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Short Term Forecasting of Indonesia's Policy Interest Rate Using ARIMA

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ABSTRACT

This study examines the short-term dynamics of Indonesia's policy interest rate and develops forecasts using an autoregressive integrated moving average (ARIMA) approach. The analysis uses 95 monthly observations from January 2018 to November 2025 to generate forecasts for December 2025–February 2026. Model selection combines stationarity testing, information criteria, and residual diagnostics. The results indicate that the series becomes stationary after first differencing. Among the three specifications considered, ARIMA(1,1,1) provides the lowest Akaike and Bayesian information criteria, while residual tests reveal no significant autocorrelation. The model projects an approximately stable policy rate of 4.74% throughout the forecast horizon. A retrospective comparison shows that Bank Indonesia maintained the policy rate at 4.75% during all three months. Although the ARIMA forecasts closely approximate the observed rates, a no-change benchmark achieves lower forecast errors over this period. These findings highlight the persistence of Indonesia's policy rate and the importance of benchmark comparisons in evaluating forecasting performance. The model provides a statistical baseline for short-term monetary analysis that can complement assessments of broader macroeconomic developments.

Keywords: ARIMA; Bank Indonesia; Forecast evaluation; Monetary policy; Policy interest rate; Time series

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INTRODUCTION

Policy interest rates are central to the assessment of monetary conditions and the formation of expectations about financing costs. For businesses, an indication of the likely direction of interest rates can inform short-term cash-flow projections and borrowing assumptions. For economic analysts, it provides a reference for interpreting changes in the monetary environment. In Indonesia, the policy rate is an administered instrument that can remain unchanged across several months before being adjusted through a policy decision. This pattern makes persistence an important feature of the forecasting problem and motivates the use of time-series methods that represent dependence on previous observations.

This study examines monthly observations from January 2018 to November 2025, encompassing periods of both increases and reductions in Indonesia's policy interest rate. The sample provides a setting for investigating how a relatively simple statistical model represents short-term dynamics across changing monetary conditions. The variable of interest is the central bank's policy rate, expressed as an annual percentage. Its institutional role is illustrated by Bank Indonesia's policy announcements, which explain interest-rate decisions in relation to economic growth and stability (Bank Indonesia, 2025). Understanding the persistence of this instrument is therefore relevant to both forecasting practice and the interpretation of the prevailing monetary environment.

Autoregressive integrated moving average (ARIMA) models provide an established framework for forecasting a variable from its own history and past innovations. Their relatively modest data requirements and explicit dynamic structure make them suitable for constructing an initial projection of a persistent economic series. Model development involves selecting a transformation, identifying candidate lag structures, estimating their parameters, and evaluating residual behavior. Information criteria guide the balance between fit and complexity, while comparisons with subsequent observations assess forecasting performance (Brooks, 2019; Hyndman & Khandakar, 2008). Together, these procedures connect the statistical properties of a model with its practical use in short-term prediction.

Previous Indonesian research offers several approaches to interest-rate forecasting. Paramitha et al. (2021) applied ARIMA(0,1,1) with drift to the BI 7-day repo rate, producing forecasts for December 2020–April 2021. Hardani et al. (2017) examined inflation, interest rates, and the composite stock price index using vector autoregression, while Jusmawati et al. (2020) applied a vector autoregressive integrated moving average framework to inflation and interest rates. These applications illustrate the scope for both univariate and multivariate models. Building on this literature, the present study focuses on a later sample and evaluates a short-horizon ARIMA forecast against an explicit persistence benchmark.

The objective of this study is to identify a suitable ARIMA specification for Indonesia's monthly policy rate and produce forecasts for December 2025–February 2026. The analysis addresses three related questions: whether differencing is required to obtain stationarity, which candidate model provides the strongest support under the information criteria, and how closely its forecasts track subsequent policy-rate announcements. Its contribution lies in combining model selection, residual diagnostics, and a retrospective comparison with a no-change forecast. This approach provides an empirical assessment of the value of a parsimonious forecasting model during a period of broadly stable policy rates.

