14 November 2025

Economic Bulletin – Issue 73

Measuring Short-Rate Dynamics in Indonesia: IndONIA, Spreads, and Out-of-Sample Accuracy

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- This study develops a practical forecast for IndONIA 1-month at quarter end and identifies the forces that shape its path. A harmonized quarterly dataset from CEIC and Bloomberg underpins the analysis, with series aligned to common timestamps, units, and currency conventions and checked against source releases.
- The baseline uses SARIMAX and Spread Analysis to map observable policy, currency, and short-tenor market information into an interpretable forecast. Machine learning and deep learning models including Elastic Net, Gradient Boosting, Random Forest, SVR, XGBoost, CatBoost, LSTM, and GRU serve as cross checks on direction, turning points, and relative magnitudes rather than substitutes for the baseline.
- Results are straightforward. Domestic policy settings and external policy benchmarks load positively on quarter-end IndONIA, while currency conditions and very short money market measures provide timely confirmation and often lead shifts in the backdrop. Equity market moves add limited incremental information once policy and currency variables are included. Out of sample tests show that the baseline captures direction and turning points with errors that are small enough for planning, and backtests track the recent decline credibly.
- Consequently, for insurance balance sheets the baseline forecast, and ML/DL cross-checks translate directly into pricing and crediting-rate guidance, ALM rebalancing and duration positioning, liquidity buffers around policy dates, and reserve sensitivity to policy and currency shocks, thereby supporting RBC compliance and stress testing.
- The framework is designed for quarterly horizons where policy and near-term market signals carry most of the weight. Very abrupt intra quarter shocks can still move outcomes between forecast points, so interim monitoring remains important. Full specifications, variable definitions, and hyperparameters are provided in the Appendix.

Introduction

Reference rates anchor intertemporal prices and capital allocation in modern finance. For insurance companies, forward curves derived from benchmark rates inform at least four core decisions:

(i) asset–liability management (ALM), including duration/convexity matching of long-dated liabilities;

(ii) setting crediting rates and calibrating guarantee features for savings-type products;

(iii) designing and valuing hedging programs (e.g., pay-fixed/receive-floating swaps priced off a reference index); and

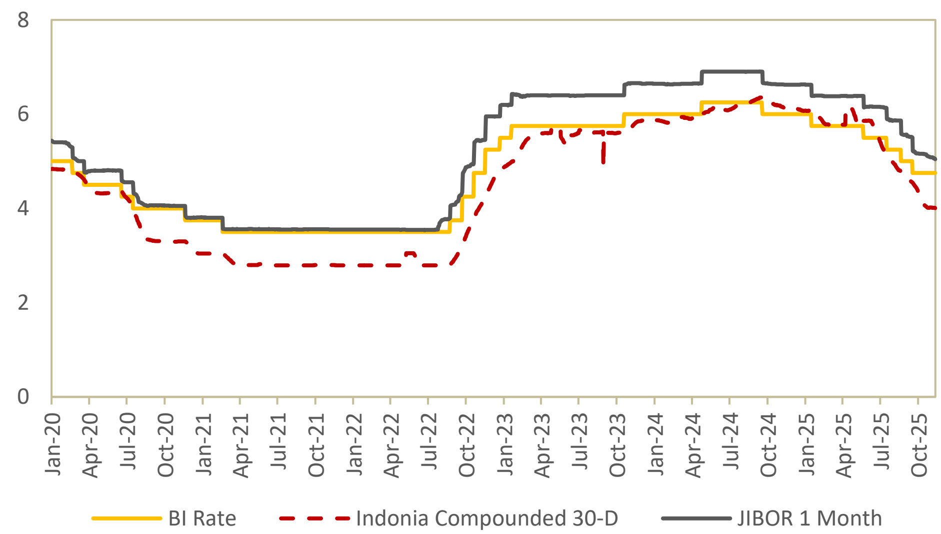
(iv) quantifying capital sensitivity under risk-based capital (RBC) frameworks and the discounting of insurance contract cash flows under International Financial Reporting Standard 17 (IFRS 17).

A credible house-view of the benchmark path is thus a prerequisite for pricing, budgeting, and stress testing. International experience underscores this point. In the United States, the transition from the London Interbank Offered Rate (LIBOR) to the Secured Overnight Financing Rate (SOFR) altered discount curves and floating-leg cash flows, compelling firms to re-estimate interest-rate risk and model governance around Alternative Reference Rates Committee (ARRC) conventions (compounded-in-arrears, observation shift, and (in specific use cases) Term SOFR). In the United Kingdom, the reformed Sterling Overnight Index Average (SONIA) became the standard reference and is accompanied by an official SONIA Compounded Index to ensure transparent tenor aggregation. In the euro area, the Euro Short-Term Rate (€STR) replaced EONIA, with a fixed spread during the interim to preserve contract economics. Comparable reforms took place in Switzerland (Swiss Average Rate Overnight (SARON) supplanting CHF LIBOR), Singapore (Singapore Overnight Rate Average (SORA) replacing SIBOR/SOR in new contracts), and Canada (Canadian Dollar Offered Rate (CDOR) cessation with migration to Canadian Overnight Repo Rate Average (CORRA). For Indonesia, where insurers historically referenced the Jakarta Interbank Offered Rate (JIBOR) for term tenors, the move to the Indonesia Overnight Index Average (IndONIA) and its compounded variants has similar implications for ALM, pricing, and capital, hence the need for a rigorous, policy-consistent forecasting framework for Compounded IndONIA (30-Days).

