5 February 2024

Economic Bulletin – Issue 44

Indonesia's Yield Curve In 2024: Machine Learning & Dynamic Nelson Siegel (DNS) Model

Reza Yamora Siregar
reza.jamora@ifg.id
Head of IFG-Progress

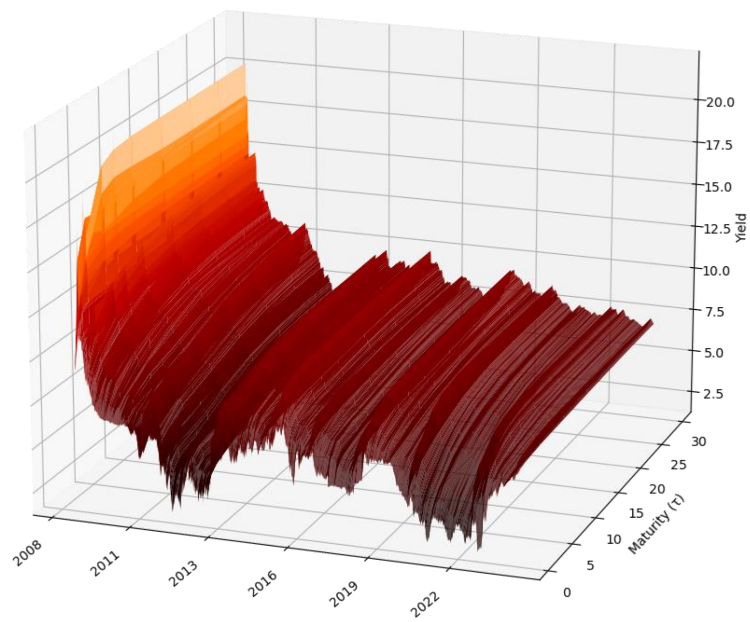
Rizky Rizaldi Ronaldo
rizky.rizaldi@ifg.id
Research Associate

- The term structure of the Yield Curve is one of the most essential tools in financial economics. All agents, both government and private firms, set them as a benchmark for implementing their policy and business decision, respectively. The yield curve can be one of the reasons for prosperous firms/countries or their declines (as evident in 2023)
- This paper aims to understand the characteristics of Indonesia's government bond yield curve, to forecast the curve for 2024 and to assess its future trajectories/volatilities. It's divided into two parts: dissecting and predicting the yield curve (Economic Bulletin – Issue 44) and exploring its interaction with various shocks (Forthcoming).
- The importance of understanding the yield curve extends beyond its movement. The spread between long-term and short-term yields, especially the 10-year and 2-year government bonds, provides valuable insights into economic growth and potential recession risks, a concept widely monitored in financial economics.
- This paper employs both Machine Learning and Parsimonious models (particularly Dynamic Nelson Siegel based models) to estimate Indonesia's 2024 yield curve.
- After thorough examination and comparison, we found that Random Walk model is still 'the king' for short horizon (particularly 1 month horizon), while our models exhibit better performance in medium to long horizon (in line with Duffee (2002), Diebold and Li (2006) & Rubín and Ayliffe (2020))
- **Based on two of our best-performing models, Indonesia's government bond for 2-year maturity will hover around 5.7% to 6.4%, 5-year maturity at ±6.5%, and 10-year maturity at 6.6% - 6.9%**
- Predictions for 2024 indicate two possible scenarios: a flattening curve akin to 2023's trend or a normalizing curve. These outcomes are influenced by critical factors such as Policy Rate and Exchange Rate, with the total government debt and its structure playing a significant role.

Indonesia's Yield Curve In 2024: *Machine Learning & Dynamic Nelson Siegel (DNS) Model*

The term structure of government bond yields (for various maturities), commonly known as the yield curve (Exhibit 1), plays a crucial and significant role for the government, central bank and private agents in Indonesia. Bank Indonesia (BI), Indonesia's central bank, watches the yield curve very closely as one of the critical factors in deciding their monetary policy stance[1], as a misstep would create an imbalance. BI also conducts its' monetary policy by selling short-term bonds and buying long-term bonds (operation twist[2]) to absorb various shocks. On the other hand, private agents such as insurance firms, banks, and firms in other sectors also use this yield curve as a benchmark of risk-free credit[3]. A higher risk-free would cause a higher cost-of-fund for their debt and would particularly weigh on the firm-level and country-level growth.

Exhibit 1. Indonesia's Term Structure of Interest Rate (Yield Curve)

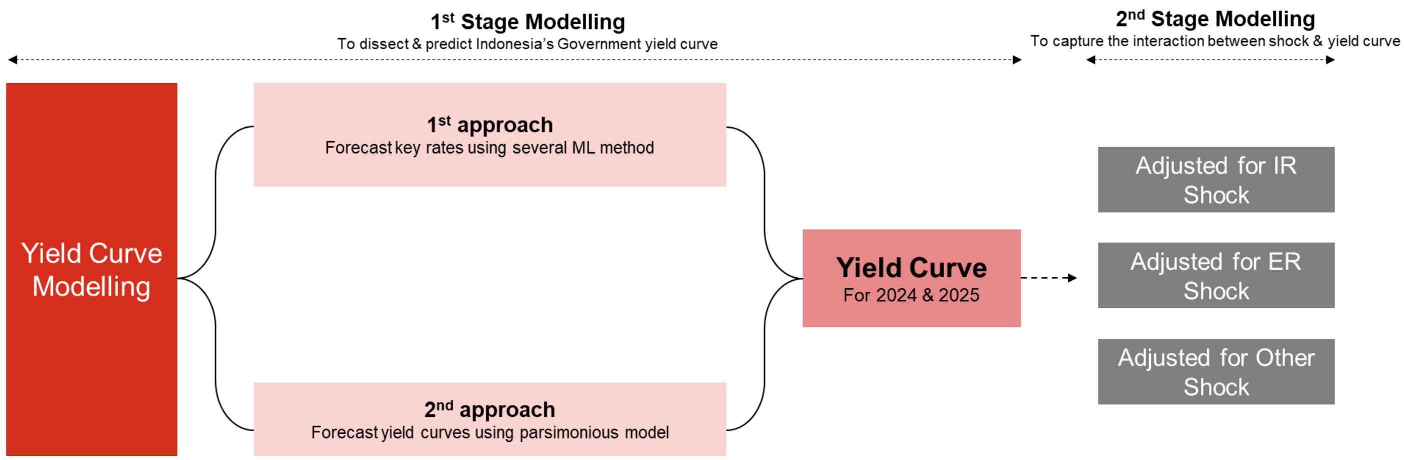


Source: Ministry of Finance, IFGP Research. Note: 3D graph is adapted from New York Times version of United States

