Estimation of the Peruvian Sovereign Bond Yield Curve using Bayesian VAR

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Abstract

This estimation adapts the affine no-arbitrage model proposed by Ang and Piazzesi (2003) to estimate the term structure of Peru's sovereign yield curve in soles over the period 2005–2025. The methodology unfolds in two stages: first, a Bayesian VAR (BVAR) is employed to estimate the parameters associated with observable macroeconomic factors; second, those parameters are combined with latent factors for bond valuation and yield estimation, subject to the no-arbitrage restriction. The results show that the BVAR(1) specification attains a superior fit relative to both the traditional VAR and the multi-lag BVAR, as indicated by metrics such as the mean forecast error, AIC, and BIC. The model enhances predictive accuracy along the short and medium segments of the curve, whereas—as consistently reported in the literature—the long end remains more challenging to forecast.

1. Introduction

The sovereign yield curve, understood as the term structure of risk-free interest rates, is an essential benchmark for the financial system: it guides public debt, risk analysis, and local and foreign investment decisions. In addition, it reflects changes in monetary policy and in investors' expectations about the economy. Its estimation is carried out using functions that relate rates to bond maturities, allowing yields to be inferred even for terms without active issuances. This tool is key for public debt management, macroeconomic assessment—where an inverted curve often foreshadows recessions—valuation and risk management, and establishing market benchmarks.

Since the 1970s, the first approaches to modeling the term structure of interest rates have emerged. McCulloch (1971) [1] proposed the use of cubic splines, whereas Vasicek (1977) [2] introduced a stochastic model for the evolution of interest rates. Subsequently, Svensson (1994) [3] extended the Nelson & Siegel specification by incorporating additional curvature parameters. In parallel, Duffie & Kan (1996) [4] developed no-arbitrage models within an affine framework, enforcing consistency across maturities. Later, Estrella & Mishkin (1997) [5] and Ang & Piazzesi (2003) [7] incorporated macroeconomic factors into affine term-structure models, thereby enhancing their explanatory power; this specification will be employed in the present article.

In the Peruvian case, sovereign bonds are issued by the Ministry of Economy and Finance (MEF) to finance the State and promote the development of the local market. These issuances are made in soles (PEN and VAC bonds) and in U.S. dollars in the international market. Based on their prices, the yield curve in soles is constructed.

The estimates made so far use Vector Autoregressions (VARs) to obtain macroeconomic factors. During this analysis, in addition to VAR estimation, another estimation will be carried out using Bayesian Vector Autoregressions (BVAR) to determine whether this estimation yields better tests and predictive ability than VAR alone. To this end, a change will be made in the first stage of the estimation; therefore, more robust parameters are expected when using the BVAR methodology.

2. Literature

2.1. Literature in Developed Countries

This document is grounded in the methodology of Ang & Piazzesi (2003) [7], who propose a two-stage estimation strategy: in the first stage, observable macroeconomic factors are identified, and in the second, together with latent factors, the parameters that define an affine function in terms of level, slope, and curvature are estimated. The methodological section develops this estimation procedure in detail. This approach integrates the empirical relationship between macroeconomic factors and interest rates with the no-arbitrage principle.

Regarding the first idea, Estrella & Mishkin (1997) [5] and Evans & Marshall (1998) [6] show how yield-curve indicators and VAR models can link the term structure of interest rates to macroeconomic factors. Likewise, the approaches of Taylor (1993) [8], Christiano, Eichenbaum & Evans (1996) [9], and Clarida, Galí & Gertler (1998) [10] emphasize short-run dynamics through monetary-policy rules and the role of policy shocks in driving economic activity. Concerning the second idea, the model relies on the pricing-kernel concept introduced by Harrison & Kreps (1979) [11] and on the methodology of Duffie & Kan (1996) [4]. The no-arbitrage principle enters because bond prices across maturities must be mutually consistent under the risk-neutral measure: this entails that the expected payoff of any bond, discounted by the stochastic discount factor, must equal its current price.

Subsequent literature has focused on improving the predictive power of the yield curve, developing new estimation techniques, and proposing alternative indicators to assess forecast quality. Mönch (2006) [15] estimates the term structure of interest rates for European Union countries using an FVAR model. Pooter, Ravazzolo, and van Dijk (2010) [16] examine the U.S. sovereign yield curve by comparing affine models with the Nelson–Siegel methodology and introducing cumulative forecast errors as a novel indicator of predictive performance.