Why JIBOR is being discontinued and IndONIA will replace it

Indonesia's benchmark-rate reform aligns with global post-LIBOR principles: move from quotation-based term rates (susceptible to liquidity and quote biases) toward transaction-based overnight rates with robust governance. Bank Indonesia (BI) defines and publishes IndONIA from actual unsecured overnight interbank transactions, and, crucially, also publishes Compounded IndONIA and the IndONIA Index to support non-overnight horizons. BI has announced that publication of JIBOR will cease on 1 January 2026. The National Working Group on Benchmark Reform (NWGBR) has issued a JIBOR Termination Transition Guide to operationalize the shift (timelines, recommended conventions, and spread-fixing dates).

Exhibit 1. Policy Rate, JIBOR-1 Month, and IndONIA Compounded 30-Days, 2020-2025



Sumber: Bloomberg, IFG Progress Analysis

As seen in Exhibit 1, movement wise, both JIBOR and IndONIA follow a similar trend with BI Rate. However, from a measurement perspective, IndONIA captures the volume-weighted cost of overnight unsecured rupiah funding in the interbank market, whereas JIBOR reflected indicative offered quotes at multiple tenors. Consistent with the International Organization of Securities Commissions (IOSCO) benchmark principles and the post-Wheatley global playbook, BI's framework emphasizes representativeness, transparency, and resilience. For market users, especially insurers with long-dated liabilities, the migration to IndONIA implies re-estimating discount curves, hedge effectiveness, and capital sensitivities under a rate that is both more transaction-anchored and policy-aligned with BI's money-market infrastructure.

Translating historical JIBOR into IndONIA terms

An immediate practical challenge is time-series continuity for risk models, pricing libraries, and performance analytics. Global practice in Interbank Offered Rate (IBOR) reform has converged on “compounded-in-arrears plus a fixed spread-adjustment” fallbacks: the floating leg references the compounded overnight risk-free rate (RFR) over the accrual period, while a five-year historical median of IBOR–RFR differences preserves contract economics. The International Swaps and Derivatives Association (ISDA) codified this methodology and commissioned Bloomberg to publish fallback adjustments; authorities (e.g., ARRC, Financial Conduct Authority (FCA), European Central Bank (ECB)) supported analogous approaches across markets. For Indonesia, mapping JIBOR 1-Month to IndONIA Compounded 30-Days involves:

(i) Adopting BI’s Compounded IndONIA over 30 calendar days (in arrears);

(ii) Calculating historical JIBOR(1M) – Compounded-IndONIA(30D) differentials over a sufficiently long window; and

(iii) Fixing a spread-adjustment, typically the five-year median around a tenor cessation trigger date, to re-express historical series, recalibrate pricing, and run parallel back-testing.

Conventions matter. Observation shift/lag, lookback/lockout, and day-count should follow published methodologies to ensure reproducibility. Cross-market precedents strengthen this design choice. The EONIA to €STR transition used a constant +8.5 basis points spread until EONIA’s final publication, demonstrating a tractable way to “bridge” legacy to RFR economics. The SONIA Compounded Index and Japan’s Tokyo Overnight Average Rate (TONA) indices (published by QUICK) similarly reduce operational variance in compounded calculations. These precedents, together with ISDA’s fallbacks, provide a robust template for JIBOR to IndONIA translation and for validating spread stability under Indonesian market microstructure.

Motivation, contribution, and report organization

This study develops an operational forecasting framework for IndONIA (Compounded 30-Days) tailored to Indonesia’s insurance sector. The motivation is twofold. First, as JIBOR sunsets, insurers must rebase product pricing, ALM strategy, and hedge design to a transaction-based reference rate, requiring a forward view of Compounded IndONIA that is internally consistent with BI’s definitions and market conventions. Second, the literature on benchmark reform, from Wheatley and IOSCO to Duffie & Stein (2015) and the Bank for International Settlements (BIS), explains the efficiency and integrity gains from transaction-anchored RFRs, but there is limited applied work that translates these insights into a sector-specific forecasting tool for Indonesian insurers. Our contributions are accordingly threefold.

(i) We construct a JIBOR → IndONIA reconciliation that is aligned with ISDA spread-adjustment practice yet adapted to BI's compounding/index methodology.

(ii) We embed macro-financial drivers (monetary stance, rupiah system liquidity, and cross-currency RFR co-movements) to forecast the 30-day compounded horizon, allowing scenario analysis around policy, liquidity, and volatility shocks.

(iii) We map model outputs to insurance use-cases, pricing/guarantee management, ALM, and capital sensitivity, under the discipline of IFRS 17 discounting guidance and RBC principles (internally used, not published in the paper).

The report proceeds as follows: Section 1 (Introduction) motivates the problem and situates Indonesia within global benchmark reforms; Section 2 (Data and Methodology) details IndONIA construction, the JIBOR-to-IndONIA translation and spread-fixing protocol, and the forecasting specification; Section 3 (Forecast Results and Discussion) presents baseline and scenarios, diagnostic tests, and implications for insurance decision-making; and Section 4 (Conclusion) summarizes policy and managerial takeaways and outlines avenues for future research (e.g., nowcasting liquidity conditions, modelling observation-lag conventions, and comparing compounded-in-arrears with potential term-rate proxies where available).