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LITERATURE REVIEW

Policy Rates and Monetary Conditions

Policy-rate developments form part of a wider system linking monetary conditions, financial markets, and economic activity. Ramadhani and Nugroho (2019) examined exchange rates, electronic money, interest rates, money supply, and inflation using Indonesian monthly data. Their analysis situates interest rates alongside other monetary variables and highlights the importance of examining transmission relationships empirically. Hardani et al. (2017) approached the forecasting problem through a joint model of inflation, interest rates, and stock-market developments. These studies provide a macroeconomic context for interpreting an interest-rate projection, particularly when monetary and financial indicators evolve together.

External financial conditions also contribute to the environment in which domestic interest rates are determined. Nareswari et al. (2024) analyzed foreign direct investment and portfolio investment within an Indonesian macroeconomic stability framework. Suripto et al. (2023) investigated foreign exchange reserves using a vector error correction model incorporating the exchange rate, exports, the BI rate, and consumer prices. Their research connects domestic monetary developments with capital flows and external-sector conditions. A univariate forecast addresses a complementary question by summarizing the historical dynamics of the policy rate itself, providing a reference path that can be interpreted alongside this broader information.

ARIMA and Financial Time Series Forecasting

ARIMA combines autoregressive dependence, differencing, and a moving-average error structure. The autoregressive component relates the current observation to earlier values, while the moving-average component captures the influence of past innovations. Differencing transforms a nonstationary series before these dynamic components are estimated. The resulting framework is well suited to a forecasting design centered on temporal patterns in a single variable (Brooks, 2019). Its practical applications extend beyond interest rates: Salwa et al. (2018) applied ARIMA to Bitcoin prices, and Vinsensia Laura (2019) used the Box–Jenkins approach to forecast the number of savers at a credit union. Aritonang (2009) places forecasting methods within the broader context of business planning.

Model selection is an empirical process in which alternative dynamic structures are evaluated for a particular series and sample. Hyndman and Khandakar (2008) describe a systematic approach to ARIMA selection, emphasizing the comparison of specifications. In Indonesia, the policy-rate application of Paramitha et al. (2021) provides a direct precedent for this approach. More broadly, Adebiyi et al. (2014) compared ARIMA and artificial neural networks for stock-price prediction, illustrating the role of comparative evaluation in financial forecasting. These studies motivate a design that uses the autocorrelation and partial autocorrelation functions to identify candidate models and then assesses their relative fit and predictive performance.

Model Selection and Forecast Evaluation

The Akaike information criterion (AIC) and Bayesian information criterion (BIC) evaluate model fit while penalizing additional parameters (Akaike, 1974; Schwarz, 1978). Their different penalty structures allow the preference for a specification to be assessed under two selection rules. Residual diagnostics complement these criteria by examining whether temporal dependence remains after estimation. The portmanteau test aggregates residual autocorrelations over a specified set of lags (Ljung & Box, 1978). A model with favorable information criteria and no detectable residual autocorrelation offers a coherent statistical representation of the observed dynamics at the lags examined.

Forecast evaluation compares model predictions with outcomes outside the estimation period. Mean absolute error (MAE) measures the average magnitude of forecast errors, whereas root mean squared error (RMSE) places greater weight on larger errors. Both measures retain the units of the forecast variable, facilitating interpretation for an interest-rate series (Hyndman & Koehler, 2006). A no-change forecast is a relevant benchmark because it projects the most recent policy rate throughout the forecast horizon. Comparing ARIMA with this baseline helps establish whether the estimated dynamics improve prediction beyond the information contained in the latest observation.

RESEARCH METHOD

Research design and data

The study uses a quantitative, univariate time-series design. The estimation sample comprises 95 monthly observations of Indonesia's policy rate from January 2018 to November 2025. The unit of observation is a calendar month, and the underlying economic variable is an interest rate quoted in percent per annum. The numerical estimation output expresses rates as proportions, so a value of 0.0475 corresponds to 4.75%. Forecasts are converted to percentage units for presentation. Changes in these percentage values are reported in percentage points or basis points, with one percentage point equal to 100 basis points.