For emerging economies, Bonomo and Lowenkron (2008) [13] estimate the sovereign external debt curve for Brazil, Colombia, and Mexico. Complementarily, Cavaca and Meurer (2021) [14] show that latent factors and shifts in U.S. monetary policy exert a significant influence on the yield curves of South American countries. For Peru, Olivares, Rodríguez, and Ataurima (2017) [12] implement the Ang and Piazzesi (2003) framework through a two-stage approach adapted to local data: the sovereign curve is derived from the SBS price vector, whereas the macroeconomic factors correspond to real-activity and inflation indicators sourced from the BCRP. The analysis covers the period 2005–2015 at a monthly frequency. Litterman (1986) and Doan, Litterman & Sims (1984) are pioneers in the use of the BVAR; this tool should improve forecasts of macroeconomic aggregates relative to traditional VAR estimates.

3. Methodology

3.1. Variables

3.1.1. Variables to Consider

Zero-coupon rates, macroeconomic variables related to inflation, and real activity. Zero-coupon yield curve rates are considered indicators of the term structure of interest rates. Regarding variables related to inflation, consumer price indices in all their variants are considered, as well as the country's commodity and import prices. Additionally, for real activity variables, unemployment and the country's growth are considered. For short-term interest rates, the shortest-maturity rate on the sovereign curve will be taken as an approximation of the policy rate. These variables will also be selected based on their availability at a monthly frequency; this applies to both macroeconomic variables and interest rates by maturity.

3.1.2. Criteria Regarding Interest Rates

In addition to availability, sovereign bond yields will also be considered based on liquidity (the level and frequency of trading, given their maturity in the sovereign bond market).

3.1.3. Data Treatment

Only for the macroeconomic (explanatory) variables will a z-score (with mean zero and variance one) be used to normalize their scale. In addition, since there will be many variables, principal component analysis (PCA) will be used to reduce dimensionality to just two components: one capturing inflation and one capturing real activity.

3.2. Problem Setup

The following methodology section is based on Ang and Piazzesi (2003).

3.2.1. Dynamics of the State Variables

The dynamics of the state variables help characterize the behavior and mutual relationships of both observable and latent components. This section, together with the short-run dynamics, corresponds to the first step in estimating the yield curve. The dynamics with 12 lags for the observable variables are categorized as follows, with f_t^o denoting the vector of observable macro factors (such as inflation or GDP) and K_1 representing the number of observable macro factors. From this, we assume a VAR(p) with $p = 12$:

$$f_t^o \;=\; A_1 f_{t-1}^o + A_2 f_{t-2}^o + \cdots + A_{12} f_{t-12}^o + u_t, \qquad u_t \sim \mathcal{N}(0, \Sigma_u) \tag{1}$$

Additionally, for the latent variables, we represent them by f_t^u, which contain K_2 latent yields (such as level, slope, and curvature). For the latent variables, we model their dynamics with a single AR(1) lag:

$$f_{t+1}^u \;=\; c_u + \Phi_{uu} f_t^u + \eta_{t+1}, \qquad \eta_{t+1} \sim \mathcal{N}(0, \Sigma_\eta) \tag{2}$$

Definitions.

- X_t: state vector with $K = K_1 p + K_2$.
- A_ℓ: Coefficient matrix of the macro VAR block (p).
- Φ_{uu}: latent factor matrix.

- $u_t \sim \mathcal{N}(0, \Sigma_u)$, $\eta_t \sim \mathcal{N}(0, \Sigma_\eta)$: macro and latent shocks, respectively.
- μ, Φ, Σ: parameters in reduced form.

3.2.2. Short-Term Dynamics

Based on contributions to monetary policy modeling, the short-term interest rate is defined, for estimation purposes, as a function of macroeconomic variables.

Short-Term Rate. The short-term rate is affine in the state:

$$r_t \;=\; \delta_0 + \delta_1' X_t \tag{3}$$

Definitions.

- r_t: Short-Term Rate (3 months given our data availability)
- X_t: State Vector $K = K_1 p + K_2$.
- δ_0, δ_1: Short-Run factor loadings for bond pricing.

3.2.3. Pricing Kernel and Bond Valuation

This section is relevant because it introduces the no-arbitrage condition, the risk price, and the affine function for modeling interest rates. This section is important for the estimation of the model in the second stage.

The pricing kernel is defined as follows:

$$m_{t+1} \;=\; \exp\bigl(-r_t \;-\; \tfrac{1}{2}\,\lambda_t'\lambda_t \;-\; \lambda_t'\varepsilon_{t+1}\bigr)\,, \tag{4}$$

Whereas the valuation of bonds, with an affine function form, is defined as follows:

$$y_t^{(n)} \;=\; A_n \;+\; B_n' X_t, \tag{5}$$

Definitions.

