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Forecasting the term structure in emerging markets using extensions of the dynamic Nelson-Siegel model*

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ABSTRACT

The dynamic Nelson-Siegel model and its extensions are used by many central banks to forecast the term structure. Their forecasting performance has been studied for many countries, but a little can be said about their accuracy for emerging market economies (EMEs). In this work we test the traditional dynamic Nelson-Siegel models, their extensions without the "curvature" factor and with inflation for six EMEs. Other extensions are model selection via BIC minimization and the Bayesian estimation with the conjugate Normal-inverse Wishart prior, which are novel in the field. The results indicate that inflation data and the Bayesian approach improve the forecasting performance relative to the traditional models. We also conclude that the multivariate dynamic Nelson-Siegel models often outperform univariate ones, while the "curvature" factor is rarely helpful for forecasting at a long horizon.

Keywords: term structure, bond market, DNS model, Bayesian econometrics, emerging markets
JEL Classification: C11, E43, E47

1 Introduction

The term structure can be useful to derive inflation and short-term rates expectations of investors, reveal arbitrage opportunities in the bond market. Policymakers and investors use this information to make decisions, but to build plans they need reliable forecasts of bond yields. Future term structure is important for fiscal authorities when they plan sovereign bond issues, for central banks when they plan their monetary policy, and for investors who want to know the projections of a bond portfolio price. Extensive research has already been carried out to create accurate yield curve forecasting models.

Despite a great number of works devoted to the yield curve forecasting, there is a small range of basic methods used. One of them is the Nelson-Siegel (NS) model (Nelson and Siegel, 1987) which is extended for forecasting in Diebold and Li (2006). The dynamic Nelson-Siegel (DNS) model proposed in Diebold and Li (2006) has proven its reliability on advanced-economy data sets. Some of its extensions have shown improvements in the forecasting ability of the DNS model for the US, the EU, Japan, and other advanced economies. Although the NS approach is used by many financial and government institutions (BIS, 2005; Diebold and Rudebusch, 2013), there is a lack of studies about its general performance in emerging market economies (EMEs).

There are two main types of models for forecasting the yield curve: affine and ad-hoc models. The former are related to the idea that there is an instantaneous risk-free rate which is an affine (linear) function of unobserved factors. In turn, those factors are driven by the affine diffusion which depends on the market price of risk, while the rates of all maturities are distinct functions of the risk-free rate. Vasicek (1977) designs the first affine model where the term premium and volatility of a yield are assumed constant over time but different across maturities. In contrast, Cox et al.

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(1985) propose the model where both term premium and volatility depend on the instantaneous rate level and thus vary over time. Duffee (2002) claims that those seminal methods fail to outperform the random walk and shows that allowing the term premium and volatility change independently helps to beat the benchmark. In later works, researchers add macroeconomic data as factors to the affine models (Ang and Piazzesi, 2003; Moench, 2008; Vieira et al., 2016) and combine affine and ad-hoc models with and without macroeconomic data (De Pooter et al., 2010). All these additions help to improve forecasting accuracy. However, it is the ad-hoc model developed by Nelson and Siegel (1987) which is widely used by researchers and practitioners. The dynamic Nelson-Siegel model (Diebold and Li, 2006) is especially popular as it highlights three main factors that drive the yield curve (level, slope, and curvature). It facilitates the yield curve forecasting by allowing to model those factors both separately or jointly. Later studies related to the DNS model show that the incorporation of macroeconomic data makes predictions more accurate (De Pooter et al., 2010; Byrne et al., 2017). Another extension is using Bayesian estimation which is shown to be a powerful tool by Laurini and Hotta (2010). Finally, Diebold and Li (2006) show that the curvature is the factor which is the least connected to the US macroeconomy and the most difficult to estimate. Thus, Diebold et al. (2008) propose using the DNS method without the curvature to model the global yield curve.

The vast majority of the yield curve forecasting studies investigate advanced economies. Emerging bond market research is usually devoted to only one country. One of the examples is Luo et al. (2012) who analyze various processes to forecast the DNS yield curve factors of China, and this work is said to be "the first to study the forecasting of the term structure of Chinese Treasury yields". Another instance is Almeida and Faria (2014) who study the forecasting performance of models proposed by Diebold and Li (2006) and Moench (2008) for Brazilian yields. Laurini and Hotta (2010) develop a flexible Bayesian approach for the yield curve forecasting, but test it only using the term structure of Brazil.

Some attempts have been made to forecast a set of emerging-economy yield curves. Coche et al. (2015) project yields for a large number of EMEs extending the DNS model through "decomposing yield curve factors into regional and economy-specific components" (Coche et al., 2015, p. 57). Although their work is mainly focused on the statistical properties of the model, the authors investigate its forecasting performance as well (though using a small test sample). The model's projections usually outperform predictions of the DNS model with AR process at horizons of up to 12 months. The regional approach seems to be useful to project the emerging-economy term structure, but it might also be useful as a starting point to find other powerful versions of the DNS model. One could begin with making single adjustments to the traditional DNS approach to show which extensions should be developed for those economies. Emerging bond markets are becoming more popular, so significant demand for the yield forecasting methods might increase alongside with a lack of information about the most appropriate models for those countries.

We contribute to the existing literature in the following ways. First, there appear to be no papers that concentrate solely on the yield curve forecasting for a set of EMEs over a similar period of time. The only work which is close to this field is done by Coche et al. (2015) who concentrates more on statistical properties of the DNS model with the regional approach. In contrast, we solely attempt to find the DNS models which could be used successfully for forecasting the yields of EMEs. Secondly, this study seems to be the first where the conjugate Normal-inverse Wishart prior is used for Bayesian vector autoregression (BVAR) in the DNS model. This prior is popular for forecasting purposes and provides a solution in a closed form (Demeshev and Malakhovskaya, 2016), so it is worth testing its term structure projection efficiency. Thirdly, this study is, to the author's knowledge, the first that questions the processes used to forecast the DNS factors of certain emerging economies. For example, Luo et al. (2012) follow Diebold and Li (2006) and use the first-order autoregression [AR(1)] without any preliminary analysis to forecast the Chinese Treasury yields, whereas we propose selecting model specifications using the Bayesian Information Criterion (BIC). In addition, we use extensions proposed in other studies: the elimination of the curvature factor and adding inflation data. As a result, this work makes a step towards understanding whether there is a unified approach to forecasting the yield curves of EMEs.

The main result of our study is that extensions of the DNS model often produce more accurate forecasts than the traditional DNS models and the random walk (RW) for EMEs. However, it is impossible to highlight the best model for all emerging countries. Beating the RW remains a difficult task at a forecast horizon of 1 month, but the DNS models usually outperform it at longer horizons. We conclude that eliminating the curvature factor and using the Bayesian approach in the DNS model help to forecast yields of unstable EMEs during the test period (Brazil and Turkey). We show that the Bayesian DNS models with inflation improve projections for developing countries, especially for those with successful inflation targeting (India and Indonesia). We also demonstrate that there is an exceptionally high uncertainty about the best models for Russia. The evidence is presented that multivariate DNS models are superior to univariate DNS models for almost any country, any horizon, and any yield, while the BVAR model often has a lower forecasting error than VAR. Finally, searching for a univariate model specification via BIC minimization seems to be ineffective for EMEs.

We proceed as follows. In Section 2 we demonstrate the forecasting models and the model selection procedure. In Section 3 we describe the data that we use to build the forecasting models. In Section 4 we present the results, while in Section 5 we conclude.

2 Model

We build various models and compare their forecasting performance using given data. We use the RW model as a benchmark model in this study. This choice is justified by the evidence in Duffee (2002); Ang and Piazzesi (2003); Diebold and Li (2006); Moench (2008) that beating the random walk is a successful result of the yield curve forecasting model. The traditional DNS model is used, where factors follow the AR(1) or VAR(1) (first-order vector autoregression) process, while its extensions are also investigated. We test BVAR process for factors with the conjugate Normal-inverse Wishart prior and select model specifications by minimizing BIC: both procedures are novelties of the study. We also test the traditional DNS models without the curvature and with inflation.

2.1 Random walk

A typical RW model without drift for yields is used:

$$y_t^{(\tau)} = y_{t-1}^{(\tau)} + \epsilon_t^{(\tau)}, \quad \epsilon_t^{(\tau)} \sim N(0, \sigma^2). \tag{1}$$

The forecast of each future yield is today's yield (so-called naive forecast). It is noteworthy that beating the RW is difficult at least in developed markets because their yields typically follow non-stationary processes (De Pooter et al., 2010).

2.2 Traditional dynamic Nelson-Siegel models

In the traditional DNS framework, a yield is modelled as the following function of time to maturity:

$$y_t(\tau) = l_t + s_t \left(\frac{1 - e^{-\lambda_t \tau}}{\lambda_t \tau} \right) + c_t \left(\frac{1 - e^{-\lambda_t \tau}}{\lambda_t \tau} - e^{-\lambda_t \tau} \right), \tag{2}$$

where $y_t(\tau)$ is a yield of time to maturity τ at time t, τ is time to maturity in months, l_t is the "level" factor at time t, s_t is the "slope" factor at time t, c_t is the "curvature" factor at time t, λ_t is a parameter that determines the exponential decay rate of the yield curve at time t (Diebold and Li, 2006). In addition, the parameter λ_t "governs where the loading on c_t achieves its maximum" (Diebold and Li, 2006, p. 215) and is usually fixed at some value. In this study we follow Diebold and Li (2006); Van Dijk et al. (2014); Byrne et al. (2017) and fix λ_t at 0.0609.

The yield curve factors could be interpreted in terms of influence on different parts of the term structure. Let the coefficients after level, slope, and curvature be "factor loadings" (Diebold and Li, 2006):

$$\left(1, \frac{1 - e^{-\lambda_t \tau}}{\lambda_t \tau}, \frac{1 - e^{-\lambda_t \tau}}{\lambda_t \tau} - e^{-\lambda_t \tau} \right). \tag{3}$$

Calculating the limits of the factor loadings, one can see that they have distinct effects on different parts of the yield curve. One can verify that:

$$\lim_{\tau \to 0} \left(\frac{1 - e^{-\lambda_t \tau}}{\lambda_t \tau} \right) = 1, \tag{4}$$

$$\lim_{\tau \to \infty} \left(\frac{1 - e^{-\lambda_t \tau}}{\lambda_t \tau} \right) = 0. \tag{5}$$

This is why the slope factor is also called a short-term factor which mostly affects the short-term end of the yield curve. Additionally, one can verify that the curvature loading tends to zero when time to maturity tends to either zero or infinity:

$$\lim_{\tau \to 0} \left(\frac{1 - e^{-\lambda_t \tau}}{\lambda_t \tau} - e^{-\lambda_t \tau} \right) = 0, \tag{6}$$

$$\lim_{\tau\to\infty}\left(\frac{1-e^{-\lambda_t\tau}}{\lambda_t\tau}-e^{-\lambda_t\tau}\right)=0. \tag{7}$$

The concavity in τ of this factor means that it is a kind of medium-term factor. The level factor is the only one that influences the long-term end of the yield curve and thus is often called a long-term factor.

To forecast yields using the DNS framework one has to project the level, slope, and curvature. This approach leads to the creation of the so-called state-space model, where the function of a yield is a measurement equation, while the equation for the yield curve factor dynamics is a transition equation. State-space models can be estimated using a joint procedure (via the Kalman filter) or a two-step procedure, and theoretically the former is superior to the latter. However, Diebold and Rudebusch (2013) show some evidence that estimation accuracy decreases only marginally when using the two-step procedure instead of the joint one. The two-step approach is also more tractable, and thus is used to forecast the term structure in this work.

There are different possible processes for modelling the yield curve factors. Diebold and Li (2006) propose AR(1) process for the level, slope, and curvature and show that it is superior to VAR(1) for US Treasury yields. However, VAR(1) is sometimes preferred to AR(1) in later works (Vieira et al., 2016; Byrne et al., 2017), so one has to identify which process is more suitable.

2.2.1 DNS with AR(1)

In the traditional framework proposed in Diebold and Li (2006) each factor among level, slope, and curvature is modelled using AR(1) process:

$$x_t=\alpha+\beta x_{t-1}+e_t,\quad x_t\in\{l_t,s_t,c_t\},\quad e_t\sim N(0,\sigma^2). \tag{8}$$

This approach could be superior to multivariate models if there is a little cross-interaction among the yield curve factors. We refer to this type of model using the term **AR(1)**.

2.2.2 DNS with VAR(1)

This approach means that a significant interaction among level, slope, and curvature is possible. The model can be written in the following form:

$$\begin{pmatrix} l_t \\ s_t \\ c_t \end{pmatrix}=\begin{pmatrix} \alpha^l \\ \alpha^s \\ \alpha^c \end{pmatrix}+\begin{pmatrix} \beta_l^l & \beta_s^l & \beta_c^l \\ \beta_l^s & \beta_s^s & \beta_c^s \\ \beta_l^c & \beta_s^c & \beta_c^c \end{pmatrix}\begin{pmatrix} l_{t-1} \\ s_{t-1} \\ c_{t-1} \end{pmatrix}+\begin{pmatrix} \epsilon^l \\ \epsilon^s \\ \epsilon^c \end{pmatrix}. \tag{9}$$

Using a more compact form:

$$X_t=\alpha+\Phi X_{t-1}+\epsilon_t,\quad \epsilon_t\sim N(0,\Sigma), \tag{10}$$

where X_t is a 3x1 vector of the level, slope, and curvature at time t, α is a 3x1 vector of constants, Φ is a 3x3 matrix of autoregressive coefficients, ϵ_t is a 3x1 vector of errors at time t. We refer to this type of model using the term **VAR(1)**.

2.3 Extensions of the dynamic Nelson-Siegel model

2.3.1 DNS with BVAR(1) and the conjugate Normal-inverse Wishart prior

The difference between VAR and BVAR models is the method of parameter estimation. While in the VAR model maximum likelihood estimation (MLE) is used, in the Bayesian approach the multiple of the prior distribution of parameters and the likelihood function is derived. The model equation is written as the VAR model:

$$X_t=\alpha+\Phi X_{t-1}+\epsilon_t,\quad \epsilon_t\sim N(0,\Sigma). \tag{11}$$

However, now the prior distributions of α, Φ, and Σ are initialized. This is an essential feature of the Bayesian approach: it is assumed that the statistics of parameters are not constants but random variables. In the literature there are different types of priors, but in this study we use the conjugate Normal-inverse Wishart prior. It is one of the most popular prior distributions in econometrics and is convenient as it provides a solution in a closed form for posterior distributions (Demeshev and Malakhovskaya, 2016). Since the study is empirical, it is of great interest to find out whether the relatively simple and widely used Bayesian method outperforms a frequentist approach. Therefore, Bayesian models that do not have a closed-form solution and thus require Markov chain Monte Carlo estimation are not considered. The conjugate Normal-inverse Wishart prior can be represented as the following conditions on the distributions of the coefficient stacked matrix ϕ and the covariance matrix of errors Σ:

$$\begin{cases} \phi|\Sigma \sim N(\underline{\phi}, \Sigma \otimes \underline{\Omega}), \quad \phi = \mathrm{vec}(\alpha, \Phi)^T \\ \Sigma \sim IW(\underline{S}, \underline{\nu}) \end{cases} \tag{12}$$

Here IW denotes the inverse Wishart distribution.

Prior distribution. To build the Bayesian model one has to provide some prior distribution of a coefficient matrix and an error covariance matrix. A prior can be adjusted by changing different λ parameters that control it[1]. This study concentrates on the importance of two λ parameters: λ_{tight}, λ_{io} (Demeshev and Malakhovskaya, 2016). λ_{tight} enters $\underline{\Omega}$ and controls the variance of coefficients in the BVAR model. When λ_{tight} goes to infinity, the parameter estimates go to MLE estimates; when it goes to 0, data has no influence on parameter estimation and the parameter estimates are simply prior beliefs. λ_{io} is important when dealing with time series that could be non-stationary and cointegrated. This is important for the yield curve forecasting because many yield curve factors seem to have a unit root according to Tables 1 and 2. Finally, it is also important to define appropriate priors for the matrix of autoregressive parameters Φ. We use coefficients obtained in the AR(1) model for each time series to define the prior mean of the coefficient before the first lag of the same time series (not allowing them to be greater than 1). Researchers usually initialize those coefficients as 1 for non-stationary series, but if the time series is non-stationary, its coefficient in AR(1) will be close to 1. We set means of other coefficients at 0 in line with common practice (Demeshev and Malakhovskaya, 2016). We refer to this type of model using the abbreviation **BVAR(L)**, where L is the maximum lag in the model.

2.3.2 DNS without curvature

In the DNS model, the "curvature" factor is sometimes omitted as it is usually estimated with low precision and has weak links to macroeconomic fundamentals (Diebold and Li, 2006; Diebold et al., 2008). While the level is the long-term interest rate, the slope is the yield spread, the curvature is a somewhat technical factor. The DNS model, therefore, has the following representation without the curvature:

$$y_t(\tau) = l_t + s_t \left(\frac{1 - e^{-\lambda_t \tau}}{\lambda_t \tau} \right). \tag{13}$$

Then, only the level and slope are modelled in the transition equation of the state-space model. We refer to this type of model using the **-NC** affix after naming the process that the level and slope follow.

2.3.3 Multivariate DNS with inflation

According to Diebold et al. (2008), the global level factor, which is related to the global yield curve built on US, German, Japanese, and UK data, is highly correlated with the average inflation of G-7 countries. Another work that confirms the close relationship between the level and inflation in the US is Diebold et al. (2006). It is more likely that there is a two-way effect between yields and inflation, so the price growth is not used as a pure exogenous variable in our study. This is because investors demand higher yields when inflation rises, while inflation increases when the economy and interest rates grow. Macroeconomic variables seem to help to forecast the yield curve (De Pooter et al., 2010; Vieira et al., 2016; Byrne et al., 2017), especially during unstable times. Thus, the first step to identify whether it is true for emerging markets, which are especially prone to shocks, is to incorporate possibly the most important macroeconomic variable for the yield curve - inflation. Following the assumption that the level factor can be closely related the country's inflation, we use the VAR(1) and BVAR(1)

[1] Do not confuse them with the λ_t parameter which determines the exponential decay rate of the yield curve.

models with the level, slope, curvature, and inflation to forecast the yield curve. (B)VAR(1) model is now represented as:

$$\begin{pmatrix} l_t \\ s_t \\ c_t \\ P_t \end{pmatrix} = \begin{pmatrix} \alpha^l \\ \alpha^s \\ \alpha^c \\ \alpha^P \end{pmatrix} + \begin{pmatrix} \beta_l^l & \beta_s^l & \beta_c^l \\ \beta_l^s & \beta_s^s & \beta_c^s \\ \beta_l^c & \beta_s^c & \beta_c^c \\ \beta_l^P & \beta_s^P & \beta_c^P \end{pmatrix} \begin{pmatrix} l_{t-1} \\ s_{t-1} \\ c_{t-1} \\ P_{t-1} \end{pmatrix} + \begin{pmatrix} \epsilon^l \\ \epsilon^s \\ \epsilon^c \\ \epsilon^P \end{pmatrix}, \tag{14}$$

where P_t is annual CPI growth at time t. In a more compact form:

$$X_t^{(P)} = \alpha^{(P)} + \Phi^{(P)} X_{t-1}^{(P)} + \epsilon_t^{(P)}, \quad \epsilon_t^{(P)} \sim N(0, \Sigma^{(P)}). \tag{15}$$

We denote these models using the affix **-P** after the name of the multivariate process that the vector of variables follows.