The analysis was conducted in Stata using November 2025 as the forecast origin. Forecasts were generated for December 2025, January 2026, and February 2026, corresponding to horizons of one, two, and three months. The empirical procedure comprises stationarity testing, candidate model estimation, information-criterion comparison, residual diagnostics, and forecast evaluation. For the final stage, the projections are compared retrospectively with the rates announced by Bank Indonesia during the three forecast months (Bank Indonesia, 2025, 2026a, 2026b). These announcements constitute the evaluation data, while the estimation period ends in November 2025.

Stationarity and specification

Stationarity is assessed using Dickey–Fuller tests of the policy rate in levels and first differences (Dickey & Fuller, 1979). The null hypothesis is that the series contains a unit root. Both test regressions include a constant, exclude a deterministic trend, and use zero augmentation lags. The tests are implemented through Stata's dfuller command (StataCorp, 2025). Rejection of the null after differencing provides the basis for modeling changes in the rate with an ARMA structure. The autocorrelation function (ACF) and partial autocorrelation function (PACF) of the transformed series then guide the selection of candidate lag orders.

Let y_t denote the policy rate in proportion form, and let $\Delta y_t = y_t - y_{t-1}$. A general nonseasonal ARIMA specification can be expressed as follows:

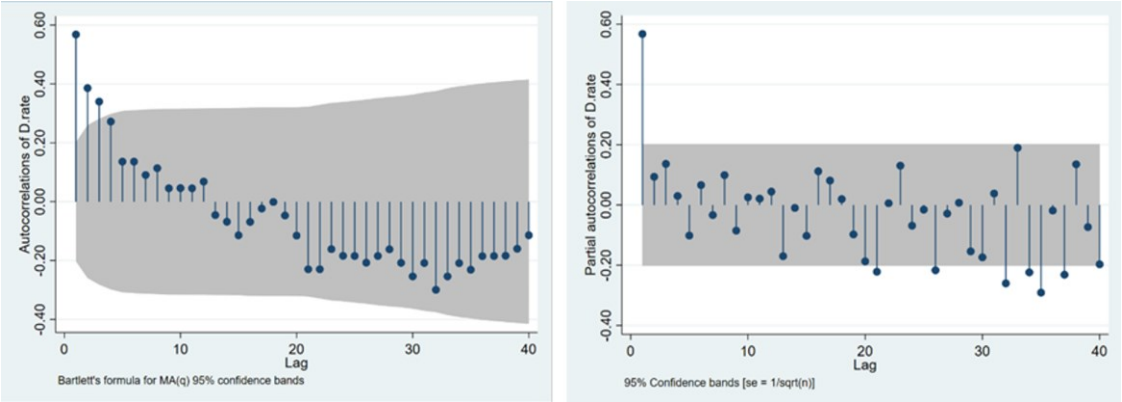
$$\varphi(B)(1 - B)^d y_t = c + \theta(B)\varepsilon_t. \qquad (1)$$

Here, B is the backshift operator, such that $By_t = y_{t-1}$. The polynomials $\varphi(B)$ and $\theta(B)$ contain the autoregressive and moving-average coefficients, respectively, and ε_t denotes an innovation with zero mean and finite variance. The parameters p, d, and q identify the autoregressive order, differencing order, and moving-average order. This formulation links the transformation of the original series to the dynamic structure used for forecasting. A positive-sign convention is adopted for the moving-average terms throughout the model representation.

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First differencing sets the integration order to d = 1. The ACF and PACF in Figure 1 guide the evaluation of three candidate specifications: ARIMA(1,1,3), ARIMA(1,1,2), and ARIMA(1,1,1). Each combines one autoregressive term with a different moving-average order, allowing the comparison to assess whether additional innovation lags improve fit sufficiently to justify their complexity. Selection uses AIC = $-2\ell + 2k$ and BIC = $-2\ell + k \ln(n)$, where ℓ denotes the maximized log likelihood, k is the parameter count, and n is the estimation sample size. The specification with the lowest criterion values is selected for forecasting.

Figure 1. Correlograms of the First-Differenced Rate



Note. Left panel: autocorrelation function. Right panel: partial autocorrelation function.