This paper is organized as follows. The first part will look into the characteristics of Indonesian government bond yield curves. Next, the study aims at estimating the bond yield curve for 2024, and at the same time unveil the complexities in tracking the movements of the yield curves.

[1] An example can be found in Monetary Policy Review report published by Bank Indonesia (see more: https://www.bi.go.id/en/publikasi/laporan/Pages/TKM-Desember-2023.aspx accessed by 4th of January 2024)
[2] See more: https://www.bi.go.id/id/publikasi/laporan/Documents/TKM_Mei_2023.pdf accessed by 4th of January 2024
[3] Indonesia's government bonds have been widely accepted as a benchmark for risk-free credit for assets in Indonesia.

Exhibit 2. Research Framework



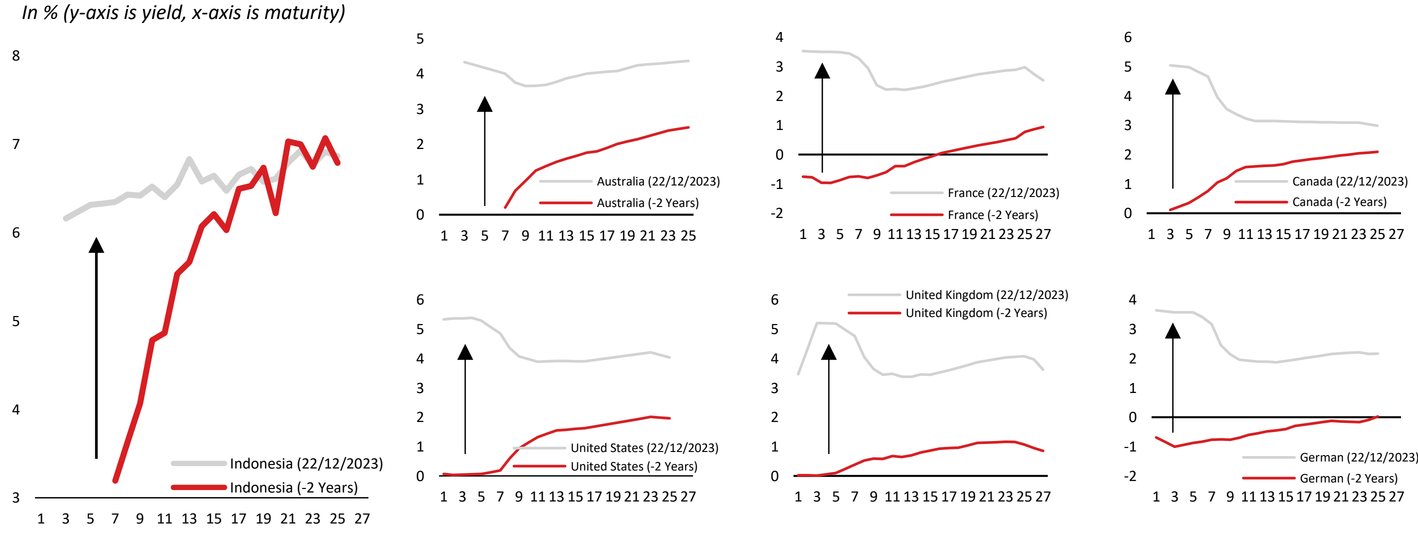
Source: IFGP Research. Note: IR stands for Interest Rate, ER stands for Exchange Rate.

Characteristics of Indonesia's Yield Curve

Generally, there are four characteristics or types of the yield curves: 1) Normal, 2) Flat, 3) Inverted, and 4) Humped. Normal yield curves typically show long-term maturities bear higher yields than the short-term maturities. This type of curve has a positive slope and often signals an economy in good condition. Conversely, when an economy is in bad shape, the yield curve would form an inverted shape or a humped (mix of inverted and flat) shape[4].

Exhibit 3. Yield Curves from The End of 2023 Vs 2-Years Prior Showed Strong Pressure Both for Indonesia & Selected Developed Markets (Inverted & Humped Shape)

In % (y-axis is yield, x-axis is maturity)