Data and Methodology

Data and Variables Used

This section outlines the data foundation and empirical frame used in the study. We combine macroeconomic information with capital market datasets from domestic and international sources, harmonized to a single frequency, calendar, and convention set. Series are standardized prior to analysis to align publication timing, business-day treatment, and compounding rules, so that comparisons across sources remain internally consistent.

Our methodological toolkit is organized as a forecasting workflow. We begin by profiling the series to establish basic properties and to guide feature preparation. Forecast models are specified to match data frequency and stability, drawing on both univariate and multivariate forms. Estimation uses rolling and expanding windows to respect the time order of information. Validation is conducted out of sample across multiple horizons, with error metrics and stability checks used to compare candidates. Model selection follows a transparent ranking procedure, and forecast outputs include point paths and uncertainty bands.

Table 1. Statistic Summary Stable of SARIMAX (Seasonal Autoregressive Integrated and Moving Average with Exogenous)

	count	mean	std	min	5%	25%	50%	75%	95%	max
IndONIA (30-Day Compounded)	26	4,62	1,34	2,79	2,79	3,11	5,05	5,85	6,08	6,31
USD/IDR Exchange Rate	49	-0,05	0,39	-1,11	-0,64	-0,28	-0,02	0,13	0,67	0,93
BI Rate	41	5,03	0,94	3,50	3,50	4,25	5,25	5,75	6,25	6,25
Federal Funds Rate	62	1,51	1,81	0,25	0,25	0,25	0,38	2,19	5,49	5,50
GDP	62	4,76	2,17	-5,32	-0,50	4,95	5,06	5,57	6,29	7,08

Source: CEIC analysed with Phyton

We assemble a quarterly dataset from CEIC and align all series on a common sample by intersecting availability with the forecast target. Observations are stamped to end-of-quarter dates, harmonized to a single business-day calendar, and standardized to consistent units and currency conventions. Missing values are handled conservatively with short, source-aware gap fills only when releases imply continuity, and potential outliers are flagged against historical ranges and verified against the original CEIC entries. This curation yields a clean, comparable panel suitable for the analyses presented in the following sections.

Table 2. Statistic Summary table of Machine Learning and Deep Learning

	count	mean	std	min	5%	25%	50%	75%	95%	max
IndONIA Compounded 30-Days	1746	4,63	1,30	2,79	2,79	3,05	4,93	5,85	6,16	6,38
1-Year Government Bond Yield	1746	5,34	1,25	2,68	3,23	4,02	5,80	6,39	6,80	7,26
BI Rate	1746	4,94	1,03	3,50	3,50	3,75	5,25	6,00	6,25	6,25
Real GDP Growth (YoY)	1706	3,80	3,01	-5,32	-3,49	4,87	5,02	5,06	5,73	7,08

CPI (YoY)	1746	2,68	1,25	-0,09	1,33	1,68	2,57	3,28	5,42	5,95
JIBOR 3-Month Rate	1746	5,62	1,34	3,75	3,75	4,06	6,12	6,79	7,21	7,39
USD/IDR Exchange Rate	1746	15013,6	831,23	13583	14003,5	14273	14850	15660	16420,75	16870
Domestic Credit to GDP	1510	51,16	2,43	47,13	47,13	50,10	51,13	53,69	54,31	54,31
Federal Funds Rate	1746	2,80	2,10	0,25	0,25	0,25	2,50	4,75	5,50	5,50
1-Month SOFR	1746	2,65	2,11	0,01	0,03	0,08	2,44	4,66	5,33	5,36
Volatility Index	1746	20,23	7,72	11,54	12,66	15,07	18,21	23,11	32,68	82,69
S&P 500 Return	1745	0,00	0,01	-0,04	-0,02	-0,00	0,00	0,01	0,02	0,03
JCI Return	1745	0,00	0,01	-0,03	-0,01	-0,00	0,00	0,01	0,01	0,02

Source: Bloomberg analysed with Phyton

Methodology: Spread Adjustment Practice

This subsection formalizes the spread-adjustment approach as an operational bridge from the Jakarta Interbank Offered Rate (JIBOR) to the Indonesia Overnight Index Average (IndONIA). While JIBOR is still being published for legacy tenors, IndONIA and its compounded variants have become the transaction-based reference for new and transitioning contracts. The objective is to obtain a forward path for IndONIA Compounded 30-Days by aligning the nearest comparable JIBOR tenor with the compounded IndONIA horizon and applying a fixed spread adjustment consistent with Bank Indonesia’s (BI) benchmark-reform framework.

The construction follows the global “compounded-in-arrears + fixed spread” template developed during the Interbank Offered Rate (IBOR) reforms. First, identify the maturity mapping JIBOR 1-Month → IndONIA Compounded 30-Days. Second, use BI-published Compounded IndONIA (and the IndONIA Index) to ensure tenor aggregation is transparent and replicable. Third, compute or adopt the spread adjustment between JIBOR(1M) and IndONIA Compounded 30-Days based on a robust historical window, typically a multi-year median difference that stabilizes idiosyncratic liquidity or quote effects. In our operational implementation for planning and scenario work, we employ the published adjustment referenced in BI materials to maintain consistency with domestic market conventions and the international fallback methodology codified by the International Swaps and Derivatives Association (ISDA).