2.3.4 DNS with processes selected by BIC

The model selection procedure in econometrics often starts with investigating the stationarity of the time series and processes that the data might follow. Diebold and Li (2006) suggest that the US Treasury yield curve factors follow AR(1) or VAR(1) processes according to the autocorrelation function (ACF) and partial autocorrelation function (PACF). Despite that the Augmented Dickey-Fuller (ADF) test shows that the level and the slope might be non-stationary, the authors do not differentiate the data and build the DNS models in levels. This is usually done to emphasize that although interest rates can be econometrically non-stationary, they are bounded due to economic reasons, and so are their factors. Many subsequent works refer to Diebold and Li (2006) when choosing AR(1) or VAR(1) to model the level, slope, and curvature (Almeida and Faria, 2014; Byrne et al., 2017), but the choice is generally not obvious. In contrast, we propose selecting processes using BIC to model the yield curve factors.

$$BIC = T \ln \left(\frac{RSS}{T} \right) + k \ln(T), \tag{16}$$

where T is a number of observations, RSS is the residual sum of squares, k is a number of estimated parameters. BIC is selected instead of, for example, AIC, because it has a larger penalty for the number of model parameters. Simplicity is a desirable property of the model, so we search for an accurate but not overparameterized model.

We search for univariate processes for the slope, level, and curvature in the family of $ARIMA(p, d, q)$ models:

$$\Delta^d x_t = \alpha + \sum_{i=1}^{p} \beta_i x_{t-i} + \sum_{j=1}^{q} \gamma_j e_{t-j} + e_t, \tag{17}$$

where $x_t = \{l_t, s_t, c_t\}$ and $e_t \sim N(0, \sigma^2)$. When choosing multivariate processes, we search for a lag in VAR model that provides the minimum BIC.

Country	Univariate models			VAR lag	
	Level	Slope	Curvature	DNS	DNS-P
Brazil	AR(1)	RWD	RWD	1	1
China	RWD	RWD	RWD	2	1
India	RWD	RWD	ARIMA(1,1,1)	1	1
Indonesia	RWD	IMA(1,1)	AR(1)	1	1
Russia	ARI(1,1)	IMA(1,1)	MA(3)	2	2
Turkey	RWD	RWD	RWD	1	1
USA	RWD	AR(1)	RWD	1	2

Table 1: Processes proposed by BIC stepwise minimization (models with and without inflation)

Country	Univariate models		VAR lag
	Level	Slope	
Brazil	AR(1)	RWD	2
China	AR(2)	RWD	2
India	RWD	RWD	1
Indonesia	RWD	IMA(1,1)	1
Russia	ARI(1,1)	IMA(1,1)	2
Turkey	RWD	RWD	1
USA	RWD	RWD	3

Table 2: Processes proposed by BIC stepwise minimization (models without curvature)

In order to find univariate models we use the stepwise procedure proposed by Hyndman and Khandakar (2008). We set the following conditions: the maximum autoregressive and moving average lags are 12, the maximum differentiation order is 2, seasonal models are not examined, and the drift is allowed. In order to find a lag for VAR models with and without inflation (DNS and DNS-P respectively) we select among models with a constant and without a trend and set the maximum lag order at 12. The obtained processes for models are presented in Tables 1 and 2.

Henceforth, we denote processes that the factors follow as "X-Y-Z", where the level follows X, the slope follows Y, and the curvature follows Z. We refer to the random walk with drift using the abbreviation **RWD**, while the RW denotes the random walk without drift.

2.4 Forecasting

2.4.1 Method

We use the rolling-origin method and an expanding window for the training sample to project the term structure. We estimate λ_{tight} and λ_{io} for BVAR models in the validation set which has the same size as the test sample. We use a small number of values in grids to make sure that a model does not overfit. The estimated "best" λ_{tight} and λ_{io} may vary per training sample and are used for all forecast horizons. More detailed information about the forecasting method is presented in Table 3.

Test sample share	20%
Forecasting type	Rolling origin
Train sample window	Expanding
λ_{tight} grid	$0.01, 0.05, 0.1, 0.2, 1, 10, 100$
λ_{io} grid	$0.01, 0.1, 1, 10, 100, 1000, 10^3, 10^4$

Table 3: Details about the forecasting method

2.4.2 Loss function

To measure the prediction error of models for each yield of maturity τ we use the Root Squared Prediction Error (RMSPE) for a prediction $\hat{y}_{t,m}^{(\tau)}$ of a model m:

$$RMSPE_{m,\tau} = \sqrt{\frac{1}{T}\sum_{t=1}^{T}\left(\hat{y}_{t,m}^{(\tau)} - y_t^{(\tau)}\right)^2}. \tag{18}$$

To calculate the prediction error for the entire yield curve we follow De Pooter et al. (2010) and use the Trace Root Mean Squared Prediction Error (TRMSPE) for a model m:

$$TRMSPE_m = \sqrt{\frac{1}{N}\frac{1}{T}\sum_{\tau\in\mathcal{Y}}\sum_{t=1}^{T}\left(\hat{y}_{t,m}^{(\tau)} - y_t^{(\tau)}\right)^2}, \tag{19}$$

where $|\mathcal{Y}| = N$ and $\mathcal{Y}$ is a cross-sectional set of yields. To improve the comparability of the models we report relative RMSPE and TRMSPE for all non-RW models in Tables 13-33. These metrics are simply the RMSPE and TRMSPE of a model divided by these statistics of the RW model:

$$rRMSPE_{m,\tau} = \frac{RMSPE_{m,\tau}}{RMSPE_{RW,\tau}}, \tag{20}$$

$$rTRMSPE_m = \frac{TRMSPE_m}{TRMSPE_{RW}}. \tag{21}$$

2.4.3 Model confidence set

To check whether the quality of models is statistically different one can use the Diebold-Mariano (DM) test proposed by Diebold and Mariano (1995). However, the main disadvantage of this method is that this procedure can only be used for pairwise comparison, whereas we study more than two models for each country and each horizon. There is a multivariate version of the DM test (Mariano and Preve, 2012), but it is valid only for non-nested models. This is irrelevant for this study, because, for example, three AR(1) models can be represented as one restricted VAR(1) model. Consequently, we use another method to select the most accurate model for each country and each horizon. The model confidence set (MCS) procedure is presented by Hansen et al. (2003, 2011) and is an appropriate method to select the best models among multiple alternatives without specific restrictions on the models. We use RMSPE and TRMSPE loss functions to select models for each yield and the entire yield curve respectively. During the MCS procedure T_{max} statistic is used to eliminate underperforming models, while a $t_{i.}$ statistic is used to rank alternatives in the confidence set (Hansen et al., 2011).

Let $L_{i,t} = L(\hat{y}_{i,t}^{(\tau)}, y_t^{(\tau)})$ be a loss function at time t for a yield forecast $\hat{y}_{i,t}^{(\tau)}$ of a model i and an actual yield $y_t^{(\tau)}$. Hansen et al. (2011) define: $d_{ij,t} \equiv L_{i,t} - L_{j,t}$ and $\bar{d_{ij}} \equiv T^{-1}\sum_{t=1}^{T} d_{ij,t}$. Hence, $\bar{d_{ij}}$ could be interpreted as an average excess loss of the model i relative to the model j for all observations. Then, $d_{i.} = \mu^{-1}\sum_{j\in\mathcal{M}} d_{ij}$, where μ is a number of competing models (a power of the set $\mathcal{M}$). $d_{i.}$ is an average excess loss of the model i relative to other models. Finally, Hansen et al. (2011) define:

$$t_{i.} = \frac{\bar{d_{i.}}}{\sqrt{\hat{var}(\bar{d_{i.}})}}, \quad T_{max} = \max_{i\in\mathcal{M}} t_{i.}, \tag{22}$$

where $t_{i.}$ is used to test the null hypothesis that the model i and other models have equal forecasting errors. T_{max} indicates the model with the highest $t_{i.}$ value. This model is eliminated if the null hypothesis that its $d_{i.}$ equals zero is rejected.

We run tests with a 10% significance level to find the best model(s) with high precision. A large confidence set implies that there is a high degree of uncertainty about the "best" model(s), while a small set means that the "best" model(s) are found among candidates with some predefined probability. MCS is used in other works related to the yield curve forecasting (De Pooter et al., 2010) and is key for this study.

3 Data

The yield curve data for Brazil, China, India, Indonesia, Russia, and Turkey are used to fit and project yield curves of the emerging-market economies. These countries are chosen for analysis because they are members of the group "Emerging and growth-leading economies" according to BBVA Research (2016). This means that the size and potential influence on the global economy of these countries are significant. Moreover, if there is an economic crisis when monetary policy is an inefficient aid, these countries could use debt instruments, and their bond issues are likely to be large to support their economies.

The US yield curve is used to compare model results for both developed and developing counties. All the analyzed yield curves are monthly local currency sovereign spot yield curves which are collected from Bloomberg as of the end of month. If there is no sovereign zero-coupon yield curve in Bloomberg for a country, the so-called "government BVAL zero-coupon yield curve" is obtained. All these spot yield curves are extracted from coupon curves using a bootstrapping procedure. All the yield time series end in February 2019, but starting dates differ per country. Table 4 shows the starting dates of each time series and the maturities of yields analyzed in the study.

To take into account interactions between the yield curve factors and macroeconomic variables, we also obtain inflation data. Annual CPI growth is collected for each country from the OECD website and is shown in Figures 19, 20, and 21. The date range of the inflation data is the same as that of the yield curve for each country.

3D plots of the emerging-market economies' yield curves, presented in Figure 1, show that their dynamics are distinct[2] The Brazilian, Indian, and Indonesian yields decreased over time, the Chinese term structure was relatively stable, while the Russian and Turkish yield curves rose. Another difference is how the yields reacted to the Global Financial Crisis (GFC) in 2007-2008. The vast majority of yields increased during that time, but the Chinese yield curve declined. The Chinese central bank cut interest rates in order to support the economy struggling because of the global crisis. This specific monetary policy affirms that China is a unique developing country, that did not suffer from capital outflow. After the GFC, all other emerging countries decreased their key rates to stimulate their economies.

Country	Starting Date	Source	Maturity
Brazil	March 2007	Bloomberg	3-, 6-month, 1-, 2-, 3-, 4-, 5-, 6-, 7-, 8-, 9-, 10-year. (Ticker: I393)
China	April 2004	Bloomberg	3-, 6-month, 1-, 2-, 3-, 4-, 5-, 6-, 7-, 8-, 9-, 10-year. (Ticker: I299)
India	November 1998	Bloomberg	3-, 6-month, 1-, 2-, 3-, 4-, 5-, 6-, 7-, 8-, 9-, 10-year. (Ticker: F123)
Indonesia	May 2003	Bloomberg	3-, 6-month, 1-, 2-, 3-, 4-, 5-, 6-, 7-, 8-, 9-, 10-year. (Ticker: I266)
Russia	March 2005	Bloomberg	3-, 6-month, 1-, 2-, 3-, 4-, 5-, 6-, 7-, 8-, 9-, 10-year. (Ticker: I326)
Turkey	April 2005	Bloomberg	3-, 6-month, 1-, 2-, 3-, 4-, 5-, 6-, 7-, 8-, 9-, 10-year. (Ticker: F965)
USA	March 1989	Bloomberg	3-, 6-month, 1-, 2-, 3-, 4-, 5-, 6-, 7-, 8-, 9-, 10-year. (Ticker: I025)

Table 4: Data sources of sovereign spot yield curves

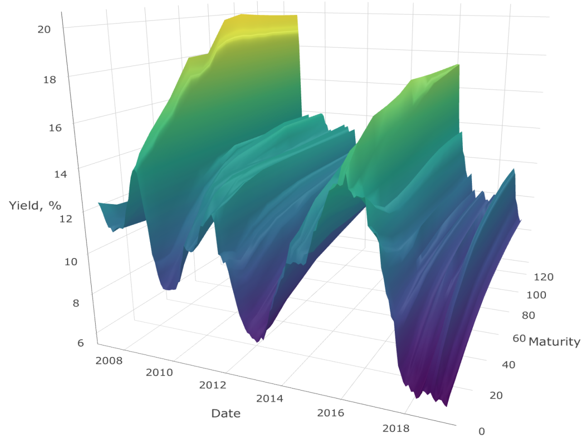
There were notable changes in the term structure not only during the GFC. The Brazilian yield curve increased sharply due to the reaction of the central bank to the rapid growth of inflation in 2015-2016. Later, inflation decelerated, while the economy remained weak, so the central bank started to cut the key rate in 2016, decreasing the yield curve. A significant shift in Indonesian yields after 2010 was due to the GFC and inflation targeting, which has been relatively successful there since 2010, which let the central bank lower the key rate. The Russian term structure increase in 2014-2015 was a reaction to geopolitics and a sharp key rate growth. Finally, Turkey had a currency and debt crisis in 2018, which set the yields at one of the highest values in the country's recent history.

Some stylized facts about the yield curve (Diebold and Li, 2006) can be checked using Table 5 and Figure 2. One of the main facts is that the average yield curve is increasing and concave. The vast majority of EME yield curves are in line with this stylized fact apart from the Turkish curve. The reason is that a typical reaction of the yield curve to a crisis is a sharp increase in short-term rates and the relatively marginal growth of long-term ones, while Turkey was in two significant crises during the sample period. Another important stylized fact is that the short end of the yield curve is more volatile than the long end. This fact is true for Brazil, China, India, Russia, and Turkey according to standard deviation of rates, whereas for Indonesia the opposite is true.

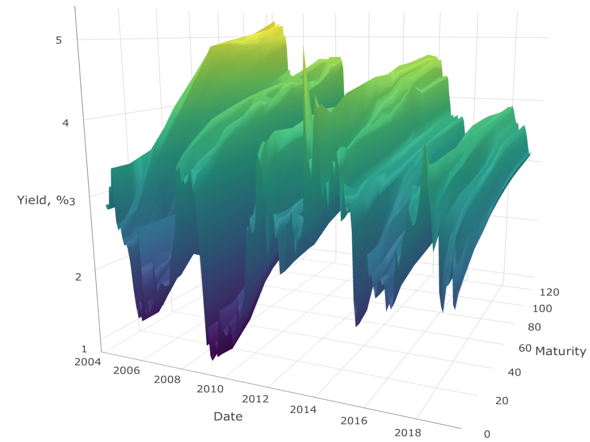
[2]Separate dynamics of 3-month, 1-year, 5-year, and 10-year yields are shown in Figures 12-17.