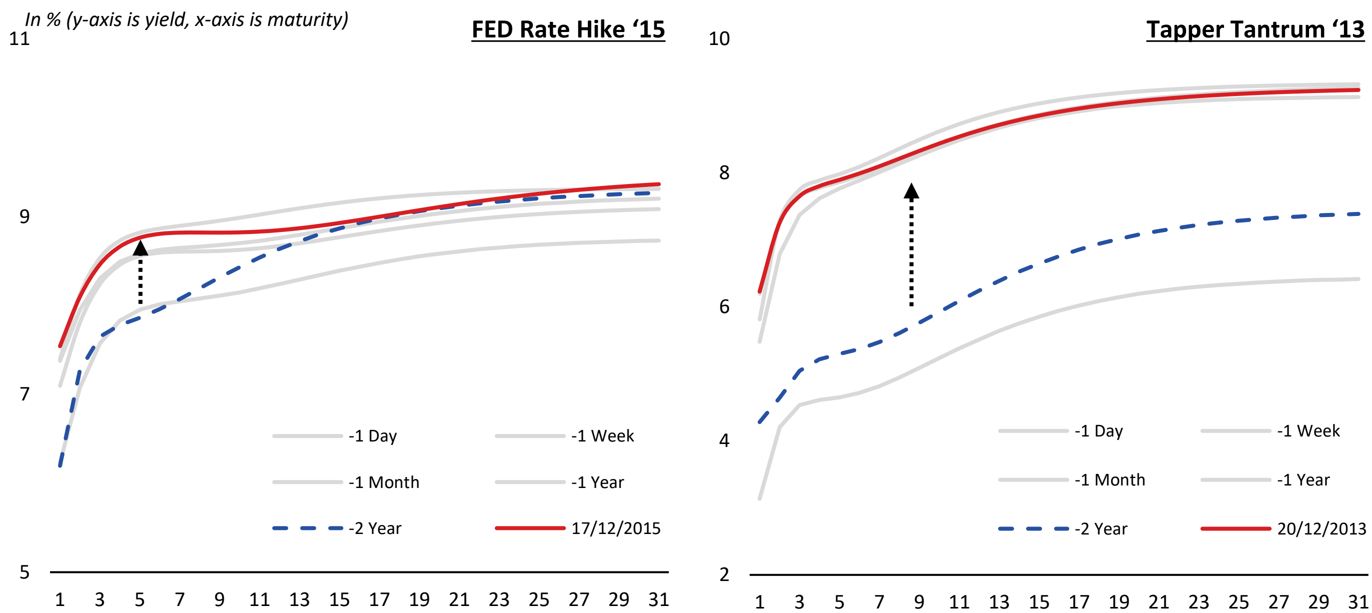
Source: Bloomberg, IFGP Research. Note: Not all the series are available between 1Y – 30Y, we interpolate the series only for graphical purpose

In recent years, particularly during the COVID-19 period (2020-2023), the yield curve movements have been forming inverted and humped shaped (indicating volatility, especially at the short end of the curve[5]). This happened not only for Indonesia but also for selected developed economies. For example, the yield for the 1-year tenor of Indonesia's government bond jumped from 3.19% to 6.34% within the last two years. This magnitude is lower if we compare it to the selected developed economies with the

[4] The shapes can be found in the Appendix 1
[5] Pattern of Indonesia's government bond for long-end of the curve unexpectedly stable. We suspect that this is due to Bank Indonesia's operation twist. Although it's very tempting, the scope of this phenomenon is beyond the objective of this paper.

average increase for 1-year yield at 4.12% (Australia at 3.80%; France at 4.02%; United States at 4.67%; Canada at 3.90%; United Kingdom at 4.38% and Germany at 3.93%) (Exhibit 3). This phenomenon has caused grave implications for many stakeholders, among which can be found on the headlines of many newspapers[6] due to its' default in debt payments (particularly for African Countries), bankruptcy, and other financial trouble caused by the spike in the yield curve.

Exhibit 4. Across Several Periods, Indonesia's Government Bond Showed High fluctuation, Especially in VUCA periods…



Source: IBPA, CEIC, IFGP Research.

If we go back further, this kind of fluctuation following the VUCA[7] condition has happened several times in Indonesia, especially in 2015 and 2013 (Exhibit 4). In 2013, when an external shock happened following the hawkish stance of the United States Central Bank (commonly known as the taper tantrum), Indonesia's government bond for all tenors jumped by ±2 full percentage points. Similarly, when the United States Central Bank increased its policy rate for the first time in almost a decade, Indonesia's government bond, especially for short-term tenor, also jumped, responding to the shock. If history is any guide, we might expect a similar movement in Indonesia's yield curve following any shock (although with a different magnitude). Anticipating this kind of reaction will be very beneficial for all economic agents[8]

Furthermore, the benefits of understanding the yield curve do not stop only at the movement of the maturities but also the indirect relationship between maturities and what it signals. One commonly used concept in financial economics is the spread[9] between long-term and short-term yield.

"A closely watched recession signal flashed red on Tuesday, as investors fretted that the Federal Reserve's efforts to tame inflation will bring about a sharp slowdown in US

[6] Among others: https://www.ft.com/content/acddb1c2-e05d-4b72-b50d-703fe6c5e521 and https://finance.yahoo.com/news/ethiopia-become-africa-next-debt-030000184.html. Accessed by 4th of January 2024
[7] VUCA stands for Volatility, Uncertainty, Complexity and Ambiguity
[8] We will go deeper for estimating the reaction for Indonesia's yield curve in the second stage of the paper (forthcoming)
[9] The Spread can be between other series as well, such as Estrella and Mishkin (1998) using 10-year and 3-month, or Engstrom and Sharpe (2018) using Forward 6-quarter and 3-month.

economic activity." –Financial Times (Duguid & Smith, 2022)

"A recession indicator that predicted every downturn since 1969 started flashing months ago" –Yahoo Finance (Hill & Goko, 2023)

The spread between 10-year and 2-year government bonds, commonly used as the benchmark for the spread, indicates several messages for economic activity, both its growth and recession. One of the most notable examples of its performance is from the US economy. This spread has been successfully preceding the recession ±1-year before the downturn. Additionally, even though it's not always a recession, the spread can reflect the pessimism and gloomy outlook for future economic activity, as asset prices are known for their forward-looking approach[10]. Although the theoretical explanation hasn't been satisfyingly clear yet, this great track record can't be put aside, and understanding this dynamic is very important for many countries, including Indonesia.