With a JIBOR 1-Month forecast in hand, we obtain the Implied IndONIA Compounded 30-Days forecast by subtracting the fixed BI-referenced spread from the JIBOR 1-Month projection (adjusting for day-count and any observation-shift conventions if required by the rulebook). This delivers a mechanically consistent forward path for the compounded overnight benchmark that is suitable for pricing, budgeting, and sensitivity analysis. In the IFG Progress slide notes, the working spread used for the 30-day compounded horizon is explicitly listed (0.75934 percentage points), and the resulting path is used as one of the report’s baseline references.

Consistent with [IFG Progress Digest Issue 10 (2023)](), the JIBOR 1-Month projection is modelled as a policy-anchored short-rate with macro-financial drivers. The earlier study documents (i) strong co-movement between JIBOR and BI 7-Day Reverse Repo Rate (BI-7DRRR), (ii) sensitivity to domestic inflation conditions, and (iii) external influences from the US federal funds rate; it then constructs scenario-weighted forecasts to produce a consolidated path for JIBOR(1M). This policy-and-macro anchored JIBOR(1M) forecast serves as the input to the spread-adjustment mapping into Compounded IndONIA (30-Days).

Methodology: Empirical Forecasting Analysis

SARIMAX

The Seasonal ARIMA with Exogenous regressors (SARIMAX) provides a flexible parametric baseline for quarterly forecasting with seasonal structure and observable drivers. The model combines nonseasonal and seasonal autoregressive and moving-average dynamics with differencing to remove low-frequency drift, and it augments the conditional mean with contemporaneous or lagged exogenous variables. Estimation proceeds by maximum likelihood using the Kalman filter, which also delivers multi-step forecasts and their uncertainty bands.

Compact difference-operator form

$$\Phi(L^s)\,\phi(L)\,\Delta^d\,\Delta_s^D y_t \;=\; \mu \;+\; \Theta(L^s)\,\theta(L)\,\varepsilon_t \;+\; \beta^\top x_t,$$

where

$$\phi(L) = 1 - \phi_1 L - \cdots - \phi_p L^p, \theta(L) = 1 + \theta_1 L + \cdots + \theta_q L^q,$$
$$\Phi(L^s) = 1 - \Phi_1 L^s - \cdots - \Phi_P L^{Ps}, \Theta(L^s) = 1 + \Theta_1 L^s + \cdots + \Theta_Q L^{Qs},$$
$$\Delta = 1 - L, \Delta_s = 1 - L^s.$$

State-space representation

For likelihood evaluation and forecasting we write SARIMAX in innovations state space:

$$\text{Observation:} \quad y_t = Z_t \alpha_t + \beta^\top x_t + \varepsilon_t, \varepsilon_t \sim \mathcal{N}(0, \sigma^2),$$
$$\text{State transition:} \quad \alpha_{t+1} = T_t \alpha_t + R_t \eta_t, \eta_t \sim \mathcal{N}(0, Q_t),$$

with Z_t, T_t, R_t, Q_t determined by (p, d, q, P, D, Q, s). The Kalman filter and smoother yield the log-likelihood, filtered states, and forecast distributions.

Variables and parameters

y_t Target series at quarter t after any deterministic pre-adjustments.

x_t Vector of exogenous regressors at t (for example policy, spread measures, or other controls aligned to quarter ends). Lags of x_t may be included by augmenting x_t.

β Coefficient vector mapping x_t to the mean of y_t.

ε_t One-step-ahead innovation with variance σ^2.

L Backshift operator, $Ly_t = y_{t-1}$.

s Seasonal period. For quarterly data $s = 4$.

d, D Nonseasonal and seasonal differencing orders.

p, q Nonseasonal AR and MA orders; $\phi_1, \ldots, \phi_p$ and $\theta_1, \ldots, \theta_q$ are their coefficients.

P, Q Seasonal AR and MA orders; $\Phi_1, \ldots, \Phi_P$ and $\Theta_1, \ldots, \Theta_Q$ are their coefficients.

μ Constant in the differenced model. When $d = 1$ and $D = 0$, μ implies a drift in the undifferenced level.

α_t State vector collecting the AR components that drive the observation y_t.

Z_t, T_t, R_t, Q_t State-space system matrices implied by the ARMA polynomials and differencing.

We complement the baseline with a compact set of benchmarks including Elastic Net, Gradient Boosting, Random Forest, SVR (RBF), XGBoost, CatBoost, LSTM, and GRU to test for nonlinearity, interaction effects, and regime-sensitive dynamics that a parametric model may miss. Models are trained and evaluated out of sample on comparable horizons, and their signals are read for direction, turning points, and relative magnitudes rather than used as replacements for the baseline. Agreement with the SARIMAX path and the inferred monetary transmission effects strengthens confidence in the forecast, while persistent divergence is documented as a robustness check. Full specifications, hyperparameters, and notation are provided in the Appendix.

Results and Discussion

Back-testing Results

This section presents the forecasting results and their interpretation ahead of the detailed tables and figures. We first report baseline SARIMAX estimates and the monetary transmission effects with spread adjustment, then compare out-of-sample accuracy across horizons using MAE and RMSE, with interval coverage to gauge calibration. We next examine concordance between the baseline and the machine-learning and deep-learning benchmarks, highlighting agreement in direction, turning points, and magnitude within predefined tolerance bands.