- X_t: state vector.
- $\lambda_t = \lambda_0 + \lambda_1 X_t$: market price of risk, affine in the state.
- m_{t+1}: Pricing kernel.
- $y_t^{(n)}$: annual compound rate.
- A_n, B_n: affine yield factor loadings derived from the Riccati equations.

3.3. Problem Setup using BVAR with 1 Lag

1) BVAR(1) Specification.

$$X_t = \mu + \Phi X_{t-1} + u_t, \qquad u_t \sim \mathcal{N}(0, \Sigma). \tag{S1.1}$$

$$Y = ZB + U, \tag{S1.2}$$

$$Y := [X_2, \ldots, X_T]' \tag{6}$$

$$Z := [\,\mathbf{1},\; X_1, \ldots, X_{T-1}\,] \tag{7}$$

$$\tag{8}$$

2) A Priori Parameters.

$$B := \begin{bmatrix} \mu' \\ \Phi' \end{bmatrix} \tag{9}$$

$$\tag{10}$$

3) Prior Minnesota (p = 1). Prior Mean:

$$\mathbb{E}[\mu] = 0, \qquad \mathbb{E}[\Phi_{jj}] = 1, \qquad \mathbb{E}[\Phi_{ji}] = 0 \ \ (i \neq j). \tag{S2.1}$$

Prior variances (hyperparameters $\lambda_1, \lambda_3, \lambda_4, \lambda_5$):

$$\mathrm{Var}(\Phi_{ji}) = \begin{cases} \lambda_1^2, & i = j, \\ \lambda_1^2 \lambda_4^2 \dfrac{\sigma_j^2}{\sigma_i^2}, & i \neq j, \end{cases} \qquad \mathrm{Var}(\mu_j) = \lambda_5^2 \, \sigma_j^2. \tag{S2.2}$$

Here, σ_i^2 denotes preliminary scale estimates (e.g., AR(1) standard errors for each series). For $p > 1$, the term is additionally multiplied by $1/\ell^{2\lambda_3}$ in the ℓ-th lag.

Normal–Inverse-Wishart Matrix Representation:

$$\mathrm{vec}(B) \mid \Sigma \sim \mathcal{N}\big(\mathrm{vec}(B_0), \ \Omega_0 \otimes \Sigma\big), \tag{S2.3}$$

$$\Sigma \sim \mathcal{IW}(S_0, \ \nu_0), \tag{S2.4}$$

con

$$B_0 = \begin{bmatrix} \mu_0' \\ \Phi_0' \end{bmatrix}, \qquad \mu_0 = 0, \qquad (\Phi_0)_{ji} = \begin{cases} 1, & i = j, \\ 0, & i \neq j, \end{cases} \tag{S2.5}$$

$$\Omega_0 = \mathrm{diag}\big(V_\mu, \ V_\Phi\big), \qquad V_\mu = \mathrm{diag}\big(\lambda_5^2 \sigma_1^2, \dots, \lambda_5^2 \sigma_K^2\big), \tag{S2.6}$$

$$V_\Phi = \mathrm{diag}\big(\{\mathrm{Var}(\Phi_{ji})\}_{j=1,\dots,K; \ i=1,\dots,K}\big). \tag{S2.7}$$

4) Posterior Parameter Estimates.

$$\widehat{\mu} \ = \ \big(\big(\Omega_0^{-1} + Z'Z\big)^{-1}\big(\Omega_0^{-1} B_0 + Z'Y\big)\big)'_{1,:} \tag{11}$$

$$\widehat{\Phi} \ = \ \big(\big(\Omega_0^{-1} + Z'Z\big)^{-1}\big(\Omega_0^{-1} B_0 + Z'Y\big)\big)'_{2:K+1,:} \tag{12}$$

$$\widehat{\Sigma} \ = \ \frac{S_0 + (Y - ZB_{\text{post}})'(Y - ZB_{\text{post}}) + (B_{\text{post}} - B_0)'\Omega_0^{-1}(B_{\text{post}} - B_0)}{\nu_0 + T - K - 1} \tag{13}$$

Whereas the parameters obtained from the VAR arise from OLS estimation, the parameters produced by the BVAR incorporate *shrinkage* adjustments toward the priors. The new parameters to be used in the estimation are shown in equations 11, 12, and 13.