Yield Curve Estimation for 2024

Given the importance of the yield curve from financial activity to actual economic activity, this paper will estimate the yield curve for Indonesia in 2024. The estimation process will be conducted using 1) Machine Learning and 2) Parsimonious. The data used for this estimation process is from the Indonesia Bond Pricing Agency (IBPA)[11] from 2008 – latest[12]. To fulfill the requirements of minimum data for training and reduce the overfitting problem, we set the training window from 2008 – 2022 and made the whole of 2023 the out-of-sample window. We also break the window into four horizons: 1) 1-month, 2) 3-month, 3) 6-month, and 4) 12-month. After producing the prediction, we calculate the RMSE values for every maturity in every horizon.

For the machine learning models, we adapted similar specifications from Maccarrone et al., (2021), Yoon (2020), Bolhuis and Rayner (2020), Hopp (2022) & Park and Yang (2022). The machine learning models are 1) Neural Network, 2) XGBOOST, 3) Decision Tree, and 4) Random Forest. For the parsimonious models (along with its contender), we follow similar specifications from Nelson and Siegel (1987), Diebold and Li (2006), Brechtken (2008), Diebold and Rudebusch (2013), Caldeira et al. (2020) & Rubín and Ayliffe (2020). The parsimonious models are based on the Dynamic Nelson Siegel (DNS) Model, which are 1) One-step DNS (Kalman Filter), 2) One-step DNS (Kalman Filter - Explosivity Correction), 3) Two-step DNS (Vector Autoregression), and 4) Two-step DNS (Vector Autoregression - Yule-Walker). The contenders are 1) Random Walk (RW), 2) Autoregression, and 3) Vector Autoregression. We set the RW as the benchmark model in this study following Duffee (2002), Ang and Piazzesi (2003), Diebold and Li (2006), and Moench (2008), and the success indicator for our estimation depends on whether the model can beat the RW.

The specifications that we use for the DNS model follows Diebold and Li (2006), Carriero

[10] Among others: Estrella and Mishkin (1998) & Rudebusch and Williams (2008)

[11] This practice normally incorporates zero-coupon bonds instead of an index. However, Indonesia's government bond does not have long-term zero-coupon bonds (for detail please refer to DJPPR official website). We understand that by using an index of coupon bonds, there will be reinvestment rate and coupon effect (alternatively, we can follow (Yunianto (2005) approach and use Sertifikat Bank Indonesia (SBI)). However, we still use those indices as they are the main benchmark used by many stakeholders in Indonesia.

[12] The earliest data available is from 2008. Key maturities that we use are <1, 1, 2, 3, 5, 7, 10, 15, 20, 25 and 30.

et al. (2012) and Diebold and Rudebusch (2013):

$$y_t^{(\lambda)} = \beta_{1t} + \beta_{2t}\left(\frac{1-e^{-\lambda\tau}}{\lambda\tau}\right) + \beta_{3t}\left(\frac{1-e^{-\lambda\tau}}{\lambda\tau} - e^{-\lambda\tau}\right)$$

Where β_1, β_2 and β_3 are the parameters. In dynamic terms, these factors will be time-varying factors that will define time-varying level, slope, and curvature. We will get the predicted parameters of $\tilde{\beta}_{1t}, \tilde{\beta}_{2t}$ and $\tilde{\beta}_{3t}$ by calculating every maturity at each point in time. These factors will then be modeled using the AR(1) process and forecasted as follows:

$$\hat{\beta}_{jt+h} = \hat{\alpha}_0 + \hat{\alpha}_1\hat{\beta}_{jt}$$

Where $\hat{\alpha}_0$ and $\hat{\alpha}_1$ are the parameters of the model, j = 1, 2, 3 and h = time ahead. After obtaining the forecasted $\hat{\beta}_{jt+h}$, we can use it to calculate the predicted $y(\tau)$ by reverse-engineering the 1st system as follows:

$$\hat{y}_{t+h}^{(\lambda)} = \hat{\beta}_{1t+h} + \hat{\beta}_{2t+h}\left(\frac{1-e^{-\lambda\tau}}{\lambda\tau}\right) + \hat{\beta}_{3t+h}\left(\frac{1-e^{-\lambda\tau}}{\lambda\tau} - e^{-\lambda\tau}\right)$$

We conduct similar mechanisms to obtain the forecasted yield curve for another second-step model, while in the first step, we assume a state-space representation following Durbin and Koopman (2012) & Rubín and Ayliffe (2020). We pick the best two models and use them for the analysis of this paper and modelling the impulse-response in the next paper. The RMSE results for all the models mentioned above can be found in the Exhibit 5. The RMSE results are divided into two sections according to the type of the models to differentiate the performance easily. The results produced several findings:

- For a 1-month horizon, RMSE results showed that Random Walk and Autoregression are the best models out of all the models. This result is consistent across all maturities. Machine learning methods and DNS-based models still can't compete.

- For the 3-month horizon, RMSE results start to shift, and we get mixed results depending on the maturities. Machine learning models began to show their performance, especially for Neural Network and XGBOOST for medium to long-term maturities. The DNS-based models also showed excellent results for both ends of maturities.

- For the 6-month horizon, we get a very similar result compared to the 3-month horizon, with machine learning and DNS-based models showing a decent result even though the random walk model is still relatively dominant as the best result, followed by Neural Network.

- For the 12-month horizon, we get an utterly mixed result with short-end maturities dominated by Random Forest and Two-step DNS, medium to long-term by Neural Network, and long-end maturities by Random Walk and Neural Network.