Table 3. Statistics Result of Diagnostic Test

Check	Value	Rule	Status
Durbin–Watson	1,96	≈ 2 (no autocorr)	PASS
Ljung-Box(8) p	0,63	p ≥ 0.05 (white-noise)	PASS
Ljung-Box(12) p	0,63	p ≥ 0.05 (white-noise)	PASS
Jarque-Bera p	0,53	p ≥ 0.05 (normal-ish)	PASS
Skewness	-0,04	|skew| ≤ ~0.5	PASS

Source: Bloomberg analyzed by Phyton

Residual diagnostics support the adequacy of the baseline specification. The Durbin–Watson statistic is near two, indicating no material first order autocorrelation in the innovations. Ljung–Box tests at lags eight and twelve yield p values above five percent, consistent with residuals that behave like white noise at business cycle horizons. The Jarque–Bera p value exceeds five percent, indicating no strong departure from normality in finite samples. Sample skewness is about −0.04, which is essentially symmetric and within common thresholds for well-behaved forecast errors. Taken together, these results indicate that the mean equation and innovation process are well specified for in sample purposes and the model is suitable for multi-step forecasting.

Table 4. Statistics Result Table of SARIMAX

Variable	Coef.	Std. Err.	z/t	P>|z|	[0.025	0.975]	Signif
Real GDP Growth	0,02	1,09E-12	2,26E+10	0	0,02	0,02	***
Domestic Credit to GDP	-0,13	4,77E-12	-2,6E+10	0	-0,13	-0,13	***
BI Rate	0,13	1,12E-11	1,12E+10	0	0,13	0,13	***
Federal Funds Rate	0,02	1,5E-14	1,15E+12	0	0,02	0,02	***
Jakarta Composite Index	-0,00	1,18E-18	-7,2E+14	0	-0,00	-0,00	***
S&P 500 Index	-0,00	1,6E-18	-4,8E+14	0	-0,00	-0,00	***

Source: Bloomberg analyzed by Phyton

The coefficient pattern is economically coherent. BI Rate and Federal Funds Rate load positively, indicating that tighter domestic and U.S. policy settings are associated with a higher quarter-end IndONIA Compounded 30-Days, consistent with policy pass-through into money-market conditions and an external financing channel. GDP Growth is also positive, which aligns with firmer short-tenor rates when domestic activity strengthens. In contrast, Domestic Credit to GDP is negative, suggesting that softer external or commodity momentum coincides with some easing at the quarter end. Equity proxies Jakarta Composite Index and S&P 500 Index carry small negative slopes after conditioning on the rate and macro blocks, implying limited incremental information for the quarter-end fix once policy and activity are in the model.

Magnitudes are read in native units. A coefficient near +0.125 on BI Rate means that a 1 unit increase in the policy series, for example 1 percentage point if the source is in percentage points, is associated with about +0.125 in IndONIA 1-month, holding other drivers constant. Federal Funds Rate shows a smaller but directionally consistent sensitivity. For index-level variables such as Jakarta Composite Index and &P 500 Index, effects are economically minor in typical quarter-to-quarter moves. The overall message is that currency and rates linked drivers dominate the conditional variation in the quarter-end IndONIA Compounded 30-Days setting, while equity conditions play a secondary role once policy and macro controls are included.

Table 5. Statistics Result of Error Metrics of Forecasting

	Indicator			
	MAE	**RMSE**	**MAPE**	**R2**
SARIMAX	0,15	0,18	2,55	0,59
LSTM	0,53	0,64	10,45	0,31
GRU	0,41	0,47	7,59	0,62
ElasticNet	0,50	0,63	10,00	0,04
GB_P50	0,33	0,41	6,47	0,59
RandomForest	0,26	0,27	5,01	0,82
SVR_RBF	0,51	0,62	9,98	0,08
XGBoost	0,41	0,46	8,11	0,49
CatBoost	0,31	0,35	6,05	0,71

Source: Bloomberg analyzed by Phyton

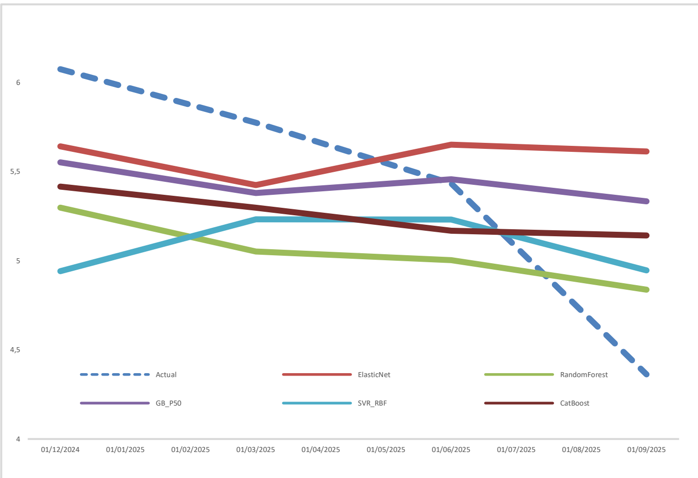
Exhibit 6 shows that SARIMAX is the primary performer on absolute accuracy. It delivers the lowest MAE at 0.151 and the lowest RMSE at 0.178 with a MAPE of 2.55 and an R^2 of 0.587. These results indicate tight point forecasts and good calibration for quarter-end IndONIA Compounded 30-Days.

