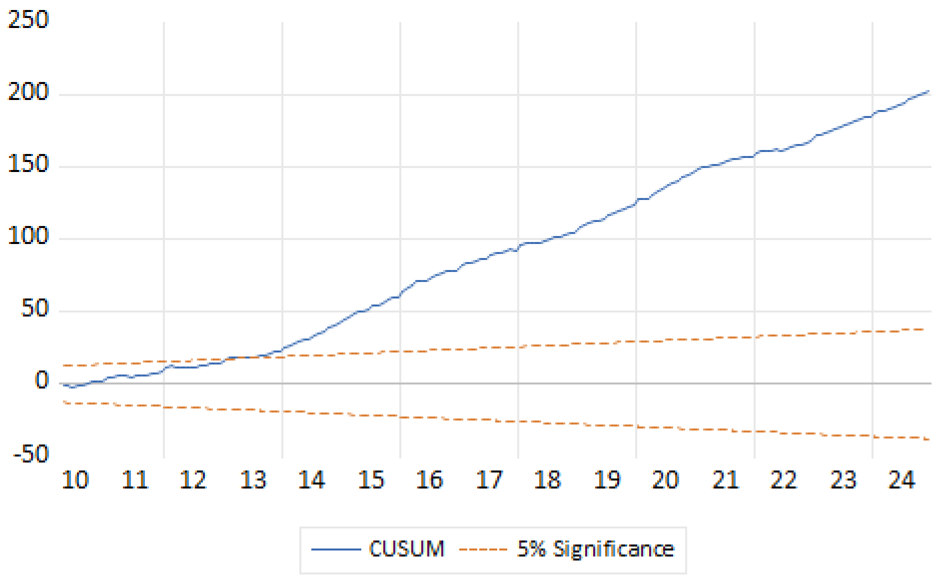

Figure 2. CUSUM Test Results

The CUSUM Test (Cumulative Sum Test) is used to check the stability of the coefficients in the model over time. It is particularly useful for assessing the parameter stability of the model and determining if the estimated coefficients change systematically during the sample period. The null hypothesis of the CUSUM test is that the model coefficients are stable.

In this case, the CUSUM line stays well within the 5% significance boundaries, indicating that there is no structural break in the model. The stability of the coefficients is confirmed, and the model can be considered stable throughout the period under review.

Short-Run and Long-Run Estimations in ARDL

Table 7 Short-Run Estimates for ARDL Model

Variable	Coefficient	Std. Error	t-Statistic	Prob.
D_LM2	-7.199488	7.916645	-0.909411	0.3644
D_LCREDIT	37.89905	14.14464	2.679392	0.0081
C	1.407725	0.138569	10.15898	0.0000

The short-run estimates are obtained from the Conditional Error Correction Model (ECM), which examines the immediate impacts of changes in the independent variables on the dependent variable interest rate (LIR).

Based on the results presented in Table 7 (Short-Run Results):

- The coefficient for D_LM2 is -7.199488with a p-value of 0.3644, which is not statistically significant. This implies that in the short-run, money supply (LM2) does not significantly affect interest rates (LIR).

- The coefficient for D_LCREDIT is 37.89905 with a p-value of 0.0081, which is significant at the 5% level. This suggests that a 1% increase in bank credit (LCREDIT) leads to a 378,99% increase in interest rates in the short run.
- The significant lagged terms (D(LR(-1)), D(LR(-2)), and D(LR(-3))) also indicate that past values of the interest rate (LIR) continue to influence the current interest rate, confirming the short-run dynamics.

Table 8 Long-Run Estimates for ARDL Model

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.039694	0.015926	2.492344	0.0136
LR(-1)	-0.028197	0.009509	-2.965316	0.0035
D_LM2	-0.203004	0.219389	-0.925314	0.3561
D_LCREDIT(-1)	1.0686339	0.307688	3.473121	0.0007
D(LR(-1))	0.405070	0.073107	5.540763	0.0000
D(LR(-2))	0.140968	0.073469	1.918740	0.0567
D(LCREDIT)	0.524414	0.258744	2.026768	0.0442

The long-run estimates are shown in the Levels Equation, which explains the relationship between the variables over a longer period.