Exhibit 5. RMSE Value Showed a Clear Pattern, Nothing Beats the Random Walk, Except Neural Network…

RMSE Value for Each Method and Maturity

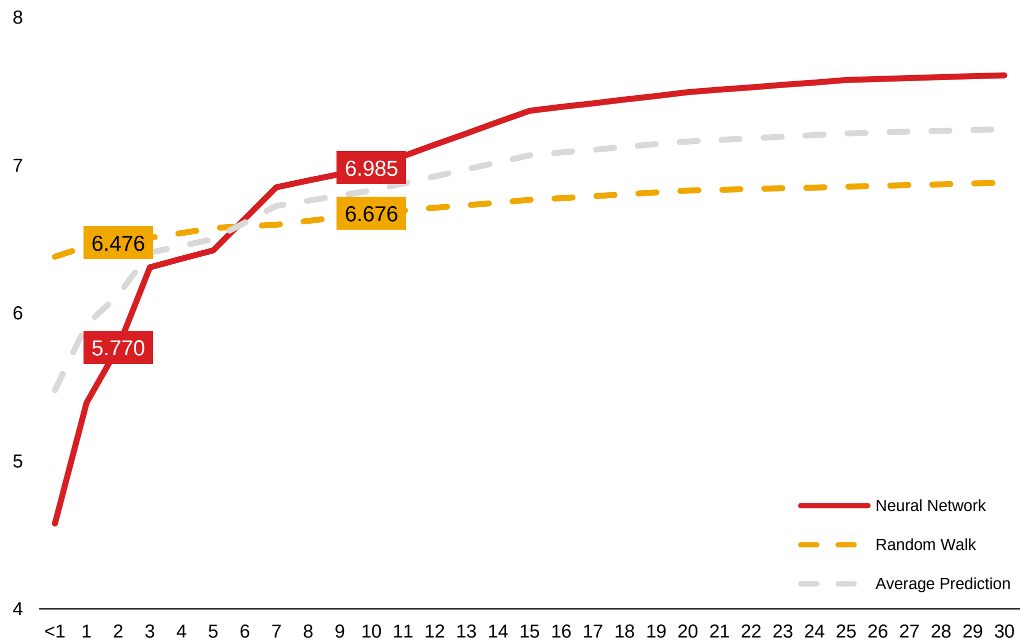
Method	Maturity										
	<1 Year	1 Year	2 Year	3 Year	5 Year	7 Year	10 Year	15 Year	20 Year	25 Year	30 Year
1 month horizon											
1st Approach – Econometrics & ML Model											
Neural Network	0.917	0.590	0.359	0.206	0.056	0.040	0.142	0.265	0.246	0.326	0.311
XGBOOST	0.733	0.816	0.326	0.430	0.216	0.305	0.330	0.391	0.422	0.724	0.905
Decision Tree	1.417	0.386	0.721	0.678	0.832	0.736	0.667	1.119	1.398	1.439	1.194
Random Forest	0.847	0.478	0.506	0.668	0.875	0.776	0.955	1.221	1.347	1.398	1.336
2nd Approach – Parsimonious Based Model											
One-step DNS (Kalman Filter)	0.086	0.106	0.034	0.113	0.177	0.171	0.127	0.084	0.079	0.084	0.094
One-step DNS (Kalman Filter - Explosivity Correction)	0.222	0.045	0.017	0.024	0.052	0.086	0.148	0.215	0.230	0.223	0.210
Two-step DNS (Vector Autoregression)	0.111	0.115	0.025	0.048	0.111	0.119	0.095	0.069	0.070	0.083	0.100
Two-step DNS (Vector Autoregression - Yule Walker)	0.131	0.093	0.028	0.082	0.147	0.156	0.132	0.104	0.106	0.121	0.139
Random Walk	0.017	0.018	0.004	0.012	0.035	0.045	0.045	0.038	0.036	0.035	0.035
Autoregression	0.024	0.018	0.008	0.020	0.044	0.056	0.065	0.074	0.080	0.084	0.086
Vector Autoregression	0.100	0.056	0.086	0.089	0.096	0.106	0.120	0.137	0.146	0.150	0.151
3 month horizon											
1st Approach – Econometrics & ML Model											
Neural Network	0.915	0.702	0.465	0.313	0.114	0.067	0.071	0.152	0.190	0.246	0.258
XGBOOST	1.054	0.958	1.284	0.974	0.148	0.198	0.235	0.285	0.392	0.451	0.590
Decision Tree	1.343	0.247	0.432	0.544	0.828	0.725	0.635	1.079	1.375	1.442	1.844
Random Forest	0.698	0.315	0.353	0.557	0.812	0.733	0.908	1.186	1.322	1.388	1.323
2nd Approach – Parsimonious Based Model											
One-step DNS (Kalman Filter)	0.136	0.336	0.131	0.172	0.390	0.440	0.401	0.345	0.345	0.363	0.380
One-step DNS (Kalman Filter - Explosivity Correction)	0.158	0.311	0.175	0.077	0.195	0.225	0.190	0.165	0.171	0.178	0.184
Two-step DNS (Vector Autoregression)	0.117	0.341	0.170	0.097	0.284	0.343	0.321	0.284	0.296	0.320	0.342
Two-step DNS (Vector Autoregression - Yule Walker)	0.101	0.274	0.113	0.161	0.378	0.440	0.420	0.384	0.397	0.422	0.444
Random Walk	0.179	0.279	0.196	0.093	0.128	0.171	0.166	0.147	0.148	0.151	0.153
Autoregression	0.211	0.284	0.177	0.081	0.167	0.226	0.252	0.277	0.302	0.318	0.325
Vector Autoregression	0.357	0.184	0.120	0.159	0.283	0.340	0.368	0.401	0.430	0.446	0.453
6 month horizon											
1st Approach – Econometrics & ML Model											
Neural Network	0.944	0.599	0.348	0.305	0.234	0.211	0.220	0.327	0.323	0.373	0.371
XGBOOST	0.922	0.905	0.936	0.715	0.240	0.368	0.458	0.470	0.501	0.497	0.590
Decision Tree	1.158	0.343	0.623	0.718	1.024	0.869	0.812	1.233	1.530	1.522	1.390
Random Forest	0.553	0.336	0.479	0.712	0.963	0.893	1.078	1.340	1.461	1.497	1.430
2nd Approach – Parsimonious Based Model											
One-step DNS (Kalman Filter)	0.296	0.352	0.168	0.333	0.602	0.678	0.659	0.609	0.605	0.619	0.636
One-step DNS (Kalman Filter - Explosivity Correction)	0.270	0.344	0.179	0.209	0.389	0.438	0.409	0.361	0.354	0.361	0.372
Two-step DNS (Vector Autoregression)	0.256	0.357	0.177	0.241	0.473	0.553	0.549	0.519	0.525	0.546	0.567
Two-step DNS (Vector Autoregression - Yule Walker)	0.162	0.254	0.204	0.375	0.632	0.718	0.717	0.688	0.697	0.718	0.739
Random Walk	0.357	0.300	0.197	0.153	0.247	0.295	0.294	0.271	0.261	0.256	0.254
Autoregression	0.417	0.308	0.181	0.183	0.320	0.395	0.448	0.501	0.533	0.549	0.557
Vector Autoregression	0.585	0.170	0.211	0.319	0.461	0.532	0.583	0.640	0.677	0.695	0.702
12 month horizon											
1st Approach – Econometrics & ML Model											
Neural Network	1.178	0.695	0.377	0.276	0.237	0.257	0.301	0.481	0.486	0.544	0.543
XGBOOST	1.019	0.963	0.771	0.593	0.333	0.374	0.561	0.564	0.598	0.582	0.630
Decision Tree	0.854	0.357	0.577	0.613	0.960	0.822	0.747	1.258	1.566	1.607	1.339
Random Forest	0.516	0.338	0.410	0.625	0.885	0.835	1.059	1.356	1.488	1.523	1.456
2nd Approach – Parsimonious Based Model											
One-step DNS (Kalman Filter)	0.736	0.599	0.316	0.398	0.674	0.791	0.828	0.825	0.830	0.843	0.859
One-step DNS (Kalman Filter - Explosivity Correction)	0.745	0.635	0.359	0.315	0.471	0.548	0.562	0.542	0.535	0.541	0.551
Two-step DNS (Vector Autoregression)	0.696	0.604	0.338	0.332	0.550	0.663	0.713	0.725	0.740	0.759	0.779
Two-step DNS (Vector Autoregression - Yule Walker)	0.508	0.420	0.293	0.464	0.760	0.893	0.955	0.977	0.996	1.018	1.039
Random Walk	0.813	0.563	0.385	0.308	0.332	0.371	0.387	0.376	0.359	0.345	0.336
Autoregression	0.918	0.577	0.345	0.299	0.397	0.487	0.591	0.707	0.760	0.780	0.788
Vector Autoregression	1.049	0.430	0.314	0.386	0.521	0.610	0.711	0.824	0.879	0.902	0.910