The selected ARIMA(1,1,1) model has the following representation:

$$\Delta y_t = c + \varphi_1 \Delta y_{t-1} + \varepsilon_t + \theta_1 \varepsilon_{t-1}. \qquad (2)$$

In Equation (2), the monthly change in the policy rate depends on its previous change and the current and lagged innovations. The autoregressive term captures persistence in rate changes, while the moving-average term represents the response to the previous period's innovation. The constant c denotes the intercept in this equation. Forecasts are obtained recursively from the fitted dynamic structure and expressed in the original percentage units of the policy rate. This representation provides a compact basis for examining how historical rate movements translate into the three-month forecast path.

Residual diagnostics and forecast comparison

Residual autocorrelation is evaluated using portmanteau tests at 12 and 24 lags. The null hypothesis is that residual autocorrelations are jointly zero over the tested lags. Stata's wntestq procedure evaluates the Q statistic using the lag count as the reference degrees of freedom (StataCorp, 2025). The analysis also applies a parameter adjustment of p + q = 2 for the fitted ARMA structure, giving 10 and 22 degrees of freedom, respectively (Hyndman & Athanasopoulos, 2021). Table 3 presents both sets of p-values to assess whether this adjustment changes the diagnostic conclusion.

The inverse autoregressive and moving-average roots provide an additional assessment of the fitted model. Inverse roots within the unit circle indicate stationarity of the autoregressive component and invertibility of the moving-average component for the first-differenced series. These conditions support the use of the estimated ARMA structure to describe changes in the policy rate. The root assessment and residual tests address complementary aspects of model adequacy: the former examines the dynamic properties of the specification, while the latter evaluates remaining serial dependence in its errors.

Forecast errors are calculated as the announced policy rate minus the ARIMA point forecast, measured in percentage points. MAE is obtained by averaging the absolute errors across the three forecast months, and RMSE is the square root of the average squared error. The benchmark holds the policy rate at 4.75% throughout the horizon. This fixed path represents a no-change forecast from the prevailing rate. Both forecasts are evaluated against the same monthly announcements, allowing a direct comparison of their performance for the December 2025–February 2026 period.

RESULTS

Stationarity Test Results

Table 1 presents the Dickey–Fuller test results. The level series produces a test statistic of −0.978 and a p-value of 0.7612, indicating that the null hypothesis of a unit root cannot be rejected. After first differencing, the statistic declines to −5.009, with a p-value below 0.001. The null is therefore rejected at the 1% significance level for the differenced series. This pattern supports treating the policy rate as integrated of order one and establishes the basis for specifying the candidate models with d = 1.

Table 1. Dickey–Fuller Unit-Root Tests

Series	N	Statistic	p-value	5% critical
Level	94	−0.978	0.7612	−2.895
First difference	93	−5.009	< 0.001	−2.896

Note. Both tests use zero augmentation lags and no deterministic trend. Source: authors' Stata output.

The effective samples comprise 94 observations for the level test and 93 for the first-difference test, reflecting the observations required by the transformations and lagged terms. The results indicate that monthly changes provide a stationary representation under the selected test specification. Accordingly, subsequent model identification focuses on dependence in these changes. Figure 1 presents the corresponding ACF and PACF, connecting the stationarity analysis with the evaluation of alternative autoregressive and moving-average structures.

ARIMA Model Selection

Table 2 compares the information criteria for the three candidate specifications. ARIMA(1,1,1) achieves the lowest AIC of −960.6224 and BIC of −950.4492. Its AIC is lower than that of ARIMA(1,1,3) by 3.0704 and that of ARIMA(1,1,2) by 7.3106. Both criteria therefore favor the specification with one autoregressive and one moving-average term. The agreement between AIC and BIC strengthens the selection of ARIMA(1,1,1) as the preferred model within the candidate set.

Table 2. Information Criteria for Candidate Models

Model	AIC	BIC
ARIMA(1,1,3)	−957.5520	−942.2922
ARIMA(1,1,2)	−953.3118	−946.5953
ARIMA(1,1,1)	−960.6224	−950.4492

Note. Lower values indicate stronger relative support within the candidate set. Source: authors' model-comparison table.