The machine-learning and deep-learning models act as technical support rather than replacements. Random Forest and CatBoost post high R^2 values at 0.822 and 0.714 yet they do so with larger MAE and RMSE than SARIMAX, which suggests better in-sample fit but weaker precision on the forecast target. Gradient Boosting and XGBoost sit in the middle with moderate errors and moderate R^2. GRU and especially LSTM show the largest errors among the benchmarks, while ElasticNet and SVR also trail the baseline.

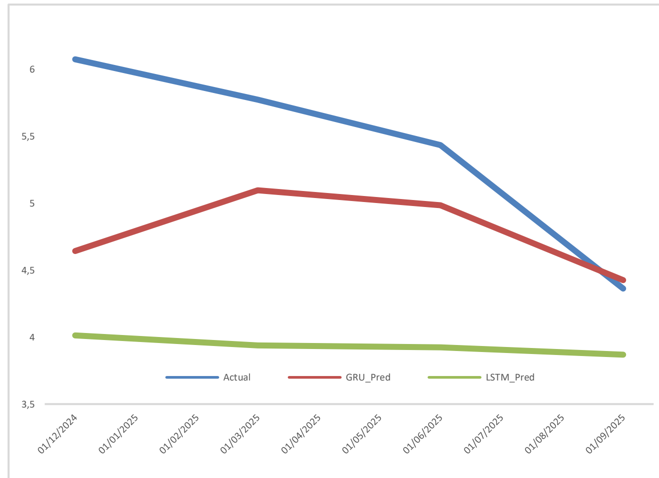
Taken together, the ranking supports the use of SARIMAX as the main forecasting engine. ML and DL models are most useful for cross-checking direction, turning points, and sensitivity to driver sets. Where their signals align with SARIMAX around policy and spread events, confidence in the baseline path increases. Where they diverge, we document the dispersion and use it as a robustness check rather than as a reason to replace the baseline.

Exhibit 2. Back Testing of Machine Learning and Deep Learning

Machine Learning



Deep Learning



Source: Bloomberg analyzed by Phyton

Exhibit 2 plots out-of-sample backtests against the realized decline in IndONIA Compounded 30-Days. In the ML panel, most models share the correct downward slope but differ in level and timing. ElasticNet and CatBoost sit persistently above the actual path (positive level bias). Random Forest and Gradient Boosting track the direction yet are too flat through mid-year, indicating under-reaction to the sharper later-quarter easing. SVR (RBF) improves around the middle of the sample but lags the final descent, suggesting a smoothness constraint from the kernel bandwidth. These patterns are consistent with the error table: ML fits can explain variance (high R^2 for tree ensembles) but deliver larger MAE/RMSE than SARIMAX due to level and timing errors.

In the DL panel, GRU captures the mid-sample crest and subsequent decline more closely than LSTM, which is damped and under-levels throughout. The GRU's better shape matching supports the baseline narrative on turning points, while LSTM's attenuation explains its weaker accuracy metrics.

Overall, the back-tests corroborate the SARIMAX trajectory on direction and turning points, with ML/DL serving as technical cross-checks rather than replacements. Where GRU and the better-calibrated ML models align with the baseline around policy and spread events, confidence in the forecast path increases. Where systematic biases appear (persistent level gaps or lagged responses), we use them as robustness signals and, if needed, adjust tuning windows or feature sets, but we continue to rely on SARIMAX for the operational forecast.

Forecast Results

This subsection synthesizes the forecast and contrasts two internally consistent approaches: a mechanical spread-adjustment mapping from JIBOR(1M) and a statistical SARIMAX model estimated directly on the compounded IndONIA target with exogenous drivers. We also clarify the technical notes that accompany Table 6.

Table 6. Benchmark Rate Outlook: INDONIA Compounded 30 Days (Spread Adjustment and SARIMAX Method)

IFGP Forecast Indonia Compound 30-D	Current (Q3'25)	FY 2025	Q1 '26	Q2 '26	Q3 '26	FY 2026	FY 2027
IFGP Forecast (JIBOR - Spread Adjustment)*	4.66 (0.306****)	**4.39 – 4.64**	**4.39 – 4.64**	**4.39 – 4.64**	**4.14 – 4.39**	**4.14 – 4.64**	**4.39 – 4.89**
IFGP Forecast (SARIMAX Method)**		**4.61 – 4.80**	**4.54 – 4.73**	**4.52 – 4.71**	**4.51 – 4.70**	**4.51 – 4.70**	**N/A**
Adjusted Bloomberg Forecasts (Weighted Average)***		**4.83**	**4.71**	**4.70**	**4.68**	**4.60**	**4.67**

Source: IFG Progress Research Analysis, Bloomberg Consensus

Approach (i) - Spread adjustment: Because this model is anchored to the JIBOR policy channel and uses a fixed wedge, its month-to-month dynamics are smooth and policy-consistent, closely tracking the assumed path for BI Rate and external rates embedded in the JIBOR forecast. It is particularly useful for budgeting and scenario translation, where managerial users need a one-for-one mapping from familiar JIBOR benchmarks to the new IndONIA environment.

Approach (ii) - SARIMAX: This model allows the IndONIA Compounded 30-Days forecast to respond directly to macro-financial shocks (for example, a sharper-than-assumed USD shock or a slower pass-through from policy cuts), potentially producing near-term deviations from the mechanically adjusted path.