Figure 1: Dynamics of yield curves in EMEs

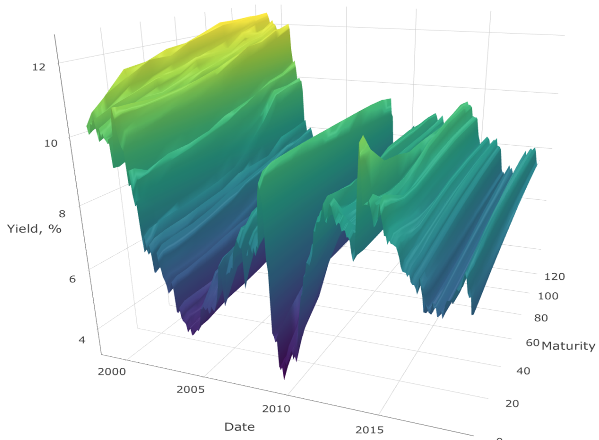
(a) Brazil



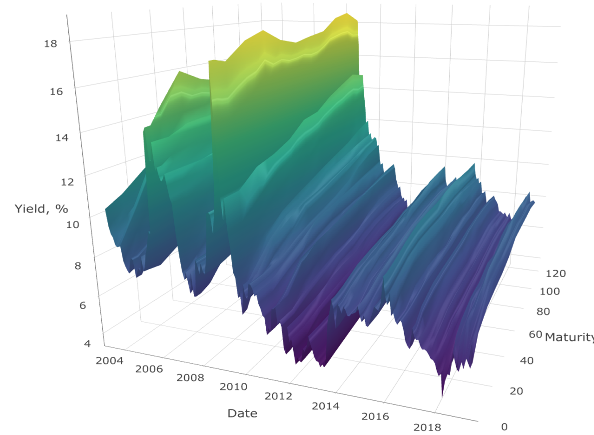
(b) China



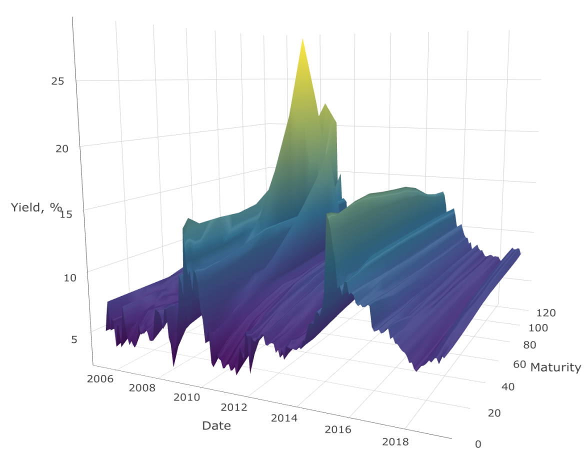
(c) India



(d) Indonesia



(e) Russia



(f) Turkey

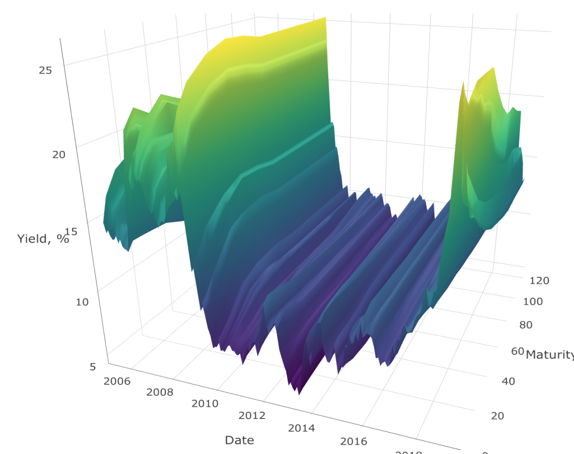
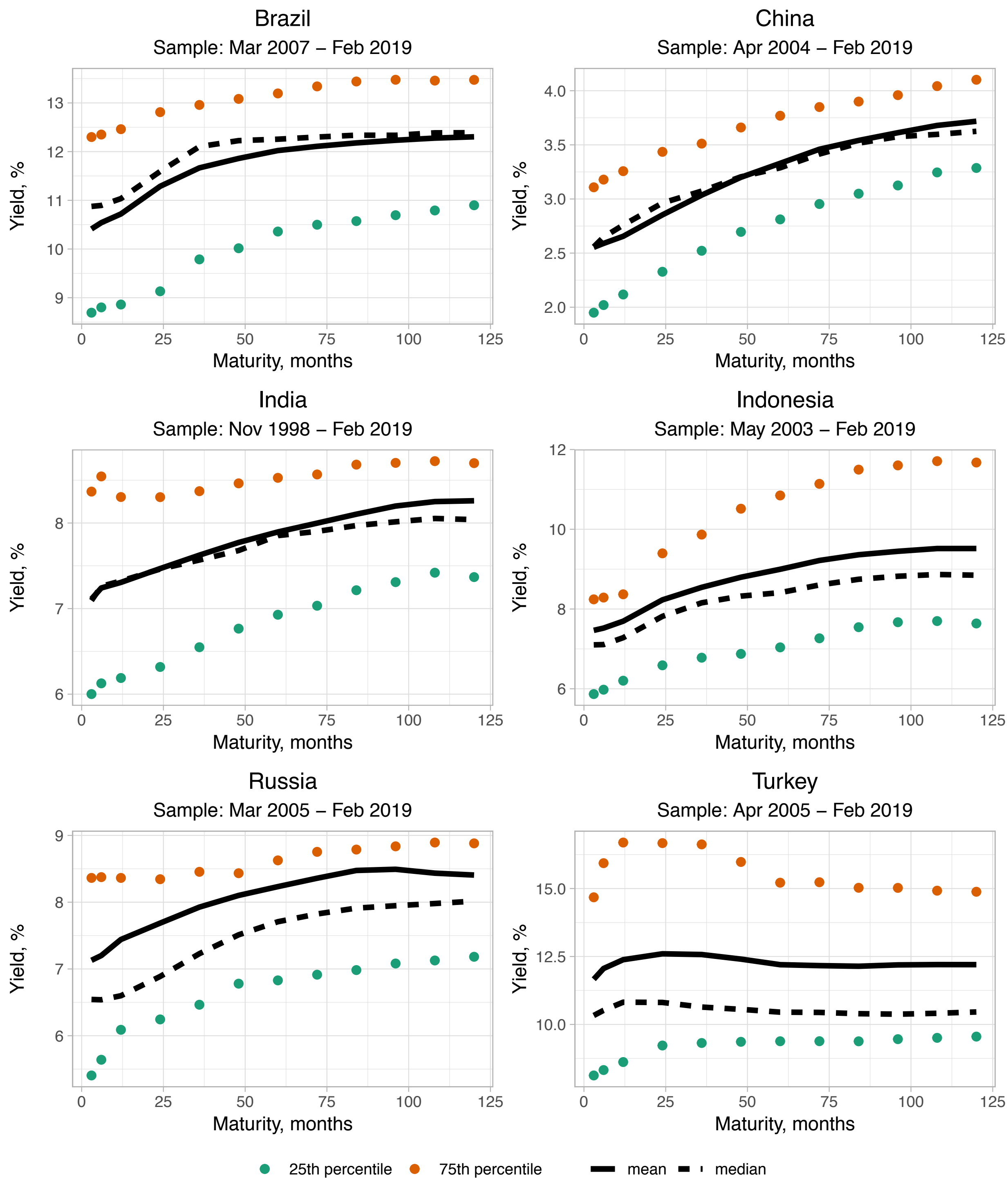


Figure 2: EMEs yield curves' statistics



Country	Statistics	3M	6M	1Y	2Y	3Y	4Y	5Y	6Y	7Y	8Y	9Y	10Y
	Mean	10.41	10.54	10.72	11.29	11.67	11.86	12.02	12.11	12.18	12.23	12.28	12.3
	Std	2.51	2.51	2.49	2.33	2.22	2.12	2.13	2.1	2.07	2.03	2.01	1.99
Brazil	Median	10.88	10.9	11.04	11.59	12.1	12.23	12.26	12.3	12.34	12.34	12.39	12.39
	25th percentile	8.69	8.8	8.86	9.13	9.79	10.02	10.36	10.5	10.57	10.69	10.79	10.9
	75th percentile	12.3	12.35	12.46	12.81	12.96	13.08	13.19	13.34	13.44	13.48	13.46	13.47
	Mean	2.55	2.59	2.66	2.85	3.04	3.20	3.33	3.46	3.54	3.61	3.68	3.72
	Std	0.77	0.76	0.74	0.7	0.64	0.61	0.61	0.6	0.58	0.58	0.59	0.59
China	Median	2.55	2.65	2.76	2.96	3.07	3.21	3.29	3.42	3.52	3.58	3.6	3.62
	25th percentile	1.95	2.02	2.12	2.33	2.52	2.7	2.81	2.95	3.05	3.12	3.25	3.29
	75th percentile	3.11	3.18	3.26	3.44	3.51	3.66	3.77	3.85	3.9	3.96	4.04	4.1
	Mean	7.11	7.24	7.31	7.47	7.62	7.77	7.9	8	8.1	8.2	8.25	8.26
	Std	1.75	1.72	1.66	1.56	1.5	1.48	1.49	1.49	1.49	1.51	1.54	1.59
India	Median	7.09	7.26	7.32	7.46	7.57	7.68	7.85	7.9	7.97	8.01	8.05	8.04
	25th percentile	6	6.13	6.19	6.32	6.55	6.77	6.93	7.03	7.21	7.31	7.42	7.37
	75th percentile	8.37	8.54	8.3	8.3	8.37	8.46	8.53	8.57	8.68	8.7	8.72	8.70
	Mean	7.47	7.52	7.69	8.23	8.54	8.8	9	9.22	9.36	9.45	9.52	9.52
	Std	2.33	2.32	2.34	2.46	2.49	2.53	2.63	2.59	2.58	2.58	2.61	2.61
Indonesia	Median	7.1	7.11	7.28	7.82	8.16	8.32	8.41	8.6	8.75	8.82	8.87	8.85
	25th percentile	5.87	5.98	6.2	6.59	6.78	6.88	7.04	7.27	7.54	7.67	7.70	7.64
	75th percentile	8.24	8.29	8.37	9.40	9.87	10.52	10.85	11.14	11.5	11.6	11.71	11.67
	Mean	7.13	7.2	7.44	7.69	7.93	8.1	8.23	8.36	8.48	8.49	8.43	8.41
	Std	2.54	2.43	2.23	2.11	2.02	1.97	2.03	2.2	2.54	2.34	2.05	1.91
Russia	Median	6.54	6.54	6.6	6.89	7.23	7.51	7.71	7.82	7.91	7.95	7.98	8.02
	25th percentile	5.4	5.64	6.09	6.24	6.46	6.78	6.83	6.91	6.98	7.08	7.13	7.18
	75th percentile	8.36	8.38	8.36	8.34	8.45	8.43	8.63	8.75	8.79	8.84	8.89	8.88
	Mean	11.7	12.1	12.4	12.6	12.6	12.4	12.2	12.2	12.1	12.2	12.2	12.2
	Std	4.39	4.58	4.73	4.71	4.52	4.29	4.06	4.01	3.97	3.94	3.9	3.87
Turkey	Median	10.3	10.5	10.8	10.8	10.6	10.6	10.5	10.4	10.4	10.4	10.4	10.5
	25th percentile	8.12	8.32	8.61	9.22	9.32	9.36	9.38	9.38	9.38	9.46	9.51	9.55
	75th percentile	14.7	15.9	16.7	16.7	16.6	16.0	15.2	15.2	15	15	14.9	14.9
	Mean	2.96	3.09	3.22	3.55	3.77	3.99	4.20	4.35	4.50	4.60	4.71	4.81
	Std	2.47	2.49	2.48	2.50	2.44	2.35	2.28	2.22	2.16	2.12	2.08	2.05
USA	Median	2.96	3.13	3.28	3.69	3.84	4.12	4.25	4.35	4.42	4.49	4.56	4.67
	25th percentile	0.28	0.44	0.61	0.99	1.44	1.76	2.02	2.37	2.57	2.69	2.83	2.95
	75th percentile	5.07	5.22	5.37	5.68	5.79	5.91	5.98	6.09	6.18	6.17	6.23	6.32

Table 5: Statistical description of yields

4 Results

The recommended models for each country, each horizon, and each yield are presented in Tables 6-12. The recommended model is the model with the lowest $t_{i.}$ statistic in the confidence set (Hansen et al., 2003, 2011). Figures 3-9 show the RMSPE of the models in the confidence set for the entire yield curve. If the confidence set contains a large number of models, only the top 5 models according to $t_{i.}$ are shown in the plots (for Russia and the US). Tables 13-31 demonstrate a (T)RMSPE of the RW model, relative (T)RMSPEs of all other models and display the confidence sets. A note about these Tables is presented at the beginning of Appendix 4.

4.1 Brazil

The recommended models to forecast the yield curve of Brazil are presented in Table 6. The performance of the models included in the confidence set for the entire yield curve is demonstrated in Figure 3[3].

Figure 3 and Table 13 show that beating the random walk is indeed tough at a forecast horizon of 1 month in accordance with Diebold and Li (2006). There is no model that is statistically better than the RW for the 1-month horizon. Univariate DNS models and DNS models without the curvature are complete failures, while (B)VAR(1) models with and without inflation sometimes outperform the RW for short- and medium-term yields. The confidence set for the entire yield curve contains only the RW, BVAR(1), and BVAR(1)-P, and one cannot conclude that the Bayesian models are superior to the RW. The reason for such a performance could be the unprecedented sharp fall of short-term rates and inflation in 2016-2018 (which is covered by the test sample). This change could be perceived as a structural break in the economy

[3] All (T)RMSPEs are shown in Tables 13-15 in Appendix.

and the monetary policy of Brazil, because both short-term yields and inflation reached their lowest levels in the period of interest. Therefore, it is difficult to forecast yields during these times at short horizons. While the TRMSPE of the RW model for Brazil looks low, it is more than four times higher than that for China, so the forecasting accuracy is relatively poor.

Yield maturity	Forecast horizon		
	1 month	6 months	12 months
3M	VAR(1)	BVAR(1)-NC	VAR(1)-NC
6M	BVAR(1)-P	VAR(1)	BVAR(1)-NC
1Y	RW	BVAR(1)	BVAR(1)-NC
2Y	RW	BVAR(1)	BVAR(1)
3Y	RW	BVAR(1)-NC	BVAR(1)
4Y	BVAR(1)	BVAR(1)-NC	BVAR(1)-NC
5Y	BVAR(1)	BVAR(1)-NC	BVAR(1)-NC
6Y	BVAR(1)	BVAR(1)-NC	BVAR(1)-NC
7Y	RW	BVAR(1)-NC	BVAR(1)-NC
8Y	RW	BVAR(1)-NC	BVAR(1)-NC
9Y	RW	BVAR(1)-NC	BVAR(1)-NC
10Y	RW	BVAR(1)-NC	BVAR(1)-NC
Entire YC	**RW**	**BVAR(1)**	**BVAR(1)-NC**

Table 6: Recommendations for Brazil

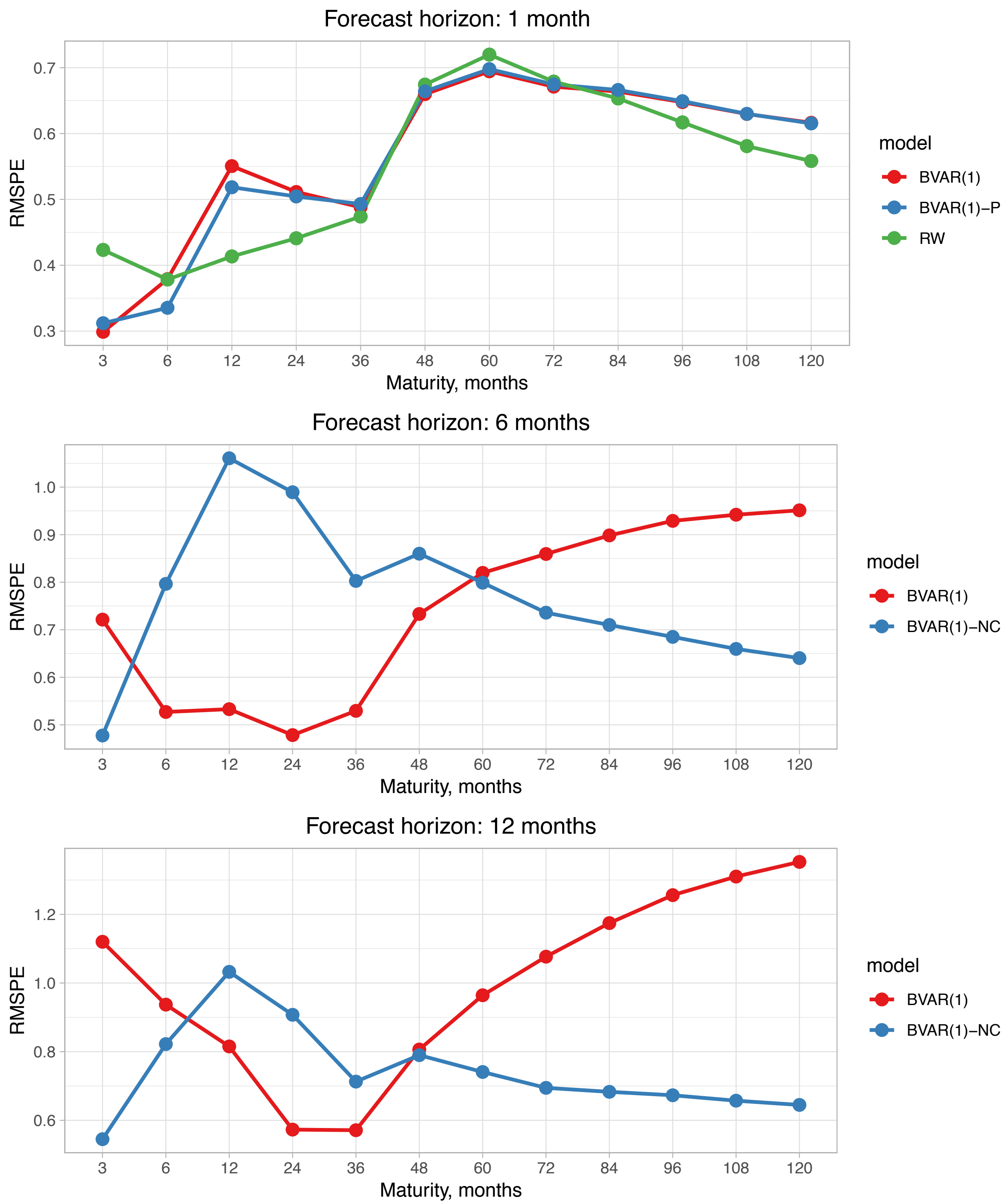
When considering a 6-month horizon, the DNS models perform relatively better according to Figure 3 and Table 14. Again, the univariate DNS models underperform systematically, but now the multivariate DNS models are statistically better than the RW for maturities of up to 4 years. The difference is indistinguishable statistically for longer maturities, but the multivariate DNS models still have lower RMSPE. The multivariate models without the curvature are among the best, while BVAR(1) has the lowest error of projections of the entire yield curve. BVAR(1)-NC produces relatively accurate forecasts for the 3-month yield and long-term rates, but underperforms for medium-term rates. The reason is that when λ, which controls the decay of the yield curve, is fixed at 0.0609, it maximizes the curvature at a 30-month maturity (Diebold and Li, 2006). The significance of the curvature is high when forecasting medium-term rates, while it vanishes when maturity tends to zero or infinity.

Finally, at a 12-month horizon, the vast majority of models are better than the RW for almost any yield (see Table 15). However, the statistical superiority is true only for BVAR(1) and BVAR(1)-NC models for any maturity of up to 4 years. Interestingly, the performance of BVAR(1)-NC relative to the RW is similar for each yield, while the BVAR(1) model performs worse at the long end of the curve than at the short end. In general, it seems that the non-overparameterized model estimated via Bayesian method can adjust more rapidly than others to the shifts in interest rates and inflation which took place in 2016-2018. Inflation data does not seem to help to improve predictions because the links between inflation and the yield curve factors, which the model learned in the training sample, appear to break after the significant key rate cut in 2016.

The confidence sets for the entire term structure built with 10% significance level are small for 6- and 12-month horizons. Thus, it is highly likely that BVAR(1) and BVAR(1)-NC models are the best among the alternatives to forecast the yield curve at these horizons[4] (see Figure 3, Tables 14 and 15).

[4] The Brazilian test sample is the smallest one (only 29 points for each maturity), so these results should be treated carefully.

Figure 3: **Brazil**: RMSPE of the models in the confidence set for the entire yield curve



4.2 China

The recommended models to forecast the yield curve of China are presented in Table 7. The performance of the models included in the confidence set for the entire yield curve is demonstrated in Figure 4[5].

Yield maturity	Forecast horizon		
	1 month	6 months	12 months
3M	AR(2)-RWD-NC	BVAR(2)-NC	BVAR(2)-NC
6M	VAR(2)	BVAR(2)-NC	BVAR(2)
1Y	RW	BVAR(2)	BVAR(2)-NC
2Y	VAR(2)	BVAR(2)	BVAR(2)
3Y	BVAR(2)	BVAR(2)	BVAR(1)-NC
4Y	BVAR(2)	BVAR(2)	VAR(2)
5Y	BVAR(2)	BVAR(2)	VAR(2)
6Y	BVAR(2)	VAR(1)	VAR(1)
7Y	VAR(2)	VAR(1)	VAR(1)
8Y	BVAR(2)	BVAR(1)	VAR(1)
9Y	RW	BVAR(1)	BVAR(1)
10Y	RW	BVAR(1)	BVAR(1)
Entire YC	**VAR(2)**	**BVAR(2)**	**BVAR(2)**

Table 7: Recommendations for China

Although the lowest RMSPE is achieved using the RW at the 1-month horizon for the yields of some maturities, other rates are well-predicted by VAR(2) and BVAR(2) (see Figure 4 and Table 16). For the vast majority of yield maturities confidence sets are quite large at this horizon. The good performance of the RW for forecasting long-term rates can be explained by the relatively stable inflation in China during the test period, which is closely related to the long end of the term structure (Diebold et al., 2006). Similarly to the case of Brazil, the DNS models without the curvature tend to fail at the middle part of the yield curve (and at the long end). Considering the average performance at the short-term horizon, the best models are the RW, VAR(2), and BVAR(2) which all have a similar RMSPE for each yield.