4. Estimate of Results

4.1. Data

The information to be downloaded will consist of interest rates and macroeconomic variables. The data sources are the Superintendency of Banking, Insurance and Pension Fund Administrators (SBS) and the Central Reserve Bank of Peru (CRBP).

4.1.1. Performance Variables

The analysis focuses on the yield curve for Peruvian government sovereign bonds denominated in soles. This information is obtained from the SBS price vector, which constitutes the source closest to a genuine local-market term structure of interest rates. The dataset consists of monthly (end-of-month observations) data and spans from November 2005 to May 2025. The time series considered corresponds to yields with maturities of 3 months, 1 year, 2 years, 7 years, 9 years, and 10 years; these maturities are selected based on correlation analysis (the 6-month and 5-year rates are assessed) and market liquidity conditions (the 14-year rate is excluded).

4.1.2. Macroeconomic Indicators

The macroeconomic variables serve as leading indicators of domestic economic conditions—in this case, inflation and real activity. As with the yield data, monthly indicators from November 2005 to May 2025 are considered. For inflation, the analysis includes the general price index, the imported-goods price index, and the food price index, all expressed year-over-year. For real-activity indicators, unemployment, primary GDP, and non-primary GDP are included, likewise described as year-over-year variations.

4.1.3. Principal Component Analysis and Z-Score

Only the macroeconomic variables are normalized and scaled to the range [0, 1]. The three inflation-related variables and the real-activity indicator are combined into a single category using principal component analysis (PCA), and only the first factor is retained.

The time-series plots of the variables, including the dimensionality reduction via PCA, are shown below in Figure 1.:

Figure 1: Time Series (2005-2025)

4.1.4. Statistical Characteristics of the Variables

The main descriptive statistics for the time series of the yield-curve indicators and the macroeconomic variables are discussed below. For the yield curve, both the means and standard deviations remain stable across maturities, with no substantial deviations from the mean or noteworthy outliers. In contrast, the macroeconomic variables display larger deviations from their means, particularly imported-goods inflation, primary GDP, and non-primary GDP. The Covid period markedly increased the standard deviation of the macroeconomic indicators and generated the most significant outliers, in addition to those associated with the 2008 global financial crisis. The table reporting the statistical summaries is presented in Table 1.

	Mean	Desv Std	Asymet	Kurtosis	Autocorrel		
					Lag 1	Lag 2	Lag 3
Yield Curve							
Yield 3m	3.67	1.73	-0.10	2.56	0.976	0.936	0.888
Yield 1y	3.82	1.63	-0.09	2.60	0.975	0.931	0.875
Yield 2y	4.16	1.55	-0.02	2.77	0.969	0.922	0.864
Yield 7y	5.69	1.22	0.06	3.01	0.952	0.890	0.827
Yield 9y	6.07	1.13	0.05	2.95	0.944	0.873	0.807
Yield 10y	6.22	1.09	0.04	2.92	0.939	0.865	0.798
Macro							
CPI Alimento	4.06	3.16	1.02	3.64	0.969	0.924	0.871
CPI Import	3.07	5.00	1.04	5.22	0.978	0.930	0.871
CPI General	3.26	1.92	1.14	4.03	0.974	0.934	0.883
Desempleo	0.01	0.66	-1.09	12.39	0.398	-0.016	-0.290
PBI Prim	3.00	6.81	-0.04	7.66	0.524	0.274	0.248
PBI Non-Prim	4.85	8.55	1.59	27.89	0.811	0.540	0.365

Table 1: Descriptive statistics and autocorrelations of the yield curve and macroeconomic variables

4.2. Analysis of Interrelations Among Variables

4.2.1. Relationship Between Macroeconomic Factors

The model begins by establishing the relationship between the macroeconomic factors. The coefficient obtained from this estimation, along with the possibility of establishing a relationship between inflation factors and real activity, will be part of the loadings used to estimate the yield curve. We calculate a VAR(8), not a VAR(12), because when we initially estimate with 12 lags, the last significant variable is obtained with eight lags. The results below show the coefficients and parameters for the VAR(8), which illustrate the relationships between the lags of inflation and real activity, both within and across equations. For the moment, the goal is to establish a relationship between the variables so that the BVAR analysis can be carried out later.

The analysis below examines how a shock to each macroeconomic factor (inflation or real activity) affects the other. The assessment is conducted using a VAR(8) and a BVAR(8). The results show that each variable exhibits a significant short-run response to its own innovations. In contrast, the cross-effects are more moderate, with inflation exerting a stronger influence on real activity. In both specifications, the qualitative patterns are similar; however, the BVAR produces smoother impulse response functions. The corresponding plots are displayed in Figure 2.