The ranking suggests that the additional moving-average terms in the larger specifications offer insufficient improvement in fit relative to their parameter penalties. A parsimonious dynamic structure is therefore adequate for representing the dependence captured by these candidate models. This finding is relevant for a monthly sample of 95 observations, in which parameter economy is a useful consideration. The selected model is subsequently evaluated through residual and inverse-root diagnostics before its forecasts are examined.

Residual Diagnostics and Inverse Roots

Table 3 presents the diagnostic results for ARIMA(1,1,1). The portmanteau statistics are 5.9496 at 12 lags and 15.4876 at 24 lags, with corresponding unadjusted p-values of 0.9186 and 0.9057. After adjusting the degrees of freedom for the two ARMA parameters, the p-values are 0.8195 and 0.8405. All exceed the 5% significance threshold, so the null hypothesis of no residual autocorrelation is retained at both lag horizons. The consistency of these results indicates that the fitted model captures the serial dependence detected over the tested lags.

Table 3. Residual and Inverse-Root Diagnostics

Diagnostic	Statistic / modulus	Unadjusted p	Adjusted p
Portmanteau Q(12)	5.9496	0.9186	0.8195
Portmanteau Q(24)	15.4876	0.9057	0.8405
Inverse AR root	0.725898	—	—
Inverse MA root	0.251258	—	—

Note. Adjusted p-values use 10 and 22 degrees of freedom for the 12- and 24-lag tests, respectively. Inverse roots refer to the first-differenced process. Source: Authors' calculations.

The inverse AR root is 0.725898 and the inverse MA root is 0.251258. Both lie within the unit circle, indicating that the autoregressive component of the differenced process satisfies the stationarity condition and the moving-average component satisfies invertibility. Together with the residual results, these diagnostics support the statistical adequacy of the selected specification for short-term forecasting. The following analysis examines how this fitted structure translates into projected policy-rate levels and how closely those projections track the subsequent announcements.

Policy Rate Forecasts and Observed Outcomes

The ARIMA model forecasts policy rates of 4.74191% for December 2025, 4.73738% for January 2026, and 4.73543% for February 2026 (Table 4). Rounded to two decimal places, the projections remain at 4.74% throughout the horizon. The decline between the first and third forecasts amounts to 0.00648 percentage points, or 0.648 basis points. The principal economic feature of the forecast is therefore stability around the prevailing rate, with only a small downward movement over the three-month period.

Table 4. Point Forecasts and Retrospective Comparison

Month	ARIMA (%)	Announced (%)	Error (bp)	No change (%)
Dec. 2025	4.74191	4.75000	0.809	4.75000
Jan. 2026	4.73738	4.75000	1.262	4.75000
Feb. 2026	4.73543	4.75000	1.457	4.75000

Note. Error = announced rate − forecast; bp = basis points. Forecasts: Authors' calculations. Announced rates: Bank Indonesia (2025, 2026a, 2026b).

Bank Indonesia maintained the policy rate at 4.75% in each forecast month (Bank Indonesia, 2025, 2026a, 2026b). The ARIMA projections are consequently below the announced rates by 0.809, 1.262, and 1.457 basis points. MAE is 0.01176 percentage points and RMSE is approximately 0.01207 percentage points, indicating small numerical deviations over the evaluation period. The no-change benchmark reproduces the observed rate exactly and achieves zero error. Thus, both forecast paths represent a stable rate environment, with the no-change path providing the closer numerical match during these three months.

DISCUSSION

Policy Rate Persistence and Forecast Dynamics

The approximately flat forecast path highlights persistence as a central feature of Indonesia's policy rate over the evaluation horizon. The model represents monthly changes through a low-order ARMA structure, and its projections remain close to the rate prevailing at the forecast origin. This outcome is consistent with an administered instrument that can remain unchanged between policy adjustments. The economic relevance of the forecast lies primarily in identifying continuity in the near-term rate environment. Its very small downward movement represents a gradual statistical adjustment within an otherwise stable projection.