Comparative Result

- **Level vs. dynamics:** The spread-adjusted series inherits the level of the JIBOR(1M) path net of the fixed wedge and thus tends to be level-stable unless the JIBOR policy assumptions change. SARIMAX can lean against that path in the short run when drivers imply different near-term liquidity or external-pressure conditions (e.g., an asymmetric USD/IDR Exchange Rate shock), before reconverging as the dominant policy cycle reasserts itself.

- **Uncertainty bands.** The standard deviation line reported below the table (post-2023 IndONIA Compounded 30-Days volatility) provides a natural scale for uncertainty bands. Spread-adjusted forecasts typically sit inside those bands unless the JIBOR/BI assumptions shift materially; SARIMAX intervals can be wider when exogenous drivers are volatile, reflecting the empirical pass-through from shocks to the compounded target.
- **Consensus cross-check:** The exhibit also references Adjusted Bloomberg forecasts: consensus paths for BI Rate are transformed to JIBOR(1M) and then mapped to IndONIA Compounded 30-Days via the same BI-referenced spread. Concordance between consensus-adjusted and our spread-adjusted paths strengthens the baseline; deviations relative to SARIMAX help identify whether macro-driver sensitivities (for example, USD shocks) warrant additional emphasis in risk scenarios.

For planning, pricing, and ALM, the spread-adjusted path is an intuitive baseline when continuity from JIBOR to IndONIA is paramount and when managerial communication benefits from a direct, fixed-wedge translation. For risk and stress testing, the SARIMAX path adds value by quantifying how compounded IndONIA reacts to policy surprises, growth news, and currency volatility, helping decision-makers bracket the plausible dispersion around the baseline. In practice, we recommend adopting the spread-adjusted series as the official house view, with SARIMAX used to define risk bands and scenario overlays that capture macro-financial uncertainty.

Conclusion

Summary

Indonesia's transition from a quotation-based term benchmark (JIBOR) to a transaction-based overnight benchmark (IndONIA Compounded 30-Days) requires a forecasting framework that is policy-consistent, empirically disciplined, and operationally transparent. The spread-adjustment methodology (mapping JIBOR(1M) to IndONIA Compounded 30-Days using a BI-referenced fixed wedge) provides a tractable baseline that preserves continuity for pricing libraries, ALM dashboards, and managerial reporting during the transition. Complementing this, a SARIMAX specification estimated directly on IndONIA Compounded 30-Days with exogenous macro-financial drivers captures shock-sensitivity and short-run deviations that matter for stress testing and capital planning. Together, the two approaches yield a coherent toolkit: one delivers a clear baseline path aligned with policy assumptions; the other supplies scenario-ready dynamics grounded in realized transmission from policy, growth, and external conditions. As JIBOR publication sunsets and IndONIA becomes fully embedded, this dual-track framework equips insurers and other financial institutions with a credible house view and risk-aware guardrails for pricing, budgeting, and strategic balance-sheet management.

Appendix

Machine Learning and Deep Learning

Elastic Net serves as a transparent linear benchmark that balances variable selection and shrinkage. The L_1component promotes sparsity among correlated predictors, while the L_2component stabilizes estimation and distributes weight across groups of related features. This tradeoff is useful when feature collinearity is material and the goal is a well-conditioned forecasting baseline.

Formula

$$\min_{\beta_0,\beta} \quad \frac{1}{n}\sum_{i=1}^{n}(y_i - \beta_0 - x_i^\top \beta)^2 + \lambda[\alpha \parallel \beta \parallel_1 + (1-\alpha) \parallel \beta \parallel_2^2].$$

Variables

β_0Intercept term. Shifts predictions up or down.

βVector of slope coefficients. Each $\beta_j$measures the marginal effect of feature x_{ij}on $y_i$in the units of yper unit of x_j.

$\lambda \geq 0$ Overall regularization strength. Larger values shrink coefficients more aggressively to reduce variance.

$\alpha \in [0,1]$Penalty mix. $\alpha = 1$is pure L1 (feature selection), $\alpha = 0$is pure L2 (shrinkage without selection). Values in between blend both.

$\parallel \beta \parallel_1 = \sum_j \mid \beta_j \mid$Size of coefficients measured by absolute values.

$\parallel \beta \parallel_2^2 = \sum_j \beta_j^2$ Size of coefficients measured by squared length.

Gradient Boosting constructs an additive ensemble of shallow trees where each stage targets the residual structure left by the previous model. With a small learning rate and depth constraints, it captures moderate nonlinearities and interactions while controlling generalization error through stage-wise regularization.

Formula

$$F_M(x) = \sum_{m=1}^{M} \nu\, f_m(x)\,, r_{im} = -\frac{\partial \ell(y_i, F(x_i))}{\partial F} \mid_{F=F_{m-1}}, F_m = F_{m-1} + \nu f_m.$$

Variables

F_M: final predictor after Mstages.

f_m: weak learner at stage m(regression tree).

$\nu \in (0,1]$: learning rate.

$\ell(y, \hat{y})$: pointwise loss (for example squared error).

r_{im}: pseudo-residual for sample $i$at stage m.

Random Forest reduces variance by averaging decorrelated decision trees. Bootstrap sampling and random feature subsets at each split produce diverse base learners, and the ensemble mean yields stable out-of-sample performance even when single trees overfit.