Block 1					Block 2				
Parametro	**Coef**	**StdError**	**Tstat**	**PValue**	**Parametro**	**Coef**	**StdError**	**Tstat**	**PValue**
Constant(1)	0.0004	0.0180	0.0199	0.9841	AR{4}(2,2)	0.3209	0.0877	3.6585	0.0003
Constant(2)	-0.0008	0.0582	-0.0141	0.9888	AR{5}(1,1)	-0.1385	0.1027	-1.3490	0.1778
AR{1}(1,1)	1.2480	0.0645	19.3420	0.0000	AR{5}(2,1)	-0.4411	0.3336	-1.3226	0.1860
AR{1}(2,1)	0.1467	0.2091	0.7019	0.4827	AR{5}(1,2)	0.0226	0.0271	0.8287	0.4087
AR{1}(1,2)	-0.0035	0.0201	-0.1727	0.8629	AR{5}(2,2)	-0.1142	0.0882	-1.2957	0.1959
AR{1}(2,2)	0.8816	0.0652	13.5280	0.0000	AR{6}(1,1)	0.0207	0.1029	0.2014	0.8404
AR{2}(1,1)	-0.2206	0.1038	-2.1254	0.0336	AR{6}(2,1)	0.5408	0.3335	1.6203	0.1053
AR{2}(2,1)	-0.2663	0.3363	-0.7919	0.4284	AR{6}(1,2)	-0.0222	0.0272	-0.8161	0.4145
AR{2}(1,2)	0.0423	0.0268	1.5803	0.1140	AR{6}(2,2)	-0.0534	0.0881	-0.6066	0.5450
AR{2}(2,2)	-0.2229	0.0867	-2.5712	0.0101	AR{7}(1,1)	-0.0600	0.1019	-0.5892	0.5557
AR{3}(1,1)	-0.1634	0.1044	-1.5657	0.1174	AR{7}(2,1)	0.3883	0.3331	1.1733	0.2398
AR{3}(2,1)	0.2821	0.3381	0.8343	0.4041	AR{7}(1,2)	-0.0241	0.0268	-0.8981	0.3697
AR{3}(1,2)	0.0158	0.0271	0.5820	0.5606	AR{7}(2,2)	0.0493	0.0869	0.5672	0.5706
AR{3}(2,2)	-0.1765	0.0880	-2.0066	0.0448	AR{8}(1,1)	-0.0408	0.0627	-0.6505	0.5154
AR{4}(1,1)	0.3020	0.1036	2.9149	0.0036	AR{8}(2,1)	0.0659	0.2032	0.3242	0.7358
AR{4}(2,1)	0.0607	0.3356	0.1808	0.8565	AR{8}(1,2)	-0.0422	0.0204	-2.0719	0.0383
AR{4}(1,2)	-0.0329	0.0271	-1.2167	0.2237	AR{8}(2,2)	-0.0596	0.0660	-0.9034	0.3632

Table 2: Results of the AR model: coefficients, standard errors, t-statistics, and p-values.

4.2.2. Short Term Dynamics

Equation 3 captures the short-run dynamics, motivating an analysis of the regression estimated in the first stage of the final procedure. The analysis relates the short-term interest rate to inflation and real activity, with a one-period lag. The first specification considered is (1) the Taylor Rule, which exhibits modest explanatory power ($R\hat{2}$ of 21%). When the model is extended to include (2) 12 lags (up to one year), the predictive capacity improves substantially (50%). However, once a short-term lag (inertia) is added, the predictive power becomes very high (96%). These results indicate the degree to which macroeconomic indicators can contribute to short-term forecasting.

For the estimation, we adopt the second specification (12 lags only), since the short-rate inertia term is already incorporated elsewhere in the model. Achieving a 50% predictive capacity for our 20-year sample provides confidence that this dynamic structure can be meaningfully integrated into the model. The results are reported in Table 3.

4.3. Estimation

4.3.1. Mean Error of the VAR and BVAR Estimation in the Macro Factor

The estimation is conducted using a VAR(8), a BVAR(8), and a BVAR(1); these three specifications correspond to the parameter estimates obtained in the first stage. Figure 3 presents a summary table of the mean forecast errors for each type of estimation. In levels, the BVAR(1) delivers superior predictive performance across maturities compared with the VAR(8), with a maximum mean error of 34 bps versus 67 bps. Note that in the VAR(8), predictive accuracy is higher at the short end and increases linearly with maturity. In contrast, the BVAR(1) exhibits a more stable forecast performance from the short to the middle segment of the curve.