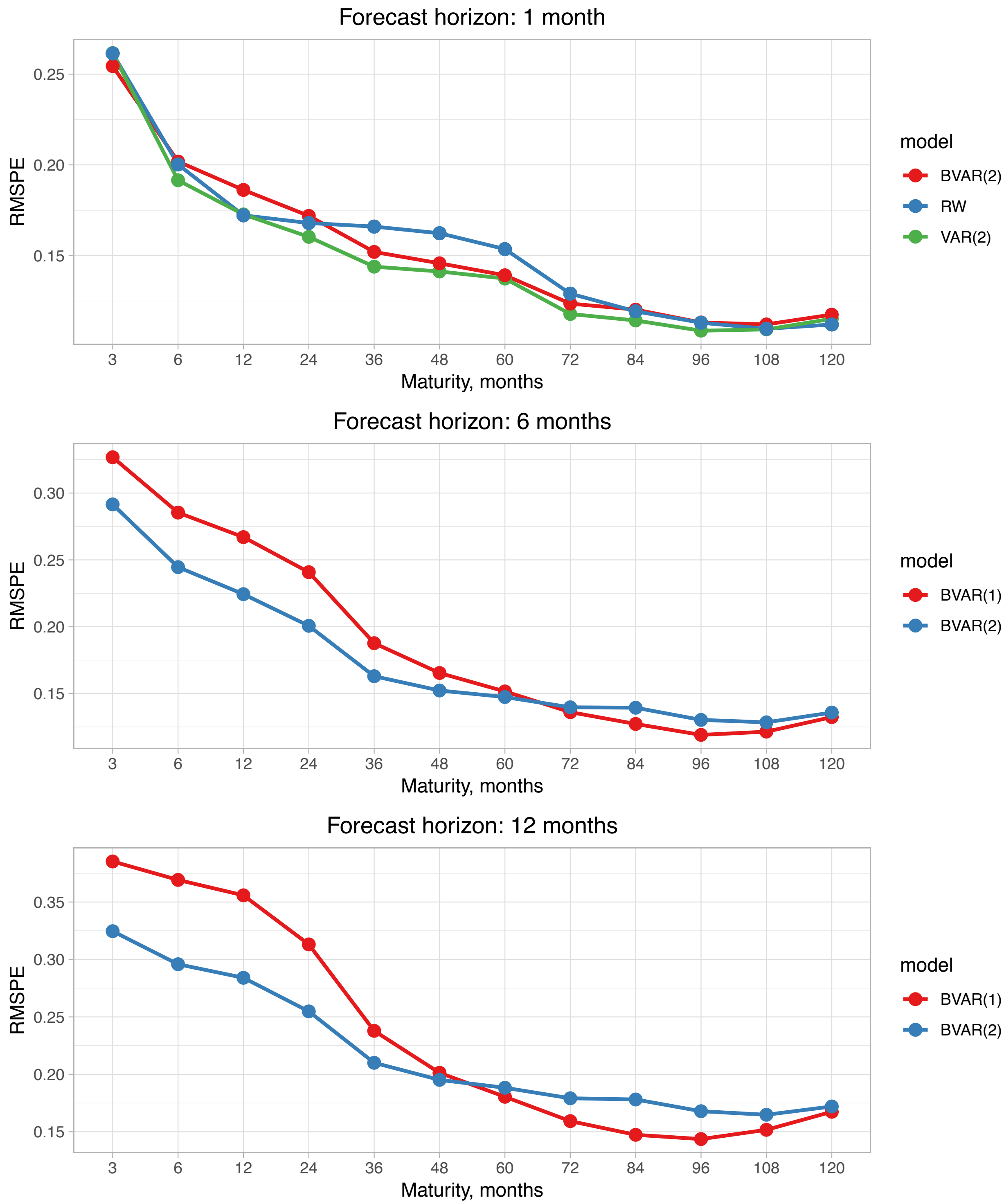
At the 6-month horizon, the multivariate DNS models significantly outperform the RW and univariate DNS models according to Figure 4 and Table 17. Bayesian models especially stand out among the alternatives being always unbeaten by the VAR models with the same maximum lag and endogenous variables. Models with the second lag seem to be useful to forecast short-term rates 6 months ahead, while the long end is forecast more accurately by the VAR and BVAR models with only the first lag. The reason could be that the short end is more volatile and is affected by monetary policy, whereas the long end is more closely related to inflation (Diebold et al., 2006). Therefore, to predict short-term rates one needs a great amount of information that the central bank uses, while to project long-term rates the most recent monthly data is enough because inflation was quite stable in China. In general, the Bayesian estimation is superior to the pure MLE as the confidence set for the yield curve consists of only BVAR(1) and BVAR(2) models.

As Figure 4 and Table 17 indicate, the results at the 12-month horizon are identical to those for the 6-month horizon. The vast majority of models outperform the RW, while BVAR(1) and BVAR(2) are in the confidence set for forecasting the entire yield curve. Inflation still seems to help marginally, which suggests that the Chinese yield curve does not depend heavily on it. The reason could be the stability of inflation in China, since it has a small variance in the test sample and thus has a little direct effect on future yields changes, especially at long horizons.

In contrast to Brazil (and some other EMEs analyzed below), the best models for China have a smaller RMSPE for long-term rates than for short-term ones. The same evidence is presented in many works about the US yield curve, which suggests that the Chinese term structure is more similar to that of advanced economies. The Chinese yields fluctuated between 1 and 5% during the sample period and did not increase sharply during the GFC. Inflation in China was relatively stable and the economy was growing constantly, so the yield curve was not affected by shocks such as in Brazil (2015-2016) or Turkey (2018-2019). The confidence sets for China are often large but rarely contain the RW and univariate DNS models, so the multivariate DNS models appear to be the most appropriate.

[5] All (T)RMSPEs are shown in Tables 16-18 in Appendix.

Figure 4: **China**: RMSPE of the models in the confidence set



4.3 India

The recommended models to forecast the yield curve of India are presented in Table 8. The performance of the models included in the confidence set for the entire yield curve is demonstrated in Figure 5[6].

Yield maturity	Forecast horizon		
	1 month	6 months	12 months
3M	AR(1)	VAR(1)-NC	VAR(1)-NC
6M	BVAR(1)	BVAR(1)-P	BVAR(1)-P
1Y	BVAR(1)	BVAR(1)-P	BVAR(1)-P
2Y	BVAR(1)	BVAR(1)-P	BVAR(1)-P
3Y	BVAR(1)	BVAR(1)-P	BVAR(1)-P
4Y	BVAR(1)	VAR(1)	BVAR(1)-P
5Y	VAR(1)	VAR(1)	BVAR(1)-P
6Y	RW	VAR(1)	BVAR(1)-P
7Y	RW	VAR(1)	BVAR(1)-P
8Y	RW	VAR(1)	BVAR(1)-P
9Y	RW	VAR(1)	BVAR(1)-P
10Y	RW	BVAR(1)-P	BVAR(1)-P
Entire YC	**AR(1)**	**BVAR(1)-P**	**BVAR(1)-P**

Table 8: Recommendations for India

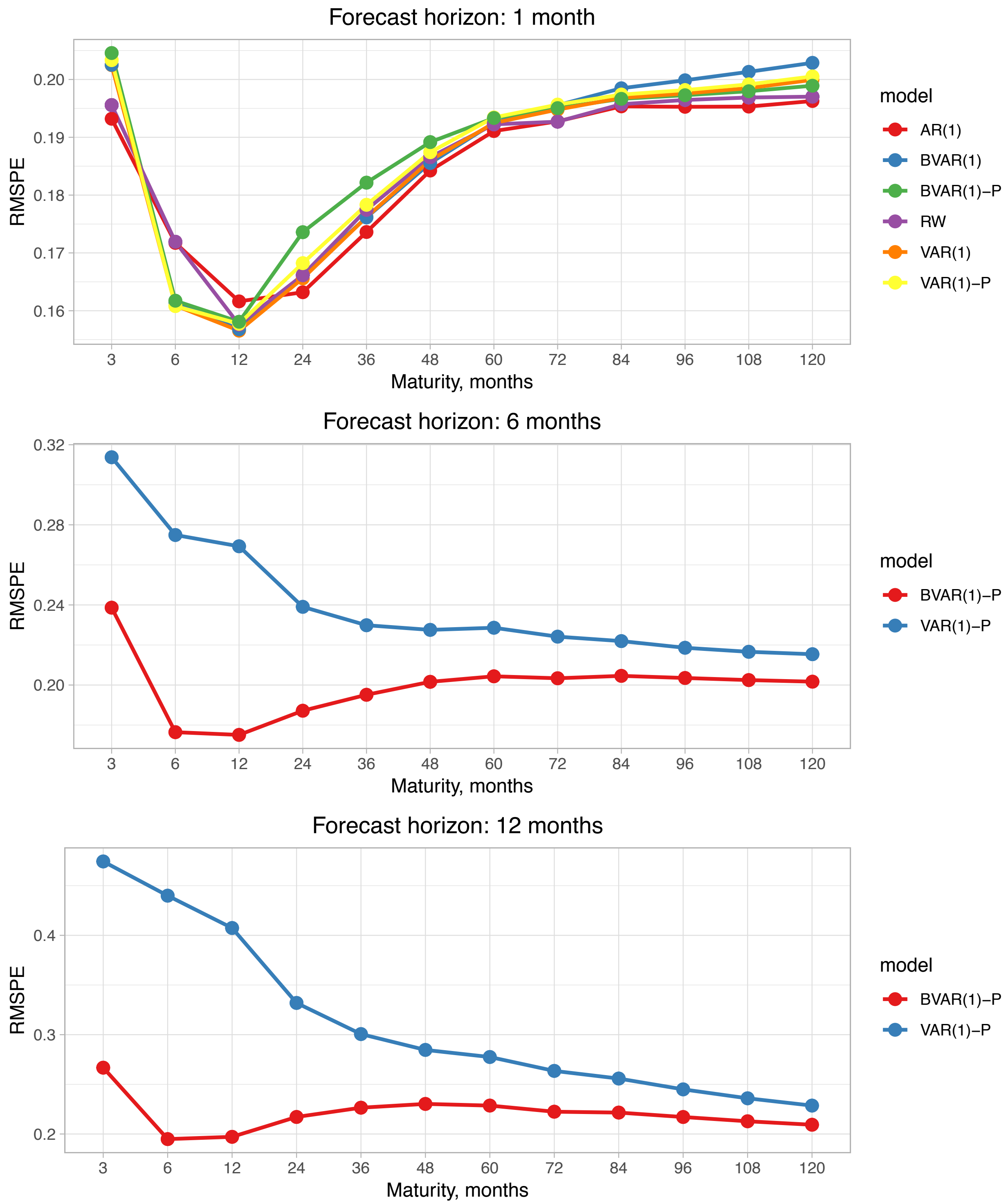
Figure 5 and Table 19 present another evidence that the random walk is one of the best forecasting models for long-term rates at the 1-month horizon. In contrast to Brazil and China, the AR(1) model usually has a lower RMSPE than other alternatives and is the most accurate for the entire yield curve according to TRMSPE. Models without the curvature are complete failures at the 1-month horizon - the fact which is also observed in Brazil and China. Other evidence is that (B)VAR models with and without inflation are almost identical, which suggests that price growth is not informative for the Indian term structure at short horizons. The RW, AR(1), VAR(1), BVAR(1), VAR(1)-P, and BVAR(1)-P are in the confidence set for the entire yield curve and their TRMSPEs are very close to each other (Figure 5).

The effectiveness of the multivariate DNS models is evident when forecasting 6 and 12 months ahead (see Figure 5, Tables 20 and 21). The AR(1) and RW exhibit similarly poor performance, whereas the multivariate versions are typically more than twice as good as the RW in terms of RMSPE. This evidence implies that the interdependence of the level, slope, and curvature is important for India at longer horizons. Moreover, the curvature factor is important for forecasting as few NC models are in the confidence set. Thus, even if the curvature factor is often fitted and forecast with low precision (Diebold et al., 2006), it still seems to be important for the Indian term structure projections.

The most accurate model in terms of TRMSPE is BVAR(1)-P at 6- and 12-month horizons. The possible reason could be the launch of an inflation targeting policy right at the beginning of the test sample in 2015. Presumably, inflation, which was often in the tolerance range of 2-6% in 2015-2019, was giving a signal to investors that Indian monetary policy could become more dovish, which actually happened. The Bayesian approach is especially useful for models with inflation since it helps to improve parameter estimation efficiency and forecasting accuracy in the high-dimension model (Demeshev and Malakhovskaya, 2016). As a result, the general recommendation for forecasting the term structure 6 and 12 months ahead is to use BVAR(1) with inflation.

[6] All (T)RMSPEs are shown in Tables 19-21 in Appendix.

Figure 5: **India**: RMSPE of the models in the confidence set for the entire yield curve



4.4 Indonesia

The recommended models to forecast the yield curve of Indonesia are presented in Table 9. The performance of the models included in the confidence set for the entire yield curve is demonstrated in Figure 6[7].

Yield maturity	Forecast horizon		
	1 month	6 months	12 months
3M	AR(1)	BVAR(1)-P	BVAR(1)-P
6M	AR(1)	BVAR(1)-P	VAR(1)-P
1Y	VAR(1)-P	BVAR(1)-P	VAR(1)-P
2Y	VAR(1)-P	BVAR(1)-P	VAR(1)-P
3Y	VAR(1)-P	BVAR(1)-P	VAR(1)-P
4Y	VAR(1)-P	BVAR(1)-P	BVAR(1)-P
5Y	RW	BVAR(1)-P	BVAR(1)-P
6Y	VAR(1)-P	BVAR(1)-P	BVAR(1)
7Y	VAR(1)-P	BVAR(1)-P	BVAR(1)
8Y	VAR(1)-P	BVAR(1)-P	BVAR(1)
9Y	BVAR(1)	BVAR(1)-P	BVAR(1)
10Y	RW	BVAR(1)-NC	BVAR(1)
Entire YC	**VAR(1)-P**	**BVAR(1)-P**	**BVAR(1)-P**

Table 9: Recommendations for Indonesia

According to Table 22, Indonesia is yet another country for which the proposed DNS models are not statistically better than the RW at the 1-month horizon. Although the VAR(1)-P model has a lower RMSPE than the RW for the vast majority of yields, it fails for 5- and 10-year rates, as other DNS models do. It is difficult to interpret such results, but the analysis shows that the RW and VAR(1)-P models are the best in forecasting the entire yield curve at the short horizon (Figure 6 and Table 22). The DNS models without the curvature are complete failures at the 1-month horizon again, while the Bayesian estimation is inferior to MLE for the DNS model with inflation.

One can see the statistically outstanding performance of VAR(1)-P and BVAR(1)-P models at the 6- and 12-month horizons in Tables 23 and 24. While BVAR(1)-P is preferred to VAR(1)-P at the 6-month horizon, especially for short-term rates and the 10-year rate (Figure 6), the models have almost identical quality at the 12-month horizon. Both models are the only ones included in the confidence set for the 6- and 12-month horizon. The most probable explanation of the superiority of the inflation models is the inflation targeting policy which was launched in Indonesia in 2001. The acceptable deviation of inflation was around 1% from the target, so this policy seems to be quite strict compared to that of, for example, India, where the tolerance range was 2-6%. Such promises given by Indonesian monetary authorities appeared to provide a reliable guidance about future interest rate dynamics. If inflation is too high, one should expect yields to increase, because the central bank should decelerate the economy to slow inflation. In contrast, when inflation is close to or lower than the target, monetary authorities may decrease interest rates to stimulate economic growth. When investors believe that the central bank will do its best to adhere to the inflation targeting policy, inflation becomes a powerful predicting variable for the term structure.

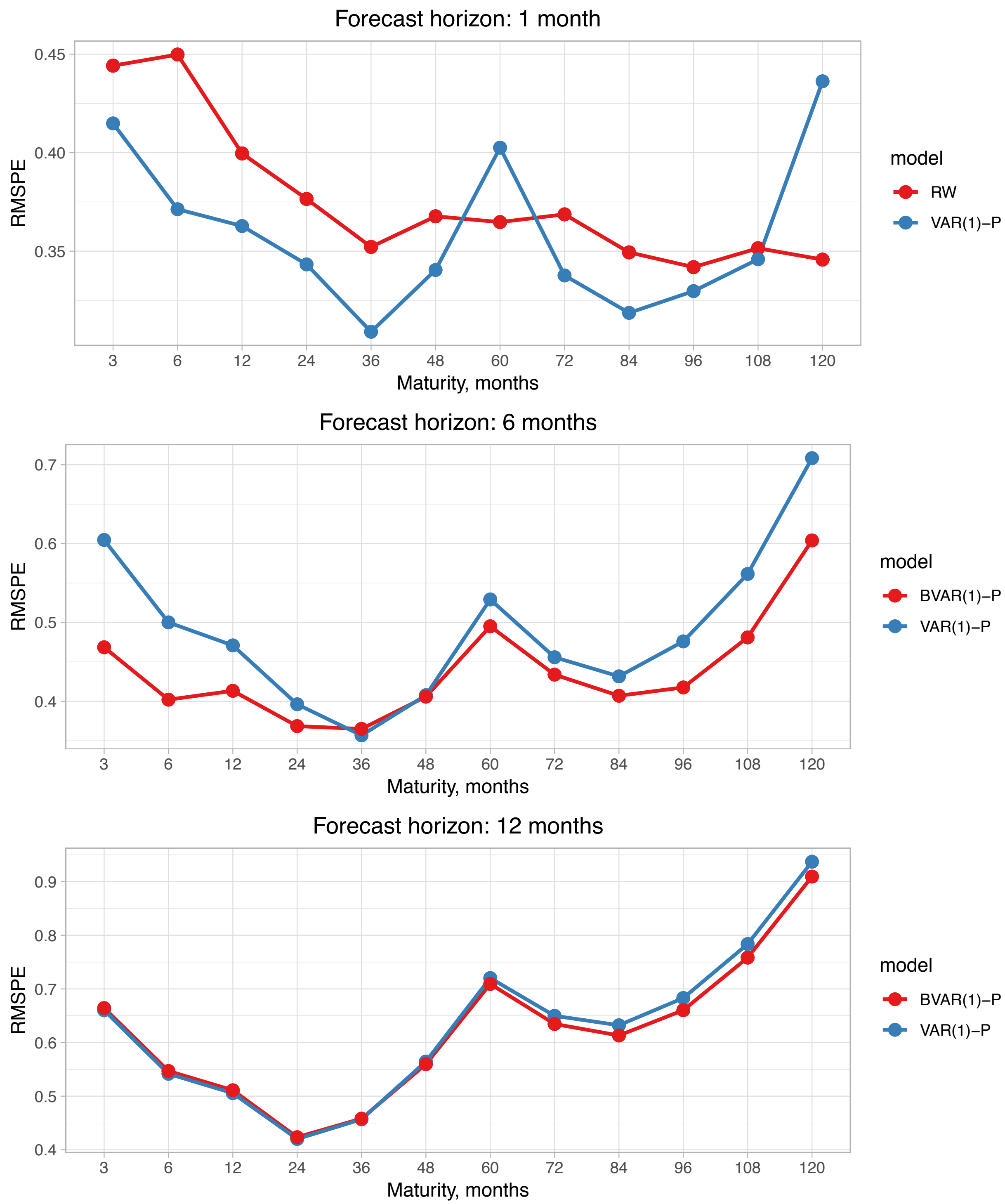
Inflation targeting in Indonesia was not absolutely successful. For example, in the first year of inflation targeting the policy was a complete failure as inflation of 12.55% was significantly higher than the tolerance range (4-6%). However, after those unsuccessful years the central bank of Indonesia did push prices down and sometimes decreased them to levels below a target. Thus, even though inflation targeting was not always successful in Indonesia, monetary authorities were giving signals that they would try to keep their promises anyway.