Source: IFGP Research.

Overall, the RMSE results are partly in line with past literature, among others, Duffee (2002), Diebold and Li (2006) & Rubín and Ayliffe (2020), that beating the random walk in the short horizon, is indeed very hard, especially in the 1-month horizon. However, as we go into the longer horizon, other models show their power and compete with the random walk model, particularly the Neural Network model (Exhibit 5).

Based on the RMSE results, we picked two of the best models to estimate the yield curve for 2024. The two models that we used are 1) Neural Network and 2) Random Walk. We also calculate the average prediction from those two models. Our prediction result can be found in Exhibit 6.

Exhibit 6. Yield Curve Prediction for 2024



Source: IFGP Research. Note: Numbers on the right side are prediction for 10-year maturity, while the left are for 2-year maturity

Our predictions indicate two different things: 1) a Condition similar to 2023 where the yield curve is flattening (Random Walk) and 2) a Condition where the yield curve is starting to normalize (Neural Network). These two predictions also imply a very different picture with a spread (10-year minus 2-year) of 0.2% for Random Walk and 1.215% for Neural Network (The average spread of the whole sample is 1.254%) (Exhibit 6).

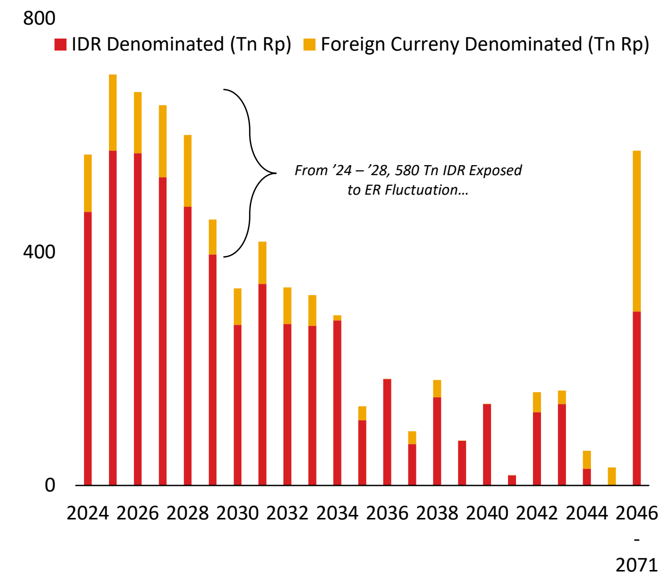
What's Ahead? Future Challenges

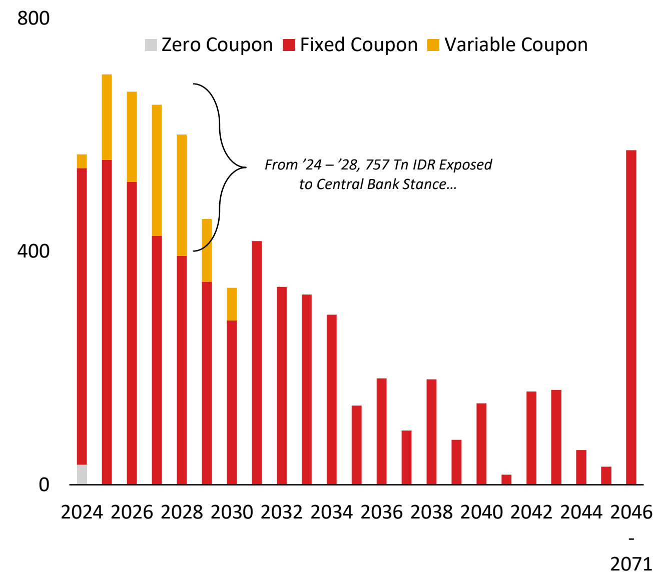
Even though our models showed an outstanding performance, we understand they are still sensitive to shocks. Defining and using the correct assumption for what might happen in 2024 will produce a better prediction. In this section, we define two of the most critical factors and sources of challenges that have a substantial degree of influence on the yield curve; they are 1) Policy Rate and 2) Exchange Rate.