4.3.2. Tests Performed for the VAR and BVAR Estimation of the Macroeconomic Factor

An information-criteria analysis is presented below to compare the three models in terms of goodness-of-fit and overparameterization. The objective is not only to assess predictive performance but also to

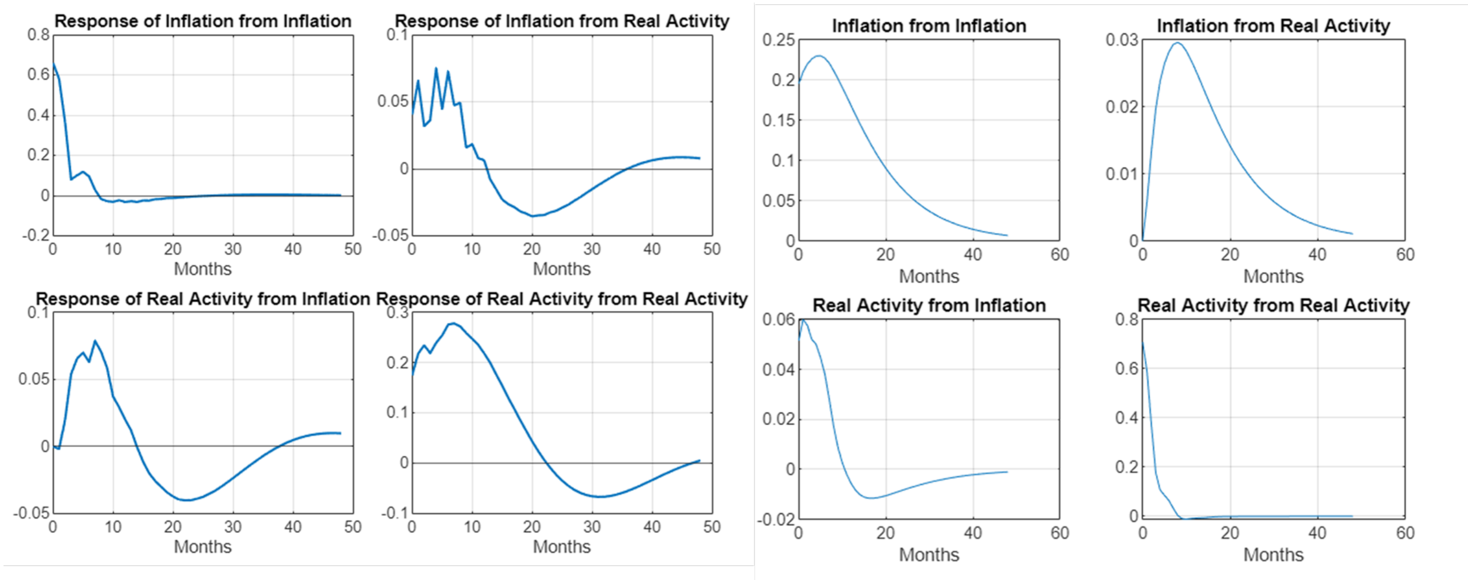

Figure 2: Impulse Responses Between Variables: VAR(8) versus BVAR(8)