The results for forecasting each yield 1 month ahead should be treated carefully as the confidence sets are quite large. However, Table 22 shows that it is highly likely that the RW and VAR(1)-P models are the best at this horizon for the entire term structure. Tables 23 and 24 indicate that even though uncertainty about the best model for certain yields

[7] All (T)RMSPEs are shown in Tables 22-24 in Appendix.

remains relatively high, it is almost certain that the (B)VAR(1)-P model is superior to other alternatives to forecast the entire yield curve 6 and 12 months ahead.

Figure 6: **Indonesia**: RMSPE of the models in the confidence set for the entire yield curve



4.5 Russia

The recommended models to forecast the yield curve of Russia are presented in Table 10. The performance of the models included in the confidence set for the entire yield curve is demonstrated in Figure 7[8]. For all horizons only the top 5 models in the confidence set are shown in Figure 7 to keep the number of lines down.

Yield maturity	Forecast horizon		
	1 month	6 months	12 months
3M	BVAR(2)-P	BVAR(2)-P	VAR(2)
6M	BVAR(2)-NC	VAR(2)	VAR(1)-P
1Y	BVAR(1)	VAR(2)	VAR(2)
2Y	RW	VAR(2)-P	VAR(2)-P
3Y	VAR(2)-P	VAR(2)-P	VAR(2)-P
4Y	VAR(2)-P	VAR(2)-P	BVAR(2)-P
5Y	ARI(1,1)-IMA(1,1)-MA(3)	VAR(2)-P	BVAR(2)-P
6Y	RW	BVAR(2)	BVAR(2)-P
7Y	RW	VAR(2)-P	VAR(2)-P
8Y	RW	BVAR(2)	VAR(2)-P
9Y	RW	BVAR(2)	BVAR(2)-P
10Y	RW	VAR(2)-P	VAR(2)-P
Entire YC	**RW**	**VAR(2)-P**	**VAR(2)-P**

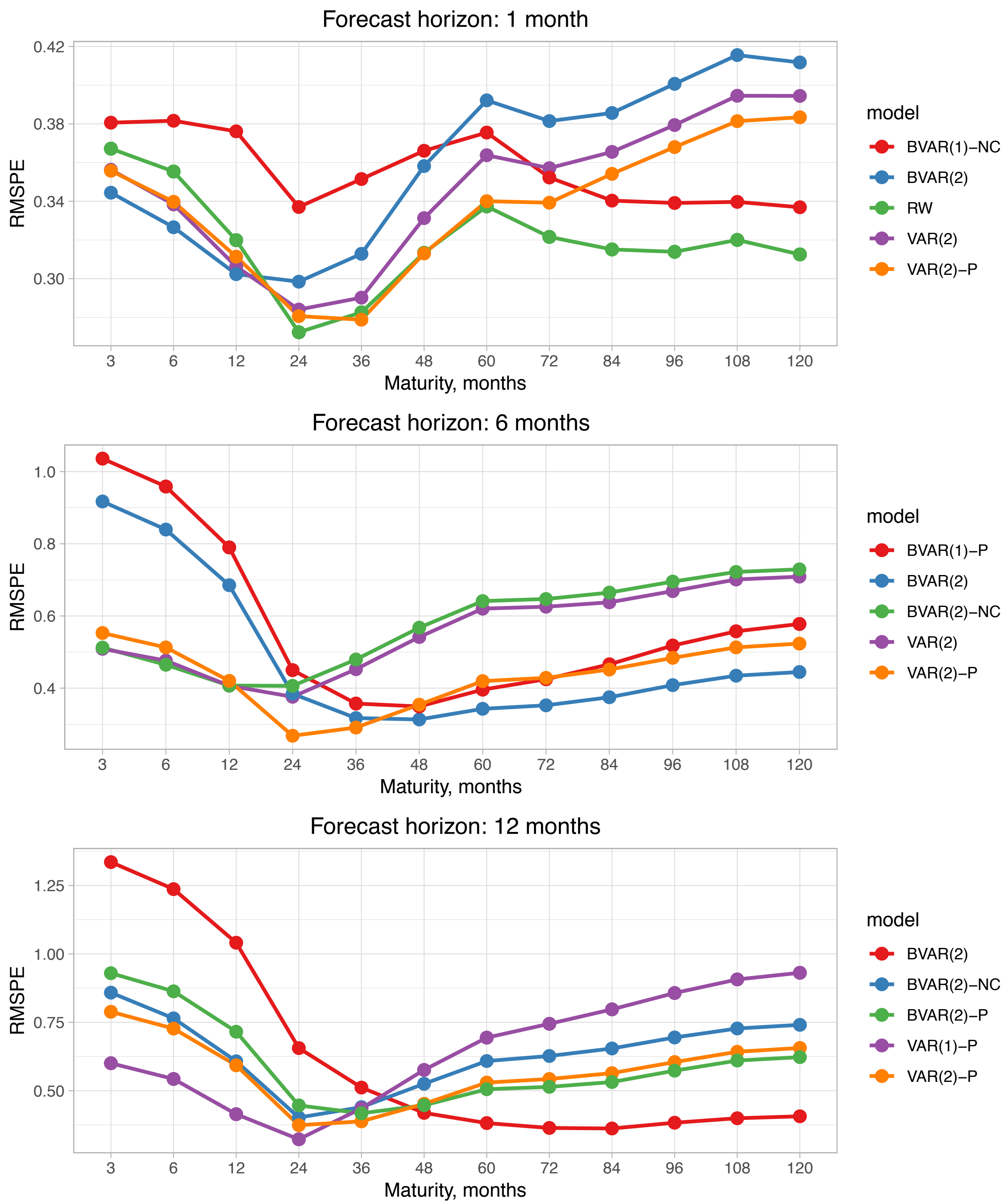
Table 10: Recommendations for Russia

Figure 7 and Table 25 illustrate that the results for Russia for the 1-month horizon are weak. Not only is the RW unbeaten during the MCS procedure (similarly to the countries already discussed), but also the model confidence sets contain almost all alternatives for this horizon. The BVAR(2) has one of the highest RMSPEs for medium- and long-term rates, but it has a low enough RMSPE for the short end to be among the best models for the entire term structure. The VAR(1), VAR(1)-NC, and VAR(2)-NC are outsiders for almost any yield according to MCS, which suggests that the MLE estimation for specific extensions should be questioned in case of Russia. In general, the RW model has the lowest TRMSPE, but this result should be treated cautiously as the confidence set consists of 7 models.

Table 26 shows that a relative RMSPE becomes lower when forecasting 6 months ahead, but the MCS procedure still eliminates a small number of competing models (on average 3 models out of 17). The similar pattern holds for the 12-month horizon (Table 27), so the level of uncertainty about the best model(s) is very high. The most accurate method for projecting the entire term structure is statistically indistinguishable from many other alternatives according to the MCS procedure. At the 6-month horizon, the DNS models are statistically better than the RW only for medium-term rates, while they are statistically similar to the benchmark for other yields. The VAR(2)-P produces the most accurate forecasts according to a TRMSPE, but, again, the confidence set for the entire yield curve is large. At the 12-month horizon the RW is not included in any confidence set, but this was expected since the yields were quite volatile in Russia during the test period. Models producing the lowest TRSMPE are the DNS models with inflation, so the inflation targeting policy launched by the Russian central bank in 2014 seems to influence positively the long-term forecasting. Again, the confidence set for the 12-month horizon is large, so other extensions should be analyzed to obtain the best model(s) with a high level of certainty.

[8] All (T)RMSPEs are shown in Tables 25-27 in Appendix.

Figure 7: **Russia**: RMSPE of the top 5 models in the confidence set for the entire yield curve according to a $t_{i.}$ statistic (Hansen et al., 2011)



4.6 Turkey

The recommended models to forecast the yield curve of Turkey are presented in Table 11. The performance of the models included in the confidence set for the entire yield curve is demonstrated in Figure 8[9].

Yield maturity	Forecast horizon		
	1 month	6 months	12 months
3M	RW	VAR(1)	VAR(1)
6M	AR(1)	VAR(1)-NC	VAR(1)
1Y	AR(1)	VAR(1)-NC	VAR(1)-NC
2Y	AR(1)	VAR(1)-NC	VAR(1)-NC
3Y	AR(1)	VAR(1)-NC	VAR(1)-NC
4Y	AR(1)	BVAR(1)-NC	BVAR(1)-NC
5Y	BVAR(1)	BVAR(1)-NC	BVAR(1)-NC
6Y	BVAR(1)	BVAR(1)-NC	BVAR(1)-NC
7Y	BVAR(1)	BVAR(1)-NC	BVAR(1)-NC
8Y	BVAR(1)	BVAR(1)-NC	BVAR(1)-NC
9Y	AR(1)	BVAR(1)	BVAR(1)
10Y	AR(1)	BVAR(1)	BVAR(1)
Entire YC	**AR(1)**	**BVAR(1)-P**	**BVAR(1)-NC**

Table 11: Recommendations for Turkey

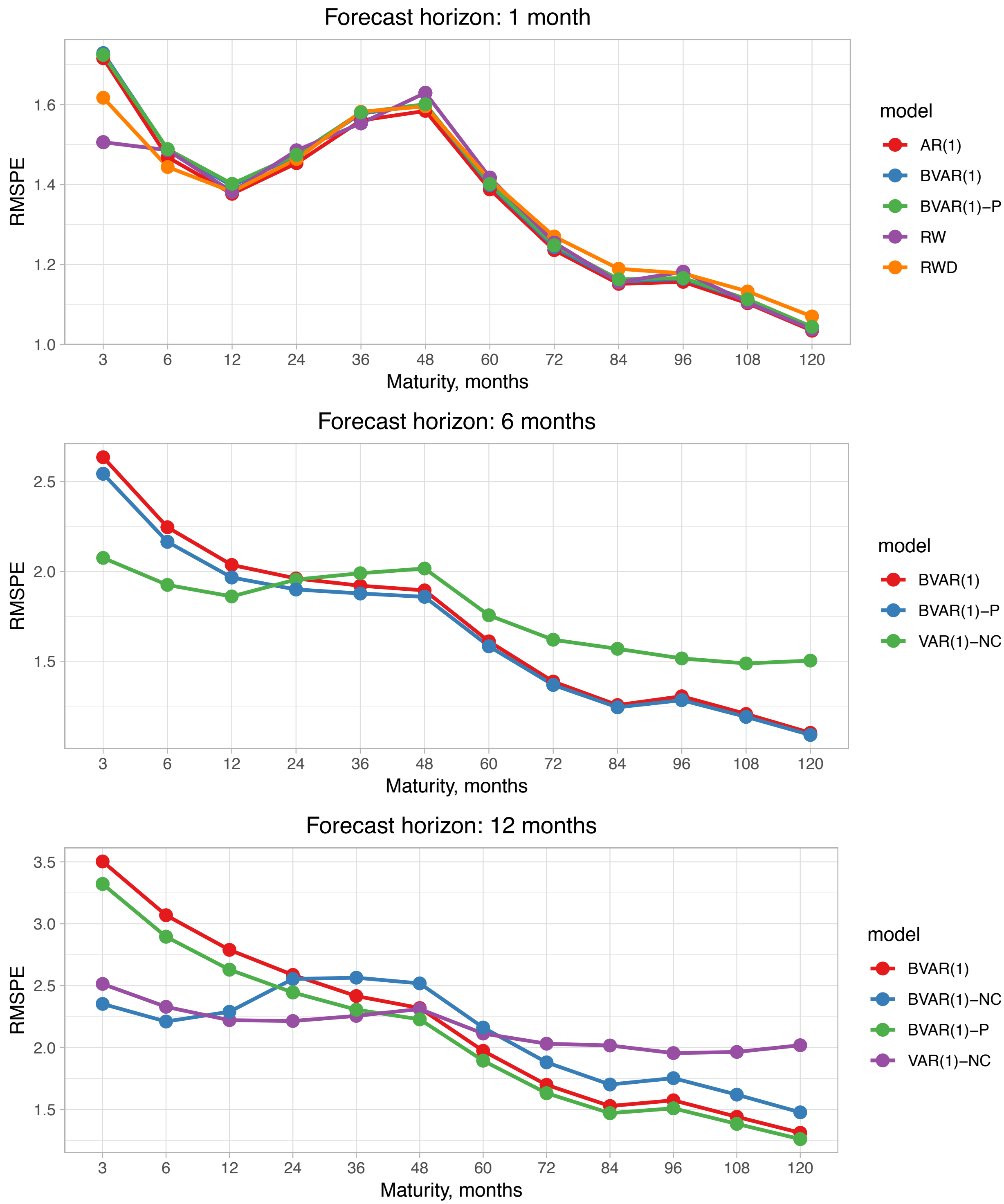
According to Figure 8 and Table 28, it is again the case that forecasting 1 month ahead is rather challenging. For any yield the confidence set contains all the alternatives, so there is total uncertainty about the best model(s). The multivariate DNS models are not as powerful as they are for other countries: AR(1) and the RWD often produce lower prediction errors than other models. Forecasting accuracy is the lowest for Turkey among all economies under study since the country suffered from the currency and debt crisis in 2018-2019. This recession significantly affected interest rates and inverted the yield curve, so the prediction errors are especially high for short- and medium-term yields (see Figure 8).

Regarding the 6-month horizon, Table 29 shows that the univariate DNS models and the RW tend to underperform. Now, interactions among the yield curve factors are important, while the curvature can be omitted without significant loss in prediction power. This is also observed in Brazil, which suggests that the curvature is uninformative for forecasting in unstable economies. These two economies are the only ones in the sample that suffered from a sharp decrease in GDP during the forecasting period. Finally, the BVAR(1)-P and BVAR(1) help to project the long end significantly, which make their TRMSPE the lowest.

The results are similar at the 12-month horizon, but now models without the curvature produce the most accurate forecasts in general (Figure 8 and Table 30). The MCS procedure results show that the prediction errors of all the models for separate yields are usually indistinguishable from each other, which again suggests high uncertainty about the best model(s) for each yield maturity. The BVAR(1), VAR(1)-NC, BVAR(1)-NC, and BVAR(1)-P form the confidence set for the entire term structure having statistically lower TRMPSEs than the alternatives. The models without the curvature are especially useful to project short-term rates of Turkey. While selection of the best model(s) for each separate yield remains a difficult task at 6- and 12-month horizons, the size of the confidence sets for the entire yield curve suggests that there is a high level of certainty about the best models.

[9] All (T)RMSPEs are shown in Tables 28-30 in Appendix.

Figure 8: **Turkey**: RMSPE of the models in the confidence set for the entire yield curve



4.7 The USA

The recommended models to forecast the yield curve of the USA are presented in Table 12. The performance of the models included in the confidence set for the entire yield curve is demonstrated in Figure 9[10]. For all horizon only the top 5 models in the confidence set are shown in Figure 9 to keep the number of lines down.