Looking at the structure and profile of the total government debt, debt denominated by foreign currency is quite significant. In 2024, the total debt in foreign currency is at 98 Tn IDR; from 2024 to 2028, the total number is at 580 Tn IDR. On the other hand, if we look at the coupon type from 2024 to 2028, the total debt that pays the coupon based on the variable rate is at 757 Tn IDR. Suppose the Exchange Rate and Policy Rate stances are as volatile and hawkish as we experienced in 2023. In that case, we should expect our yield curve to lean more towards a flattening curve or, as the Random Walk model predicts, with a different level. However, if that is not the case, we should expect our yield curve to normalize and lean toward our Neural Network model (Exhibit 7).

Exhibit 7. What's Ahead? Exchange Rate & Interest Rate Will Be the Deciding Factors For 4 – 5 Years Ahead

In Tn IDR (Debt profile by maturity (left); Debt profile by maturity & type of coupon (right))





Source: Ministry of Finance, IFGP Research.

Conclusion

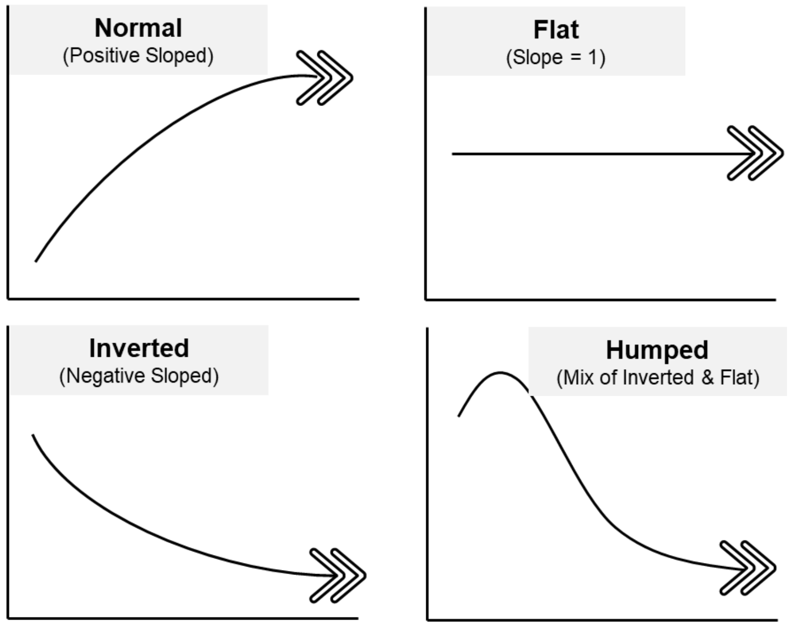
Yield curves play a vital role for many agents, both government and private agents. The government (notably the Central Bank) watches this curve closely in making their monetary policy, while private agents use the curve as a benchmark in making their strategic decisions. The movements of the yield curve, whether the level, slope, or curvature, will impact all those agents.

During VUCA periods, the yield curve will react to the pressure, for example, flattening (inverted) in 2023 & 2015 and increasing in level for 2013. In the future, we might expect the same response from the yield curve, although in different magnitudes. These kinds of movements expose risks to the economy, as can be seen by various unwanted consequences, from the bankruptcy of massive firms to default in debt payments. A strong outlook and prediction for the yield curve is crucial for all agents, including in Indonesia. This paper produced several models that performed very well. Our model's prediction for 2024 showed two distinct results: 1) Optimism and 2) Pessimism. Our models estimate that the 10-year government bonds yield will be in the range of 6.6% - 6.9%, *ceteris paribus*. (the updated result will be posted on the IFG Progress website at https://www.ifgprogress.id/).

Lastly, we will expand this estimation and build several scenarios in the second stage of the paper in line with the challenges we will face in 2024.

APPENDIX

Appendix 1. Four Types of Yield Curve



Source: Various, IFGP Research.

Appendix 2. *References*

Ang, A. and Piazzesi, M. (2003) ‘A no-arbitrage vector autoregression of term structure dynamics with macroeconomic and latent variables’, Journal of Monetary Economics, 50(4), pp. 745–787. doi:10.1016/s0304-3932(03)00032-1.

Ayliffe, K. and Rubín, T. (2020) A Quantitative Comparison of Yield Curve Models in the MINT Economies. rep. EPFL Scientific Publications.

Bolhuis, M. and Rayner, B. (2020) ‘Deus Ex Machina? A framework for macro forecasting with machine learning’, SSRN Electronic Journal [Preprint]. doi:10.2139/ssrn.3579665.

Brechtken, G.L. (2008) The Dynamics of Interest Rates in the Czech Republic, Hungary and Poland: A Vector Autoregressive Latent Yield and Macro Factor Approach. thesis.

Caldeira, J.F. et al. (2020) ‘Forecasting the term structure of interest rates of the BRICS: Evidence from a nonparametric functional data analysis’, Emerging Markets Finance and Trade, 57(15), pp. 4312–4329. doi:10.1080/1540496x.2020.1808458.