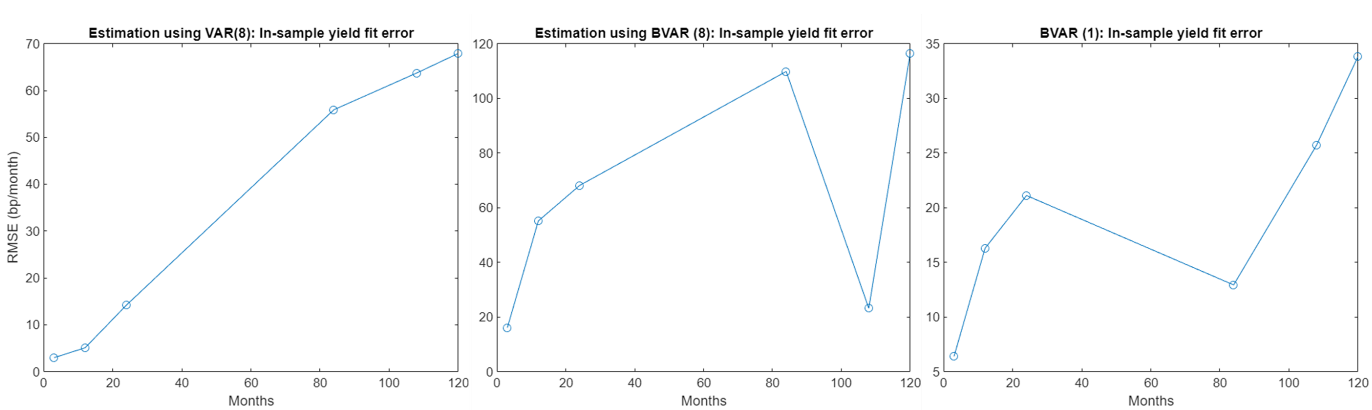

Figure 3: Average Prediction Error by Maturity: VAR(8), BVAR(8), and BVAR(1)

Lag	(1) Taylor-Rule		(2) 12 Lags		(3) Short Term Inertia		
	Inflation	**Real Activity**	**Inflation**	**Real Activity**	**Short Term Rate**	**Inflation**	**Real Activity**
t	0.0078	0.0005	-0.0055	0.0023	–	0.0010	0.0007
$t-1$	–	–	0.0052	0.0008	0.9545	0.0030	0.0001
$t-2$	–	–	0.0020	0.0002	–	-0.0027	-0.0008
$t-3$	–	–	0.0016	0.0012	–	0.0004	0.0007
$t-4$	–	–	0.0042	0.0005	–	0.0012	0.0000
$t-5$	–	–	-0.0020	0.0001	–	-0.0028	-0.0007
$t-6$	–	–	0.0029	0.0004	–	0.0035	0.0007
$t-7$	–	–	-0.0012	0.0007	–	-0.0034	-0.0001
$t-8$	–	–	-0.0046	-0.0004	–	-0.0020	-0.0007
$t-9$	–	–	0.0025	0.0008	–	0.0040	0.0005
$t-10$	–	–	0.0001	0.0008	–	-0.0017	0.0004
$t-11$	–	–	-0.0001	0.0004	–	0.0002	-0.0001
$t-12$	–	–	0.0064	0.0031	–	0.0003	0.0003
R^2	21%		50%		96%		
AR(1) Resid	0.97		0.94		0.26		

Table 3: Lag coefficients for three specifications of the Taylor rule.

evaluate the degree of parameter proliferation. The best-performing specification is the BVAR(1), which attains an AIC of –17,588 and a BIC of –17,474—both lower than those of the other models—indicating a superior fit achieved with relatively few parameters. Although the VAR(8) is also a strong estimator with solid predictive capacity, the BVAR(1) relies on fewer parameters and delivers better forecasts across the entire curve. In contrast, the BVAR(8) employs a large number of parameters and exhibits the weakest predictive performance among the three models across most maturities. The information-criteria results are summarized in Table 4.

	VAR(8)	**BVAR(8)**	**BVAR(1)**
AIC	−16,053	−3,640	−17,588
BIC	−15,940	−3,527	−17,474

Table 4: Criterios de información para distintas especificaciones

4.3.3. Loading de Factores

The charts show how macroeconomic and latent factors load onto the yield curve at different maturities. In the top panel, inflation has a positive weight that declines with maturity, while real activity has little impact. This suggests that inflation is the macro variable with the greatest explanatory power for the sovereign curve. In the bottom panel, latent factors are more relevant: L2 dominates across all maturities, while L1 and L3 capture variations of smaller magnitude but that are complementary at longer horizons. The loadings are shown in Figure 4.

4.3.4. Prediction of the estimate using the BVAR(1)

The charts compare the observed and fitted yields for 1-, 7-, and 10-year Peruvian sovereign bonds. In all cases, the fitted series closely tracks the observed one, which reflects the model's ability to capture the term structure dynamics. The fit is firm in the short and medium segments, with coefficients of