Yield maturity	Forecast horizon		
	1 month	6 months	12 months
3M	BVAR(2)	BVAR(2)	BVAR(2)-NC
6M	VAR(2)-P	VAR(3)-NC	BVAR(2)
1Y	RW	BVAR(3)-NC	BVAR(2)-NC
2Y	RW	BVAR(2)	BVAR(2)
3Y	BVAR(1)	BVAR(2)	BVAR(2)
4Y	BVAR(2)	BVAR(2)	VAR(2)
5Y	RW-AR(1)-RW	BVAR(2)-P	VAR(2)
6Y	BVAR(1)	BVAR(2)-P	VAR(1)
7Y	BVAR(1)	BVAR(1)-NC	VAR(1)
8Y	RW	BVAR(2)	VAR(1)
9Y	RW	BVAR(2)	BVAR(1)
10Y	RW	BVAR(2)	BVAR(1)
Entire YC	**RW**	**BVAR(2)-P**	**BVAR(2)**

Table 12: Recommendations for the USA

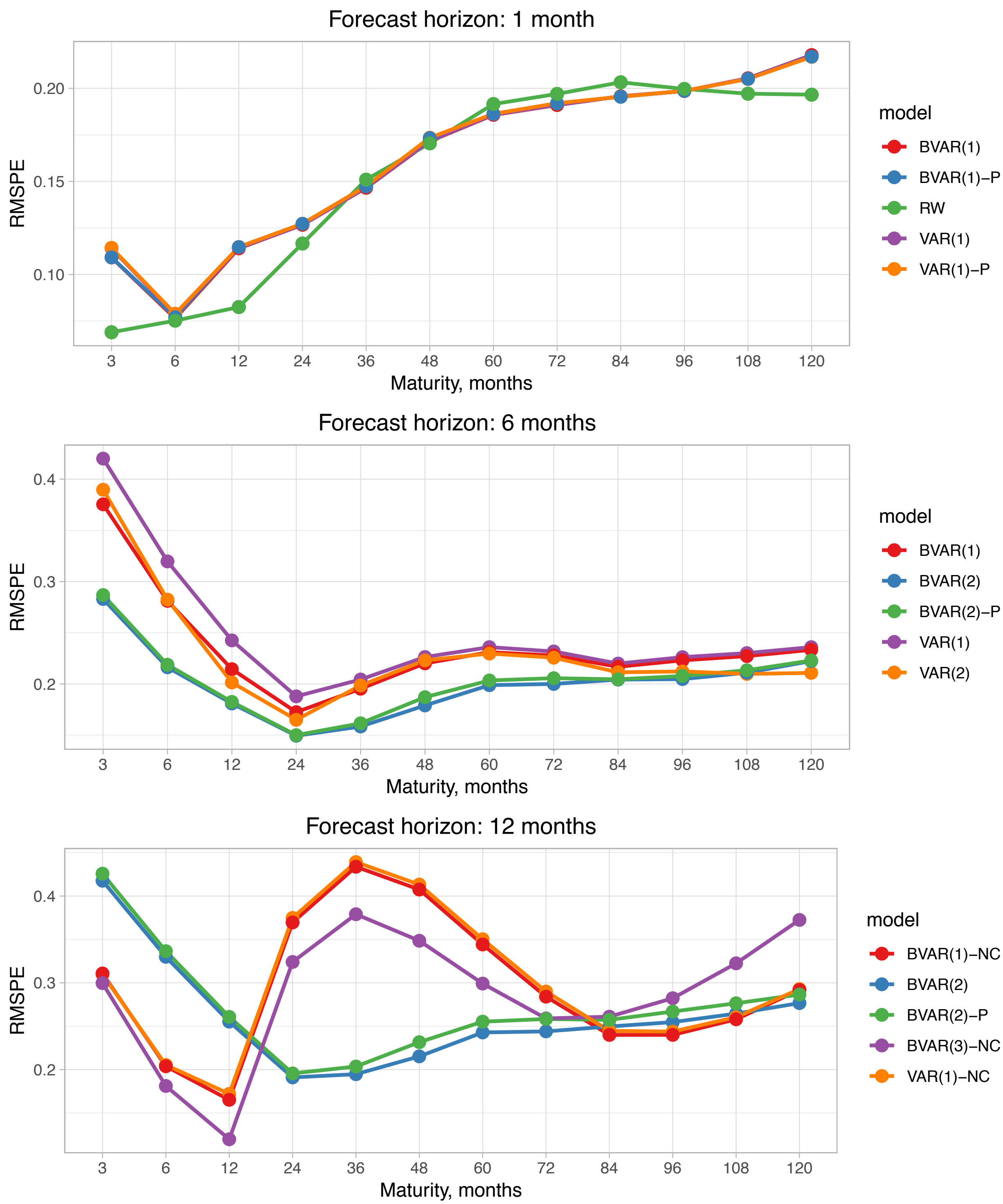
The minimization of BIC proposes various alternatives to the traditional DNS models, but they barely help to outperform the RW at the short forecast horizon. Figure 9 and Table 31 indicate the decent performance of the RW to forecast US yields 1 month ahead, which is not novel (Diebold and Li, 2006). However, after the times of the GFC other explanations could be used. Particularly, the low-interest-rate policy implemented by the Federal Reserve after the global crisis made US yields less volatile. This resulted in the more stable term structure, making the RW a powerful model to forecast yields, at least at short-term horizons. The size of the confidence sets for the 1-month horizon suggests a high level of uncertainty about the best model, but the NC models underperform with high probability.

The DNS models are still not better than the RW for short-term rates at the 6-month horizon (Table 32), perhaps, due to the low-interest-rate policy. The multivariate DNS models are the best for projecting medium- and long-term yields, but the confidence sets are sizeable for these rates. A high level of uncertainty about outperforming models remains for the entire yield curve as well, which is unlike most other countries under study. The BVAR(2) and BVAR(2)-P models have the lowest TRMSPE, but this performance is not statistically better than that of the other multivariate DNS models.

Figure 9 and Table 33 show that the situation for the 12-month horizon is rather mixed. Some models fail for short-term rates, some blunder for medium-term ones. In Table 33 one can see why Diebold et al. (2008) propose omitting the curvature factor for advanced-economy curves: the VAR(1)-NC and BVAR(1)-NC are superior to the VAR(1) and BVAR(1) in terms of a TRMSPE value. The BVAR(2) with and without inflation produces the most accurate forecasts, which suggests that Bayesian estimation is worth using for the US term structure. However, the confidence sets for yields and the entire yield curve are large, so other extensions of the DNS model should be tested.

[10] All (T)RMSPEs are shown in Tables 31-33 in Appendix.

Figure 9: **The USA**: RMSPE of the top 5 models in the confidence set for the entire yield curve according to a $t_{i.}$ statistic (Hansen et al., 2011)



4.8 Overall results for emerging market economies

The two main purposes of the study are to find trustworthy yield curve forecasting models for each emerging country of interest and to identify whether there are some forecasting models that systematically outperform others regardless of the country. In order to outline the general answers to these questions, we highlight the following results:

1. **The degree of certainty about the best models for each country and each horizon varies significantly**. While promising models for the entire yield curve are likely to be found for Brazil, China, India, and Indonesia, this is not true for Russia and Turkey. The most difficult tasks are to find the most accurate models for each yield separately and the best-performing methods at the 1-month horizon. Thus, it is not possible to highlight a single model that is superior to others for the EMEs in general.
2. **Beating the RW at the 1-month horizon using the DNS models is a difficult task.** While at longer horizons the DNS models are often superior to the RW, at the 1-month horizon they are always statistically indistinguishable from the RW at 10% significance level.
3. **The DNS models without the curvature are often the least accurate at the short forecast horizon, but they can be useful for unstable economies.** The DNS-NC models are complete failures for Brazil, China, India, and Indonesia and are usually one of the outsiders for Russia and Turkey at the 1-month horizon. However, they are one of the best at longer horizons for Brazil and Turkey according to the MCS procedure. These counties are similar as both suffered from a sharp fall in GDP during the test sample. While Brazil had decreasing inflation and declining interest rates, as the central bank aimed to stimulate the economy, Turkey faced soaring inflation and increasing rates to support the local currency. Both economies were unstable during the test sample, so the DNS-NC models seem to be superior to others in these circumstances. The probable reason is that they capture only common features of the yield curve (the long-term rate and spread) and pay no attention to the curvature which is usually estimated with low precision (Diebold and Li, 2006). This estimation error seems to increase in times of economic downturns.
4. **Model selection via BIC minimization is often inefficient for univariate models, while its usefulness for multivariate models is unclear.** BIC minimization usually implies the use of the univariate models which do not produce significant forecasting improvements because they are rarely included in the confidence set (especially for the entire yield curve). Regarding (B)VAR lag selection, the results are not clear. When BIC minimization proposes a lag higher than 1, confidence sets tend to be too large to make any conclusions (Russia) or contain similar models with the first and larger lags (China). If the procedure does not propose a lag larger than one (Brazil, India, Indonesia, Turkey), nothing is said about multivariate models with larger lags in this study.
5. **BVAR models with inflation data are often among the statistically best models, especially for EMEs with successful inflation targeting.** This is evident when considering forecasting 6 and 12 months ahead. Except for the Chinese yield curve, which does not depend heavily on inflation, confidence sets for separate yields often include models with inflation for each country. The BVAR model with inflation seems to be superior to VAR with inflation because it deals more successfully with a large number of parameters in the DNS-P model.
6. **Multivariate DNS models are superior to univariate DNS models**. Multivariate DNS models are systematically better according to the MCS procedure or have a lower (T)RMSPE and a $t_{i.}$ statistic than univariate DNS models for almost any country, any horizon, and any yield. In some rare situations univariate models are statistically the best, but this happens only at the short horizon. The general results of forecasting model selection suggest that interactions among the level, slope, and curvature are significant for predicting the term structure of EMEs.
7. **BVAR is usually superior to VAR.** The Bayesian estimation with the conjugate Normal-inverse Wishart prior helps to deal with high dimensions for inflation models. Besides, the contribution of the prior initialized using validation data and AR(1) coefficient estimates seems to be important. Therefore, the Bayesian estimation outperforms MLE. Since the results are obtained using the conjugate Normal-inverse Wishart prior, we conclude that more complex and flexible Bayesian approaches may produce more accurate predictions.
8. **There is no clear difference or similarity among the best models for EMEs and the USA**. One of the reasons is that the confidence sets for the US are too large to choose the most accurate models. Nevertheless, we can distinguish one similarity between the emerging and advanced economies. That is, the DNS models without the curvature are often the worst statistically at the 1-month horizon for the entire US and EME yield curves.
9. **The extensions of the DNS model often improve forecasts of the traditional DNS models for the yield curves in EMEs**. For the vast majority of countries and horizons the proposed extended DNS models have

lower (T)RMSE, and in some cases this difference is statistically significant. It is typical that either only extensions of the DNS model are included in the confidence set or both the extended and traditional versions are present. The most powerful extended models are Bayesian models and multivariate models with inflation. However, further studies should be carried out to find even more accurate extensions, especially for Russia.

5 Conclusion

Powerful tools to forecast the term structure of sovereign bond yields have already been created for some developed countries, while emerging markets are rarely the focus of studies. However, the integration of EMEs into the financial system of advanced economies could result in high losses if investments in developing countries are made without reliable forecasts of future asset prices. The bond market is one of the largest financial markets in the world, while sovereign bonds are the most popular debt instrument in many developed and emerging markets. This situation leads to the need to predict a future path of sovereign yields in order to make profitable investment plans and decrease risks. Some steps should be taken to create a unified approach for developing countries, so we investigate this problem testing different models on EME data.

The study shows that some extensions of the DNS models are superior to the traditional DNS models to project yields of emerging markets. Models without the curvature are the most effective if an economy is unstable but are ineffective at short horizons. Inflation data is helpful in general, especially for countries with successful inflation targeting. Multivariate DNS models are clearly more appropriate than univariate ones for forecasting purposes, while the Bayesian estimation of the multivariate models is often superior to the MLE. Other findings are that forecasting 1 month ahead is a challenging task and uncertainty about the best models is high for Turkey and especially for Russia.

Further steps to improve the performance of the DNS forecasting models for EMEs should be taken. First, extensive macroeconomic data sets could be used instead of only inflation data (Vieira et al., 2016). Secondly, other prior distributions could be tested when using a BVAR model to project yield curve factors. Thirdly, a comparison of the one-step approach to the two-step approach for estimating the DNS factors using emerging economy data could be beneficial. Finally, the performance of machine learning tools such as gradient boosting and neural networks for forecasting the EME term structure seems to be yet unknown. Later works may use our results about which extensions of the DNS models are worth developing and which (for example, univariate processes) are obvious underperformers.

6 Appendix

6.1 The US yield curve

Figure 10: Dynamics of the US yield curve

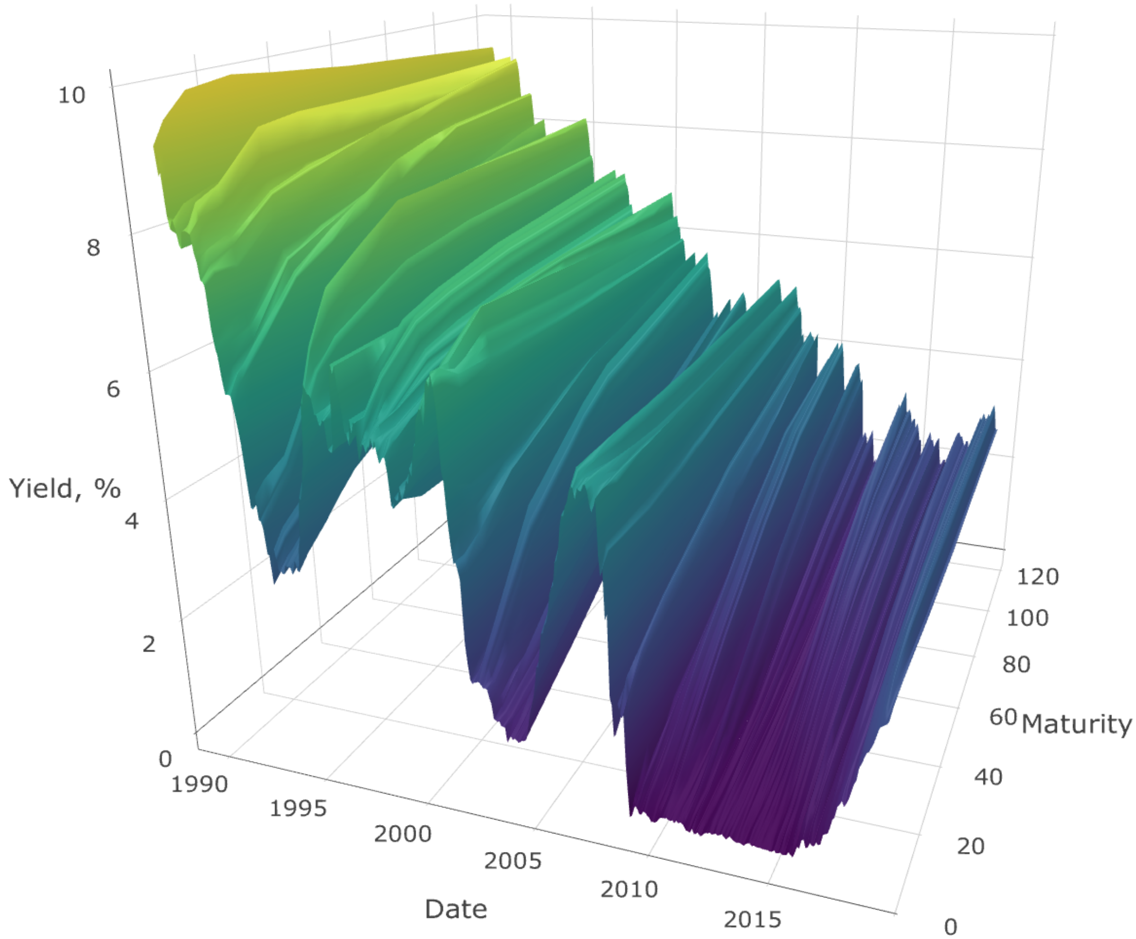
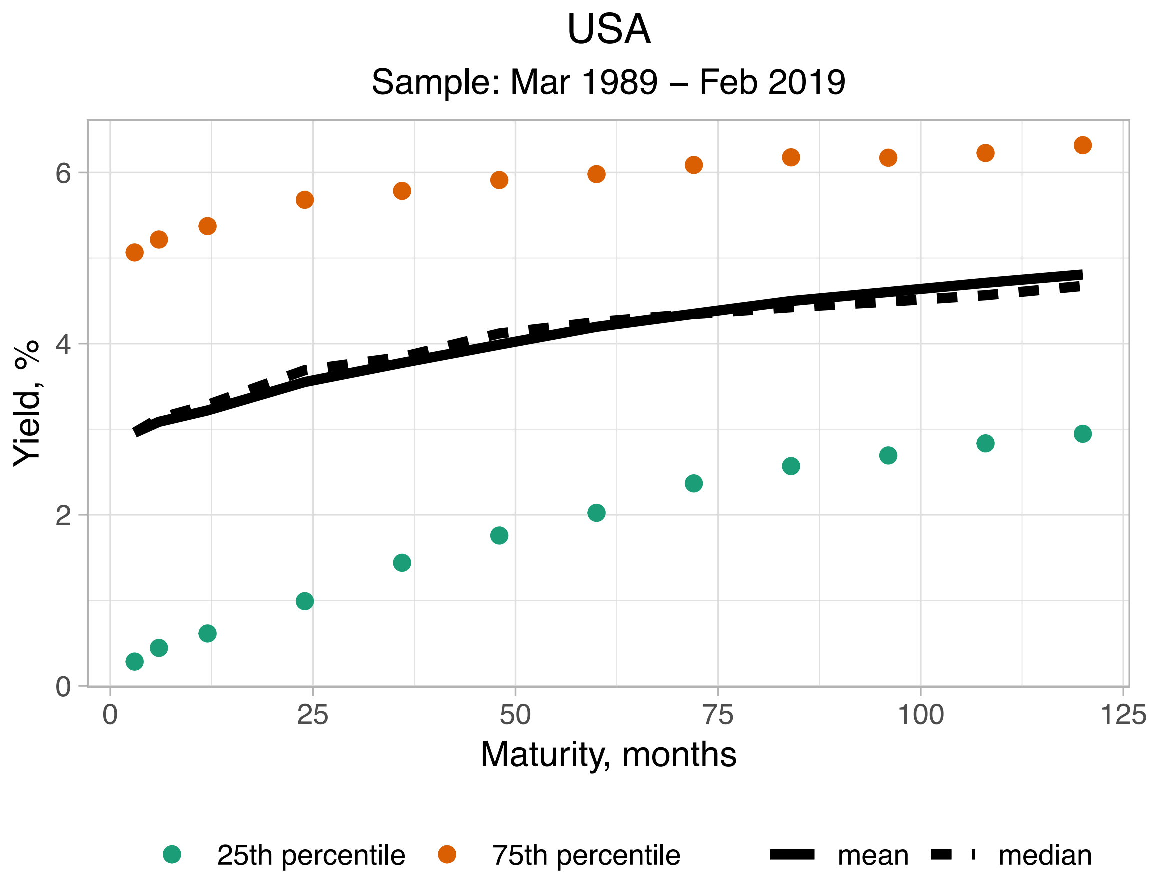


Figure 11: The US Yield curve's statistics



6.2 Dynamics of some yields

Figure 12: Brazil (the first test observation is marked with a red line)