The observed policy decisions reinforce this interpretation. In December 2025, Bank Indonesia linked its decision to maintain the rate to exchange-rate stability, stronger policy transmission, and support for economic growth (Bank Indonesia, 2025). This institutional explanation complements the statistical result by placing the unchanged rate within a broader monetary assessment. The ARIMA projection summarizes the historical pattern, while the policy announcement describes the economic considerations accompanying the decision. Together, they provide a clearer interpretation of the forecast horizon as a period of policy-rate continuity.

Forecast Accuracy and the Persistence Benchmark

The retrospective comparison shows that the ARIMA forecasts closely approximate the subsequent rates, with errors below 1.5 basis points in every month. At the same time, the no-change benchmark achieves an exact match because the announced rate remains at 4.75%. This result illustrates the value of persistence as a forecasting baseline for an administered interest rate. Small errors are informative about numerical proximity, while the benchmark comparison establishes how much additional predictive value the fitted dynamics provide. In this evaluation period, the most recent observation contains sufficient information to reproduce the realized rate path.

The finding complements the model-selection literature by showing how relative fit and forecast performance contribute different information to an empirical assessment. AIC and BIC favor ARIMA(1,1,1) among the estimated alternatives, whereas the forecast comparison favors the no-change path during the stable evaluation period. This distinction is consistent with the emphasis on forecast evaluation in Hyndman and Koehler (2006). It also provides a useful extension of Indonesian ARIMA applications such as Paramitha et al. (2021), by explicitly relating a selected model's predictions to a simple benchmark. Evaluation across periods containing rate adjustments would further clarify the circumstances in which the dynamic specification adds predictive value.

Implications for Monetary Analysis

An approximately stable rate projection can provide a baseline for short-term analysis of the financing environment. The main implication of the forecast is continuity around 4.74%, rather than a substantial movement over the next three months. Analysts can use such a reference path when organizing alternative scenarios and assessing new monetary information. Its interpretation is strengthened by considering developments in lending conditions, credit availability, and economic activity alongside the policy rate. This approach connects a concise statistical projection with the wider information relevant to monetary and financial analysis.

The Indonesian literature provides a basis for this broader interpretation. Nareswari et al. (2024) examine capital flows within a macroeconomic stability framework, and Suripto et al. (2023) investigate reserve dynamics alongside domestic and external variables. Ramadhani and Nugroho (2019) similarly situate interest rates within relationships involving money supply and inflation. These perspectives indicate useful dimensions for extending the information set of future forecasting models. The present results establish a univariate reference against which such extensions can be assessed, using a common evaluation horizon and the same no-change benchmark.

CONCLUSION

This study develops short-term forecasts of Indonesia's policy interest rate using 95 monthly observations from January 2018 to November 2025. The stationarity tests support first differencing, and ARIMA(1,1,1) achieves the lowest AIC and BIC among the three specifications considered. Residual diagnostics detect no significant autocorrelation at 12 and 24 lags, while the inverse roots satisfy the stationarity and invertibility conditions for the differenced process. The model projects a rate of approximately 4.74% throughout December 2025–February 2026, indicating a broadly stable near-term rate environment.

Comparison with subsequent announcements shows that Bank Indonesia maintained the policy rate at 4.75% during all three months. The ARIMA forecasts closely approximate these outcomes, although the no-change benchmark achieves lower errors over this period. The study contributes an Indonesian forecasting application that connects model selection and diagnostic adequacy with an explicit assessment of realized performance. Its findings highlight the importance of policy-rate persistence and support the use of ARIMA as a statistical baseline for monetary analysis. Future research can evaluate multiple forecast origins and incorporate inflation, output, and credit conditions to assess whether a broader information set improves predictive performance.

LIMITATION

The evaluation covers three months from a single forecast origin, limiting the assessment of performance across different monetary conditions. The candidate set comprises three

ARIMA specifications, and the unit-root tests use zero augmentation lags. Structural changes and alternative lag specifications may affect the estimated dynamics. In addition, the analysis focuses on point forecasts; prediction intervals would provide a fuller assessment of forecast uncertainty. The univariate design captures historical dependence in the policy rate, while the contribution of other macroeconomic variables remains a direction for further investigation.

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