Carriero, A., Clark, T.E. and Marcellino, M. (2012) ‘Common drifting volatility in large Bayesian Vars’, Working paper (Federal Reserve Bank of Cleveland) [Preprint]. doi:10.26509/frbc-wp-201206.

Diebold, F.X. and Li, C. (2006) ‘Forecasting the term structure of government bond yields’, Journal of Econometrics, 130(2), pp. 337–364. doi:10.1016/j.jeconom.2005.03.005.

Diebold, F.X. and Rudebusch, G.D. (2013) Yield curve modeling and forecasting [Preprint]. doi:10.23943/princeton/9780691146805.001.0001.

Dodd, D. (2023) ‘Business bankruptcies surge under impact of high interest rates’, Financial Times, 19 December. Available at: https://www.ft.com/content/acddb1c2-e05d-4b72-b50d-703fe6c5e521 (Accessed: 04 January 2024).

Duffee, G.R. (2002) ‘Term Premia and interest rate forecasts in affine models’, The Journal of Finance, 57(1), pp. 405–443. doi:10.1111/1540-6261.00426.

Duguid, K. and Smith, C. (2022) ‘US yield curve inverts in possible recession signal’, Financial Times, 30 March. Available at: https://www.ft.com/content/abb3f7a7-b878-423a-a691-d5214639cbc3 (Accessed: 04 January 2024).

Durbin, J. and Koopman, S.J. (2012) Time series analysis by State Space Methods. Oxford: Oxford University Press.

Estrella, A. and Mishkin, F.S. (1998) ‘Predicting U.S. recessions: Financial variables as leading indicators’, Review of Economics and Statistics, 80(1), pp. 45–61. doi:10.1162/003465398557320.

Hill, M. and Goko, C. (2023) ‘Ethiopia Bond Coupon Miss to Make It Africa’s Latest Default’, Yahoo Finance, 11 December. Available at: https://finance.yahoo.com/news/ethiopia-become-africa-next-debt-030000184.html (Accessed: 04 January 2024).

Hopp, D. (2022) ‘Economic nowcasting with long short-term Memory Artificial Neural Networks (LSTM)’, Journal of Official Statistics, 38(3), pp. 847–873. doi:10.2478/jos-2022-0037.

Maccarrone, G., Morelli, G. and Spadaccini, S. (2021) ‘GDP forecasting: Machine learning, linear or autoregression?’, Frontiers in Artificial Intelligence, 4. doi:10.3389/frai.2021.757864.

Moench, E. (2008) ‘Forecasting the yield curve in a data-rich environment: A no-arbitrage factor-augmented VAR approach’, Journal of Econometrics, 146(1), pp. 26–43. doi:10.1016/j.jeconom.2008.06.002.

Nelson, C.R. and Siegel, A.F. (1987) ‘Parsimonious modeling of yield curves’, The Journal of Business, 60(4), p. 473. doi:10.1086/296409.

Park, S. and Yang, J.-S. (2022) ‘Interpretable deep learning LSTM model for intelligent economic decision-making’, Knowledge-Based Systems, 248, p. 108907. doi:10.1016/j.knosys.2022.108907.

Sharpe, S. and Engstrom, E. (2018) ‘The near-term forward yield spread as a leading indicator: A less distorted mirror’, Finance and Economics Discussion Series, 2018(055). doi:10.17016/feds.2018.055.

Yoon, J. (2020) ‘Forecasting of real GDP growth using machine learning models: Gradient boosting and Random Forest approach’, Computational Economics, 57(1), pp. 247–265. doi:10.1007/s10614-020-10054-w.

Yunianto, H. and Ekaputra, I.A. (2005) Pemodelan ‘Term Structure of Interest Rate’ di Indonesia. thesis. Fakultas Ekonomi dan Bisnis Universitas Indonesia,. Available at: https://lib.ui.ac.id/m/detail.jsp?id=103269&lokasi=lokal (Accessed: 04 January 2024).

Source: Various, IFGP Research.

PT. Bahana Pembinaan Usaha Indonesia (Persero)
Graha CIMB Niaga Building, 18th Floor
Jl. Jendral Sudirman Kav. 58
RT.5/RW.3, Senayan, Kebayoran Baru
Kota Jakarta Selatan, DKI Jakarta 12190
(+62) 021 2505080
Indonesia Financial Group
PT. Bahana Pembinaan Usaha Indonesia – Persero
@indonesiafinancialgroup
@ifg_id

Indonesia Financial Group (IFG)
Indonesia Financial Group (IFG) is the State-Owned Insurance and Underwriting Holding Enterprises consisting of PT Asuransi Kerugian Jasa Raharja, PT Jaminan Kredit Indonesia (Jamkrindo), PT Asuransi Kredit Indonesia (Askrindo), PT Jasa Asuransi Indonesia (Jasindo), PT Bahana Sekuritas, PT Bahana TCW Investment Management, PT Bahana Artha Ventura, PT Bahana Kapital Investa, PT Graha Niaga Tata Utama, dan PT Asuransi Jiwa IFG. IFG is the holding established to have the role in national development through the development of complete and innovative financial industry through investment, insurance, and underwriting services. IFG is committed to bring the change in financial sector particularly insurance, investment, and underwriting to which it is accountable, prudent, and transparent with good corporate governance and full of integrity. The collaborative spirit with good corporate governance that is transparent has become the basis for IFG to become the leading, trustworthy, and integrated provider of insurance, investment, and underwriting services. IFG is the future of financial industry in Indonesia. It is time to move forward with IFG as the driving force of inclusive and sustainable ecosystem.

Indonesia Financial Group (IFG) Progress
The Indonesia Financial Group (IFG) Progress is the leading Think Tank established by Indonesia Financial Group as the source of progressive ideas for the stakeholders, academics, or even the business players in bringing forward the financial service industry.