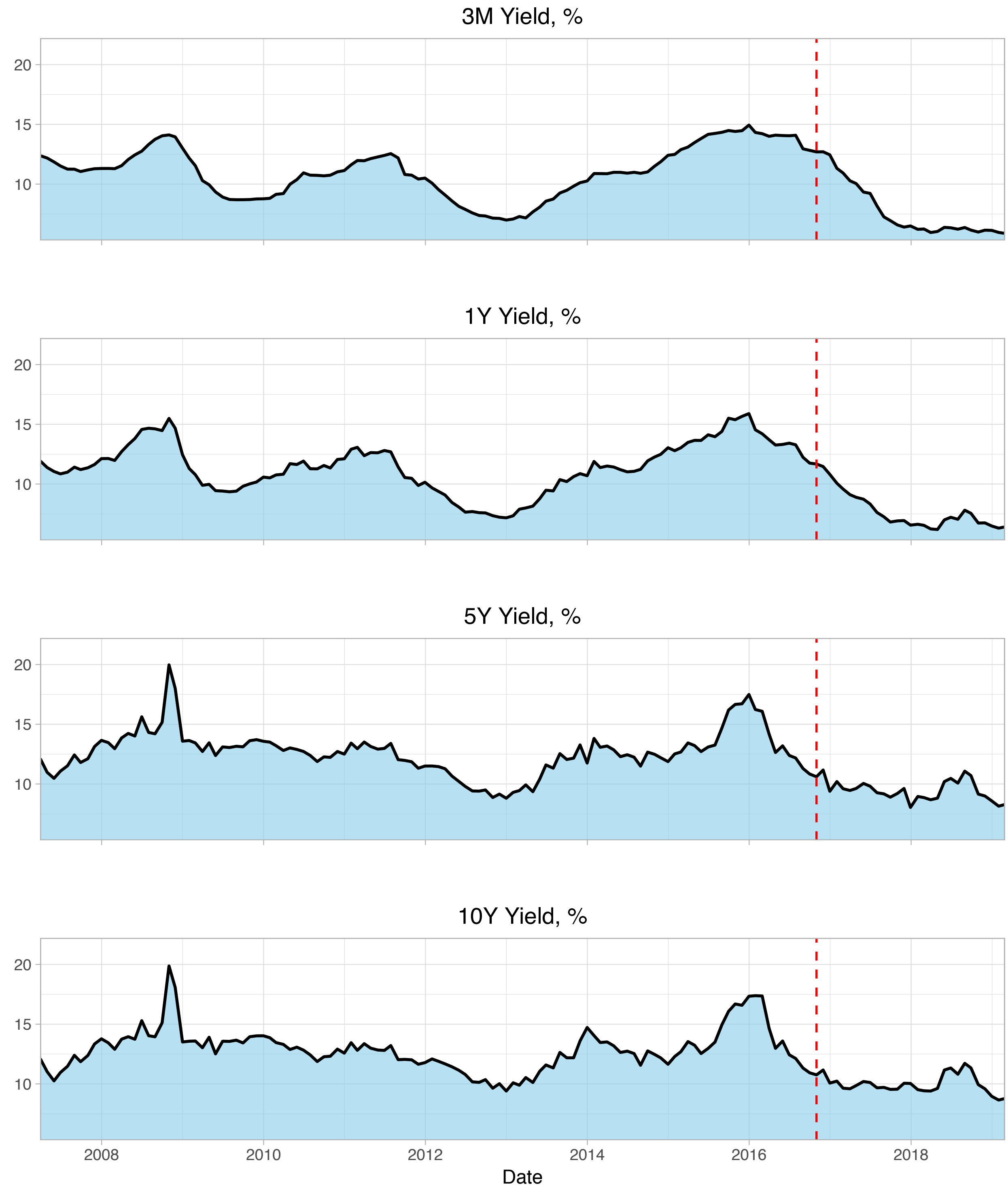


Figure 13: China (the first test observation is marked with a red line)

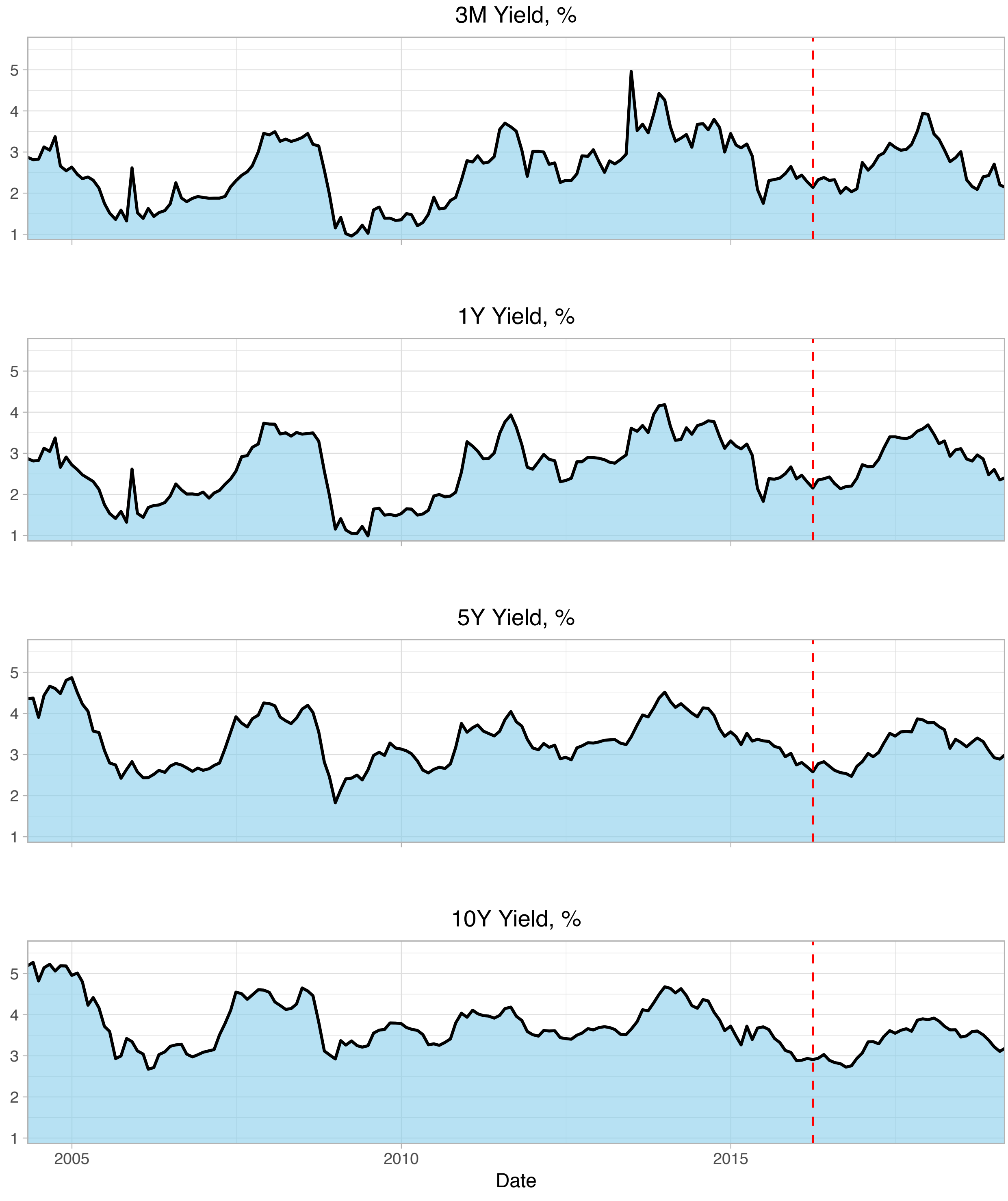


Figure 14: India (the first test observation is marked with a red line)

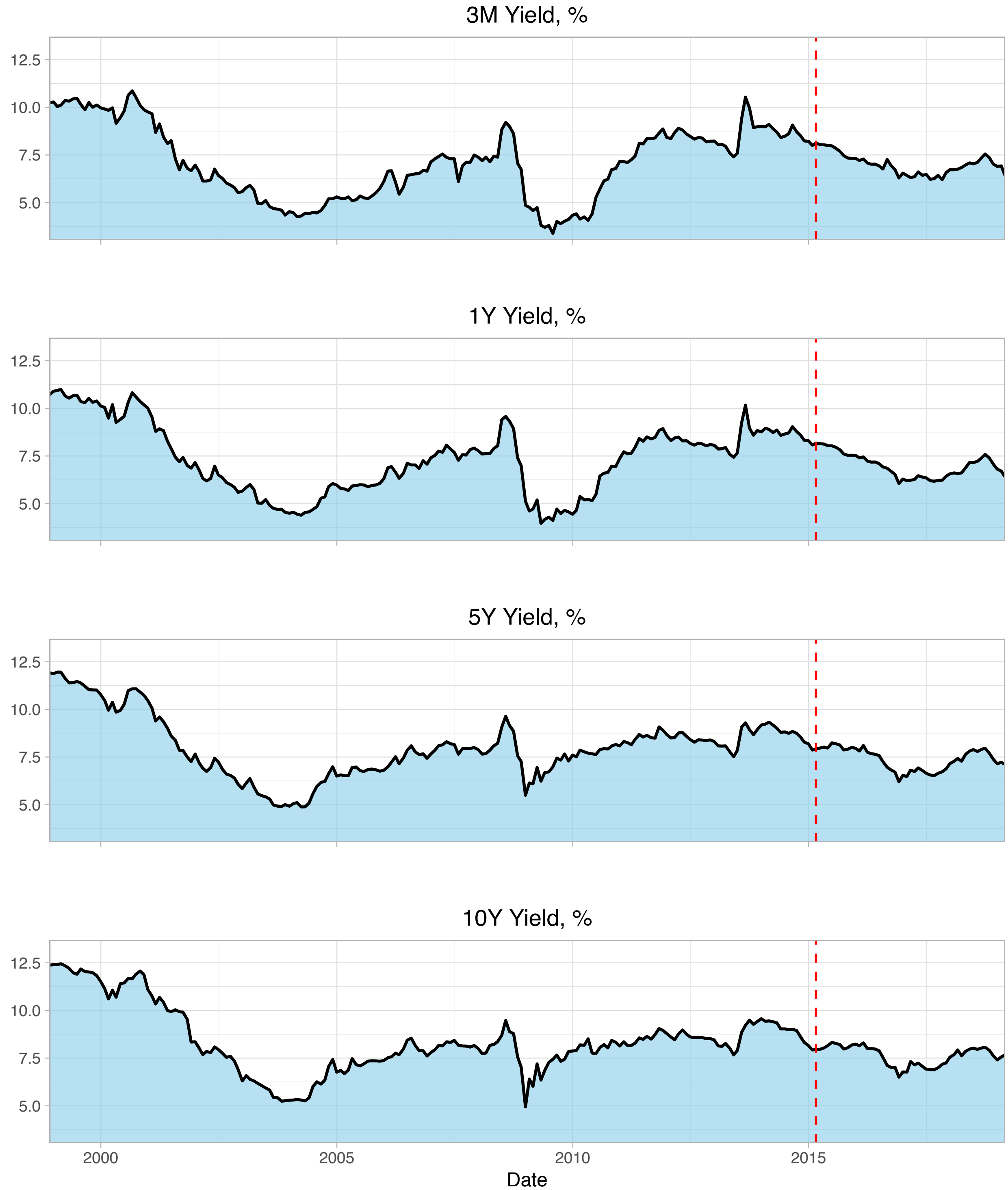


Figure 15: Indonesia (the first test observation is marked with a red line)

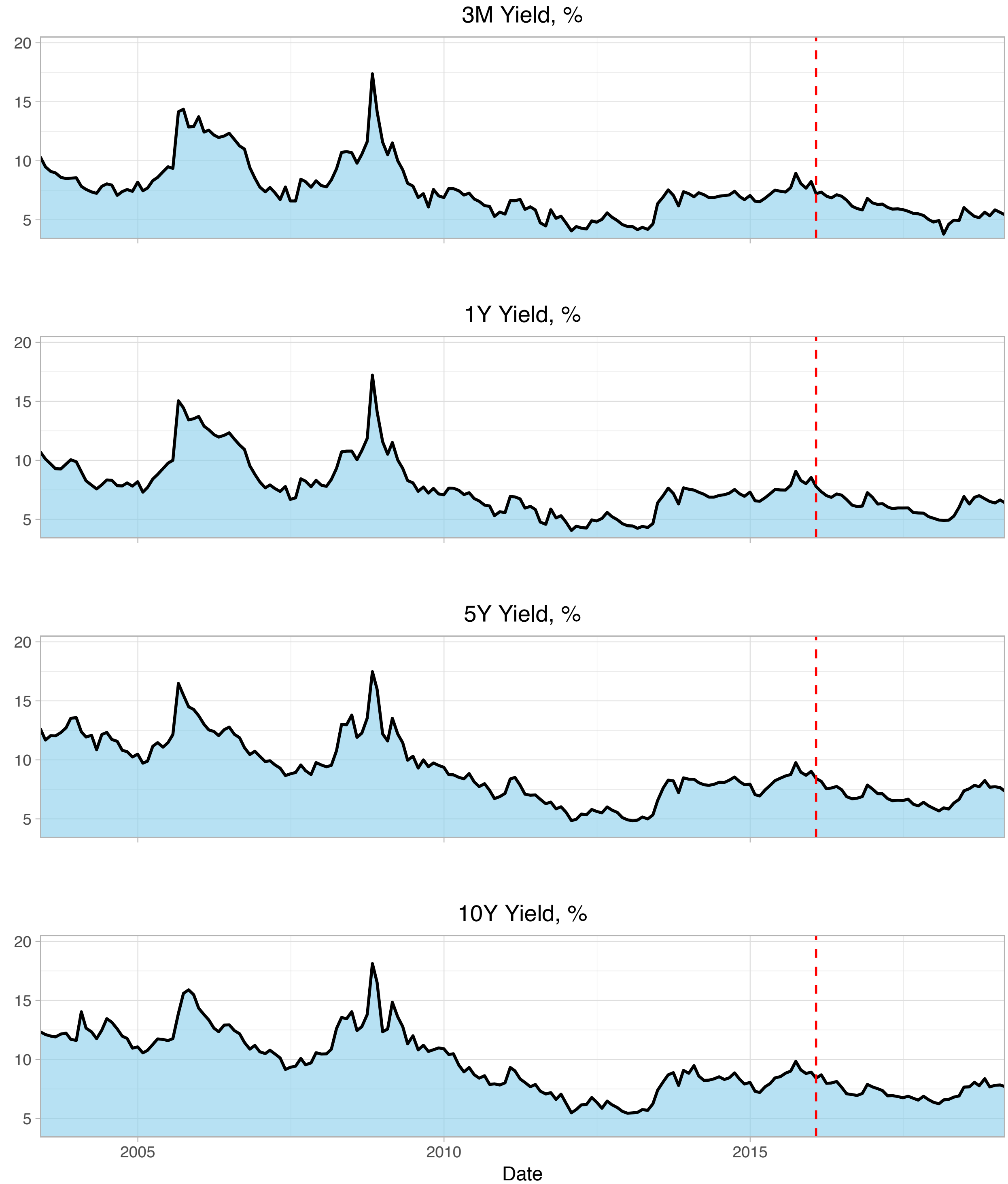


Figure 16: Russia (the first test observation is marked with a red line)

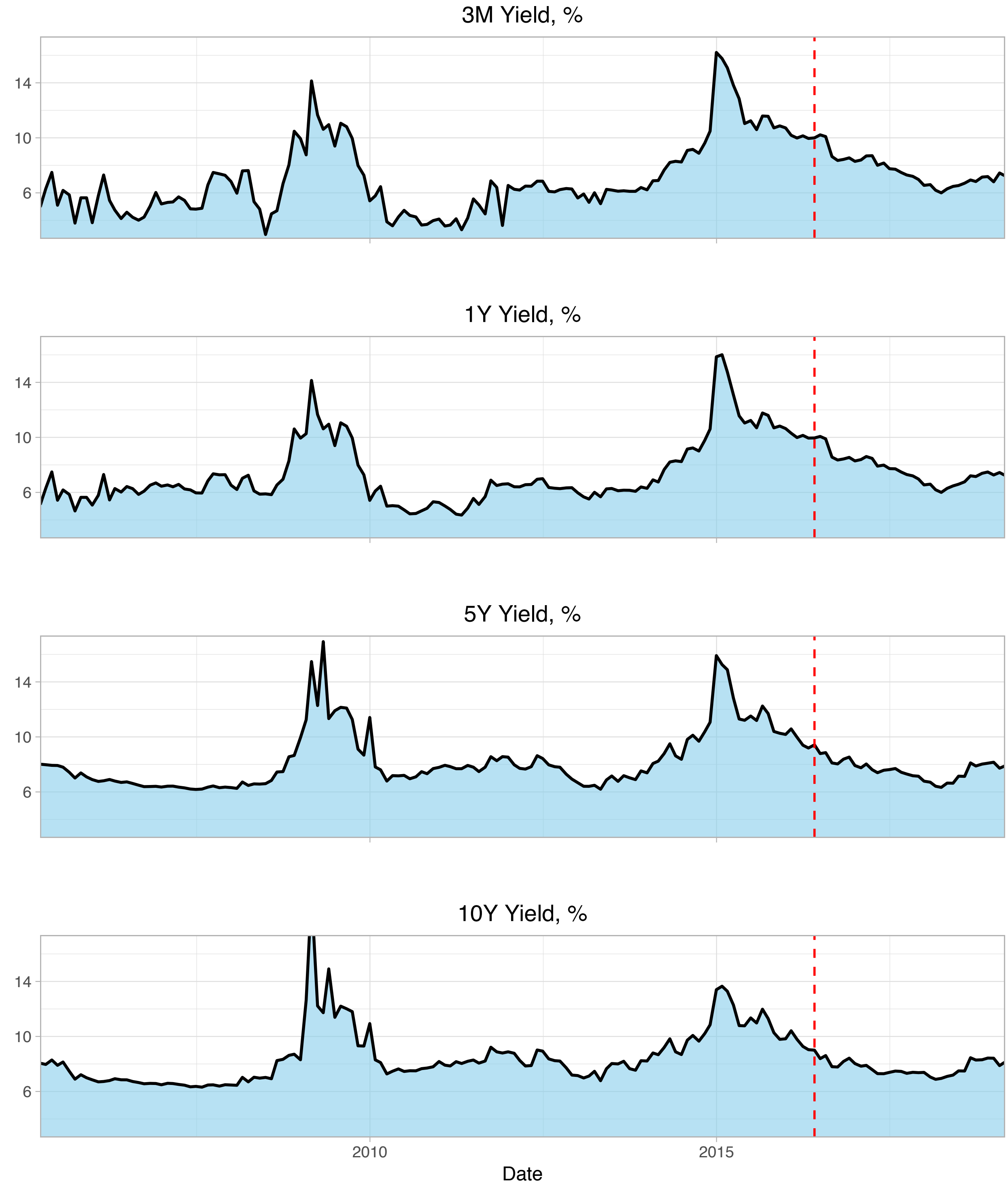


Figure 17: Turkey (the first test observation is marked with a red line)