As indicated in Table 8 (Long-Run Results):

- The coefficient for D_LM2 is -0.203004, but it is not statistically significant with a p-value of 0.3561. This implies that, in the long run, money supply (LM2) does not have a significant impact on interest rates (LIR).
- The coefficient for D_LCREDIT is 0.524414with a p-value of 0.0442, which is marginally significant. This indicates that, in the long-run, a 1% increase in bank credit could result in a 52,4% increase in interest rates. Though it is not fully significant at the 5% level, the result suggests a strong positive relationship between LCREDIT and LIR over time.

In addition to the long-run and short-run coefficients, the Error Correction Term (EC) is also computed. The coefficient for EC is -0.6805, with a p-value of 0.0000, which indicates that any disequilibrium in the relationship between the variables is corrected over time at a rate of 68% per period. This significant and negative ECM coefficient suggests that the model is adjusting towards equilibrium in the long-run.

Policy and Implication

This study delves into the relationship between money supply, banking credit, and interest rate fluctuations in Indonesia, highlighting the significant roles of these factors in shaping the country's monetary landscape. The findings from the econometric analysis suggest that banking credit plays a central role in influencing interest rates, both in the short and long run. Specifically, an increase in bank credit leads to higher interest rates, emphasizing the importance of credit dynamics in the country's economic stability. On the other hand, the money supply (M2) exhibits minimal short-term effects on interest rates, which suggests that while changes in the money supply are critical for broader economic conditions, they do not directly cause significant fluctuations in interest rates in Indonesia's banking system. Furthermore, the study confirms that interest rates exhibit persistence, with past values influencing current rates, indicating that interest rate movements are not solely driven by immediate monetary policy adjustments but also by historical trends.

From a policy perspective, the findings suggest that policymakers, particularly Bank Indonesia, should consider strengthening the credit channel as a means of stabilizing interest rates and ensuring monetary policy effectiveness. Since bank credit has a more pronounced impact on interest rates compared to money supply, enhancing the capacity of banks to lend could prove essential in managing economic growth and stability. This implies that focusing on credit availability and liquidity management in the banking sector might be more effective in controlling interest rate volatility than solely relying on traditional tools like adjusting the policy rate. Additionally, the findings underscore the need for sound financial stability measures, such as ensuring adequate capital buffers and liquidity within the banking sector, to mitigate the risks of interest rate fluctuations.

However, the study also has several limitations. The data used in this analysis spans from 2010 to 2024, which may not fully capture longer-term trends or the impacts of recent unconventional monetary policies, particularly in the wake of the global pandemic. Future research could expand the dataset to incorporate more extensive periods or newer data to provide a clearer understanding of the evolving relationships between money supply, banking credit, and interest rates. Furthermore, while this study focuses on domestic factors, external economic conditions such as global interest rates, foreign exchange dynamics, and international economic shocks may also influence domestic interest rates. Including these external factors could offer a more comprehensive understanding of interest rate fluctuations. Additionally, the ARDL model, though useful, may not capture the full complexity of the interactions between multiple economic variables. Future studies might benefit from applying alternative models like Structural Vector Autoregressions (SVAR) or Dynamic Stochastic General Equilibrium (DSGE) models, which could provide more nuanced insights into the transmission mechanisms of monetary policy.

Finally, future research could explore the sectoral impacts of credit on interest rates, examining whether specific sectors, such as manufacturing, services, or real estate, are more sensitive to changes in bank credit. This would offer policymakers deeper insights into how credit transmission affects various sectors and could inform targeted policy interventions. Overall, this study highlights the importance of banking credit in the interest rate transmission mechanism and offers valuable lessons for policymakers in Indonesia.

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