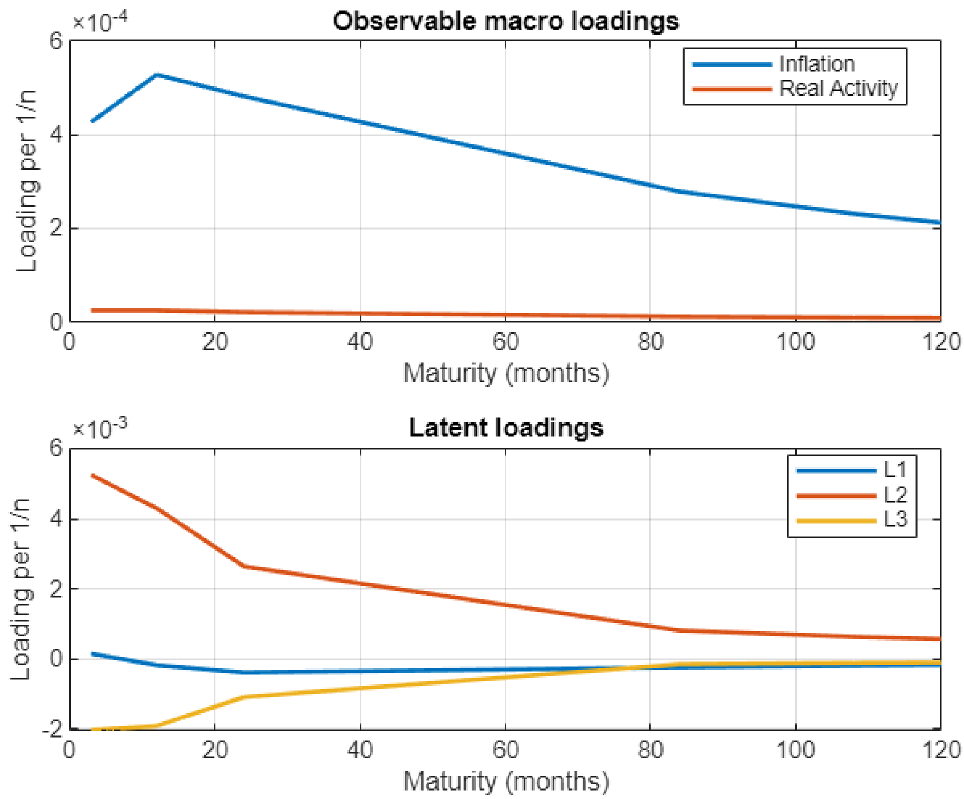

Figure 4: Factor Loading for BVAR(8)

determination close to 0.99 and relatively low RMSE errors (12–16 basis points per year). In the long segment, the fit is slightly weaker, with a coefficient of determination of 0.90 and an increasing RMSE, suggesting lower predictive capacity for long maturities such as the 10-year bond. The forecasts are shown in Chart .5.

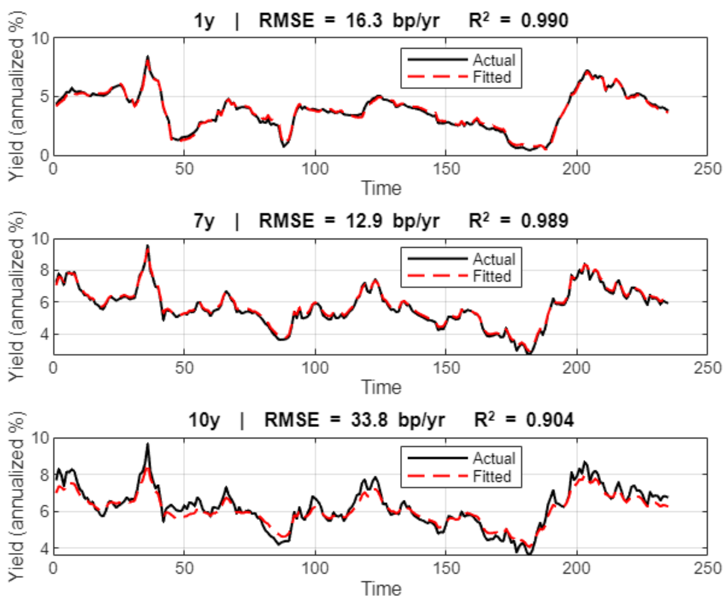

Figure 5: Forecast of 1y/7y/10y Rates for the BVAR(1)

5. Conclusion

This analysis adapts the Ang and Piazzesi (2003) framework to Peru's sovereign yield curve in soles, using an affine model with no-arbitrage restrictions and a Bayesian VAR in the first stage. The results show that inflation is the most influential observable macroeconomic factor in the dynamics of the curve, while latent factors—especially those associated with the slope—dominate across all maturities. The comparison of specifications shows that the BVAR(1) achieves better performance than the VAR(8) and the BVAR(8), with fewer fitting errors and more favorable AIC and BIC values, highlighting the advantage of choosing parsimonious models in contexts of limited data and high volatility. The model captures the evolution of the short- and medium-term segments more accurately. However, it struggles to predict long-term yields, reflecting liquidity constraints and external shocks typical of emerging countries such as Peru. The results of this analysis underscore the potential advantages of incorporating new alternative estimation approaches into the traditional VAR.

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