Formula

$$\hat{y}(x) = \frac{1}{T}\sum_{t=1}^{T} h_t(x).$$

Variables

T: number of trees.

h_t: tree trained on a bootstrap sample with random feature subsampling.

$\hat{y}(x)$: ensemble prediction.

SVR with an RBF kernel seeks a function that is flat in feature space while allowing small errors inside an εtube. The kernel induces flexible nonlinear fits; the regularization and tube width control the bias–variance tradeoff and robustness to local noise.

Formula

$$\min_{w,b,\xi,\xi^{\backslash *}} \frac{1}{2} \parallel w \parallel^2 + C\sum_{i=1}^{n} (\xi_i + \xi_i^{\backslash *})\text{s.t. } \mid y_i - w^\top \phi(x_i) - b \mid \leq \varepsilon + \xi_i^{(\backslash *)},\ \xi_i^{(\backslash *)} \geq 0,$$

$$\hat{y}(x) = \sum_{i=1}^{n} (\alpha_i - \alpha_i^{\backslash *})\, K(x_i, x) + b, K(x_i, x) = \exp\left(-\gamma \parallel x_i - x \parallel^2\right).$$

Variables

w, b: weights and intercept in feature space.

$\phi(\cdot)$: implicit feature map induced by the kernel.

$C > 0$: penalty on violations of the εtube.

ε: tube half-width.

$\xi_i, \xi_i^{\backslash *}$: slack variables.

$\alpha_i, \alpha_i^{\backslash *}$: dual coefficients.

$\gamma > 0$: RBF kernel bandwidth.

XGBoost refines tree boosting with second-order optimization and explicit structure penalties. By using gradient and curvature information, it selects splits that provide the largest regularized gain, while leaf and structure penalties curb complexity and improve generalization.

Formula

$$\mathcal{L} = \sum_{i=1}^{n} \ell(y_i, \hat{y}_i) + \sum_{m=1}^{M} \Omega(f_m), \Omega(f) = \gamma T + \frac{\lambda}{2} \sum_{j=1}^{T} w_j^2 ,$$

$$\text{Gain} = \frac{1}{2} [\frac{G_L^2}{H_L + \lambda} + \frac{G_R^2}{H_R + \lambda} - \frac{(G_L + G_R)^2}{H_L + H_R + \lambda}] - \gamma.$$

Variables

ℓ: loss with gradients $g_i = \partial_{\hat{y}} \ell$ and Hessians $h_i = \partial_{\hat{y}}^2 \ell$.

f_m: tree at stage m with T leaves and leaf weights w_j.

$\lambda \geq 0$: L_2 penalty on leaf weights.

$\gamma \geq 0$: penalty for adding a leaf.

$G_{.} = \sum g_i$, $H_{.} = \sum h_i$ over a node's samples; subscripts L, R denote left and right children.

CatBoost is a gradient boosting algorithm designed to handle categorical features through ordered target statistics and ordered boosting. By computing encodings that only use past information in a permutation, it mitigates target leakage and typically yields stable performance on mixed data.

Formula

$$\text{TS}_i(c) = \frac{\sum_{j \in \mathcal{P}(i)} y_j + a\,\mu}{\mid \mathcal{P}(i) \mid + a}, F_M(x) = \sum_{m=1}^{M} f_m(x) .$$

Variables

c: categorical feature.

$\mathcal{P}(i)$: indices preceding i in a permutation.

μ: prior mean of the target.

$a > 0$: strength parameter for shrinkage toward μ.

f_m: tree at stage m.

F_M: final additive model.

The LSTM captures long-range temporal dependencies using a gated cell that regulates information flow. Input, forget, and output gates modulate the cell state so that relevant signals persist while noise and short-lived shocks are attenuated.

Formula

$$
\begin{aligned}
i_t &= \sigma(W_i x_t + U_i h_{t-1} + b_i), f_t = \sigma(W_f x_t + U_f h_{t-1} + b_f), \\
o_t &= \sigma(W_o x_t + U_o h_{t-1} + b_o), \tilde{c}_t = \tanh\,(W_c x_t + U_c h_{t-1} + b_c), \\
c_t &= f_t \cdot c_{t-1} + i_t \cdot \tilde{c}_t, h_t = o_t \cdot \tanh\,(c_t).
\end{aligned}
$$

Variables

x_t: input vector at time t.

h_t: hidden state.

c_t: cell state.

i_t, f_t, o_t: input, forget, and output gates with logistic $\sigma(\cdot)$.

$W., U., b.$: weight matrices and biases.

$\tilde{c}_t$: candidate cell update.

The GRU is a streamlined gated architecture that blends previous and candidate states using update and reset gates. With fewer parameters than LSTM, it often trains efficiently while preserving the capacity to model medium- and long-horizon dependencies.

Formula

$$
\begin{aligned}
z_t &= \sigma(W_z x_t + U_z h_{t-1} + b_z), r_t = \sigma(W_r x_t + U_r h_{t-1} + b_r), \\
\tilde{h}_t &= \tanh\,(W_h x_t + U_h (r_t \cdot h_{t-1}) + b_h), \\
h_t &= (1 - z_t) \cdot h_{t-1} + z_t \cdot \tilde{h}_t.
\end{aligned}
$$

Variables

z_t: update gate controlling carryover from h_{t-1}.

r_t: reset gate controlling use of h_{t-1}in the candidate.

$\tilde{h}_t$: candidate hidden state.

Other symbols as defined for LSTM.

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