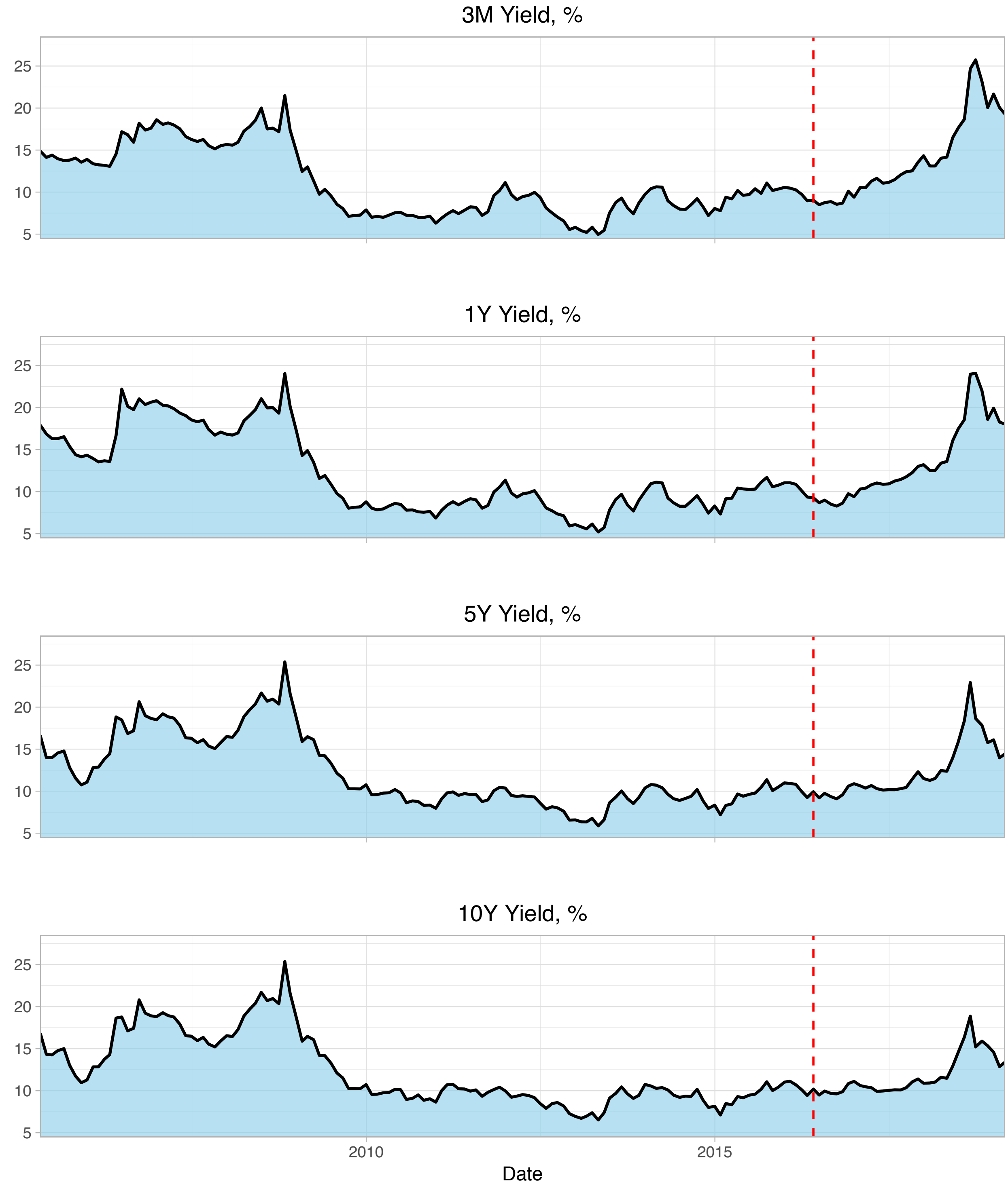
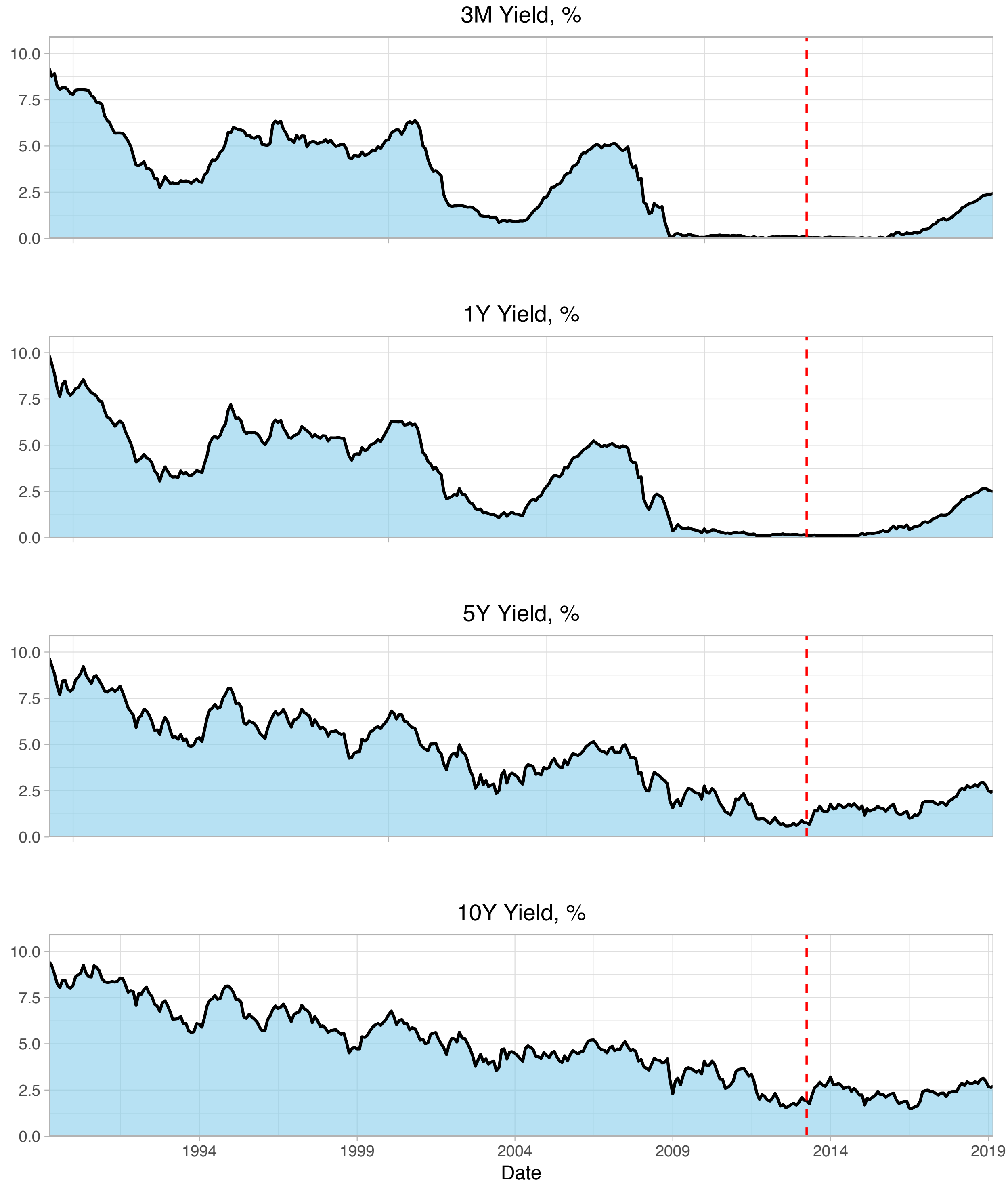


Figure 18: The USA (the first test observation is marked with a red line)



6.3 Inflation data

Figure 19: CPI annual growth, %: Brazil, China, India (the first test observation is marked with a red line)

Figure 20: CPI annual growth, %: Indonesia, Russia, Turkey (the first test observation is marked with a red line)

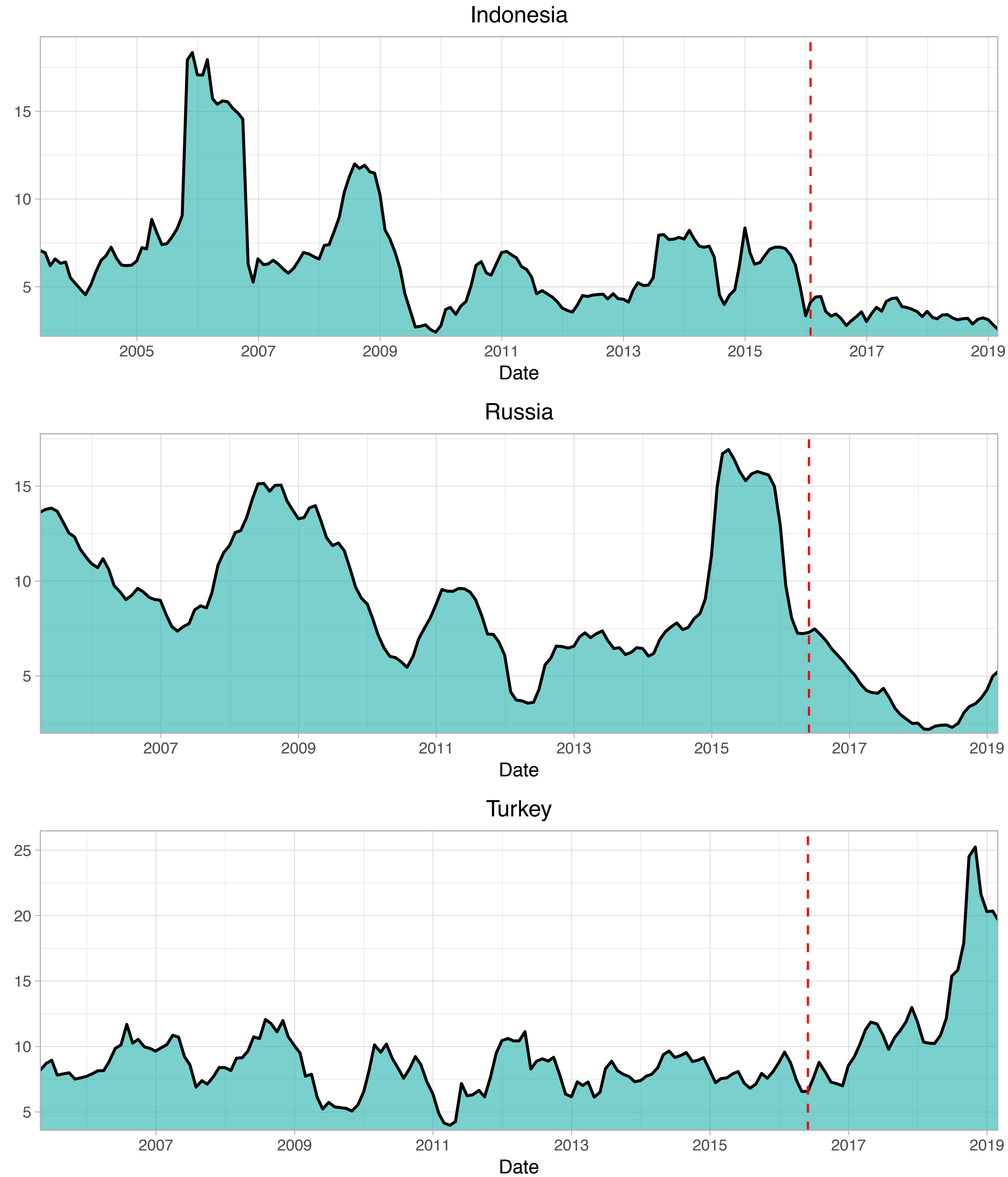
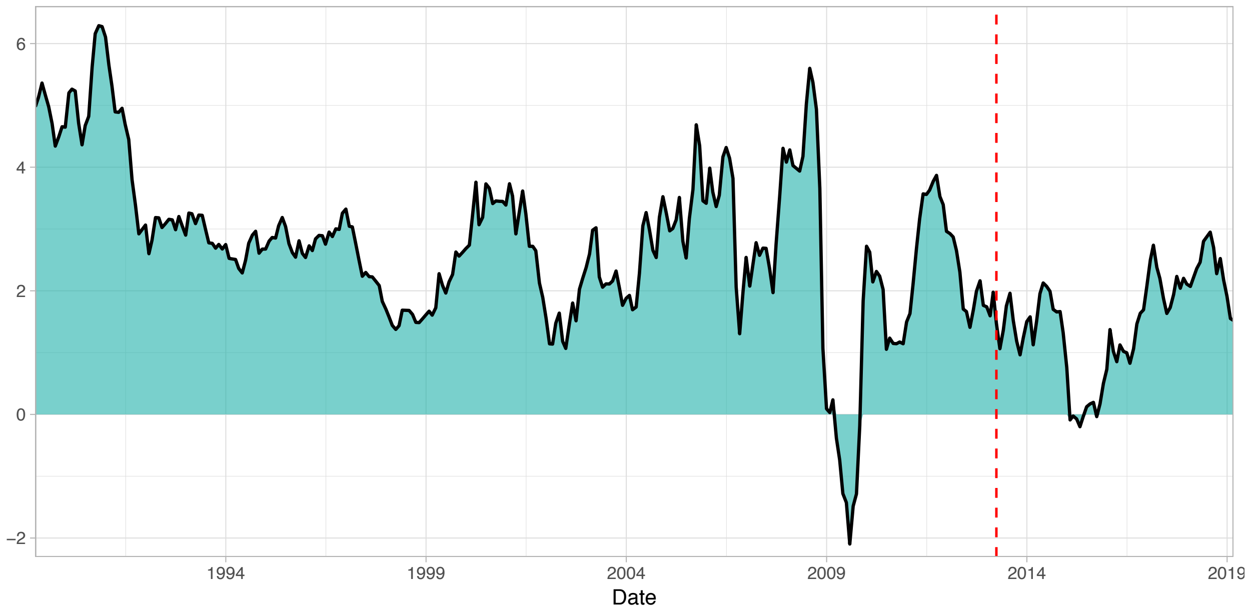


Figure 21: CPI annual growth, %: the USA (the first test observation is marked with a red line)



6.4 Tables with models' performance

Note

1. For the RW forecasts RMSPE for yields of certain maturities and TRMPE for the entire yield curve are presented.
2. ***For all other forecasting models only (T)RMSPE relative to (T)RMSPE of the RW are reported***. For example, a statistic for AR(1) less than 1 means that RMSPE of AR(1) forecasts is lower than that of the RW forecasts.
3. Asterisk (*) after (relative) (T)RMSPE means that a model belongs to the model confidence set which contains the "best" model with ***90% probability*** for a given horizon and a given maturity.
4. Relative (T)RMSPE that are lower than 1 are shown in **bold**.

6.4.1 Brazil

Model	3M	6M	1Y	2Y	3Y	4Y	5Y	6Y	7Y	8Y	9Y	10Y	Entire YC
RW	0.42*	0.38*	0.41*	0.44*	0.47*	0.67*	0.72*	0.68*	0.65*	0.62*	0.58*	0.56*	0.56*
AR(1)	1.43	2.18	2.30	1.81	1.40	1.13	1.10*	1.14*	1.19	1.25	1.32	1.37	1.38
VAR(1)	**0.71***	1.03	1.38	1.21	1.06	**0.99***	**0.98***	1.01*	1.04	1.08	1.12	1.15	1.06
BVAR(1)	**0.71***	1.00*	1.33*	1.16	1.03*	**0.98***	**0.96***	**0.99***	1.02*	1.05	1.08	1.10	1.03*
AR(1)-RWD-RWD	1.43	2.18	2.30	1.81	1.40	1.13	1.10*	1.14*	1.19	1.25	1.32	1.37	1.38
AR(1)-NC	1.80	2.98	3.47	3.18	2.58	1.82	1.62	1.62	1.63	1.68	1.74	1.78	2.03
VAR(1)-NC	1.17	2.22	2.87	2.77	2.28	1.69	1.50	1.50	1.52	1.57	1.63	1.66	1.79
BVAR(1)-NC	1.70	2.87	3.38	3.12	2.53	1.79	1.60	1.60	1.62	1.66	1.72	1.76	1.99
AR(1)-RWD-NC	1.80	2.98	3.47	3.18	2.58	1.82	1.62	1.62	1.63	1.68	1.74	1.78	2.03
VAR(1)-P	**0.73***	**0.91***	1.30	1.19	1.07	1.00*	**0.99***	1.01*	1.04	1.08	1.12	1.14	1.05
BVAR(1)-P	**0.74***	**0.89***	1.25	1.14*	1.04*	**0.98***	**0.97***	**0.99***	1.02*	1.05*	1.08*	1.10*	1.03*

Table 13: (T)RMSPE, 2016:10 - 2019:2, 1-month forecast horizon

Model	3M	6M	1Y	2Y	3Y	4Y	5Y	6Y	7Y	8Y	9Y	10Y	Entire YC
RW	2.06	1.98	1.81	1.49	1.30	1.44*	1.52*	1.51*	1.51*	1.49*	1.47*	1.46*	1.60
AR(1)	1.38	1.51	1.67	1.82	1.87	1.63	1.5	1.48	1.47	1.48	1.49	1.49	1.56
VAR(1)	**0.26***	**0.27***	**0.49***	**0.70***	**0.78***	**0.78***	**0.76***	**0.75***	**0.75***	**0.76***	**0.76***	**0.76***	**0.63**
BVAR(1)	**0.35**	**0.27***	**0.29***	**0.32***	**0.41***	**0.51***	**0.54***	**0.57***	**0.59***	**0.63***	**0.64***	**0.65***	**0.48***
AR(1)-RWD-RWD	1.38	1.51	1.67	1.82	1.87	1.63	1.5	1.48	1.47	1.48	1.49	1.49	1.56
AR(1)-NC	1.42	1.59	1.80	2.02	2.10	1.82	1.68	1.63	1.59	1.59	1.59	1.59	1.68
VAR(1)-NC	**0.26***	**0.47***	**0.76***	1.05*	1.18*	1.14*	1.07*	1.06*	1.05*	1.07*	1.07*	1.08*	**0.91**
BVAR(1)-NC	**0.23***	**0.40***	**0.59***	**0.66***	**0.62***	**0.60***	**0.53***	**0.49***	**0.47***	**0.46***	**0.45***	**0.44***	**0.49***
AR(1)-RWD-NC	1.42	1.59	1.80	2.02	2.10	1.82	1.68	1.63	1.59	1.59	1.59	1.59	1.68
VAR(1)-P	**0.35**	**0.29***	**0.48***	**0.70***	**0.79***	**0.78***	**0.76***	**0.75***	**0.75***	**0.75***	**0.76***	**0.76***	**0.64**
BVAR1-P	**0.36**	**0.27***	**0.42***	**0.61***	**0.67***	**0.67***	**0.66***	**0.64***	**0.64***	**0.64***	**0.64***	**0.64***	**0.55**

Table 14: (T)RMSPE, 2016:10 - 2019:2, 6-month forecast horizon

Model	3M	6M	1Y	2Y	3Y	4Y	5Y	6Y	7Y	8Y	9Y	10Y	Entire YC
RW	3.84	3.78	3.57	3.25	3.04	3.11*	3.19*	3.21*	3.25*	3.24*	3.25*	3.26*	3.34
AR(1)	1.01	1.05	1.10	1.10	1.06	**0.99**	**0.94**	**0.91**	**0.88**	**0.87**	**0.86**	**0.85**	**0.98**
VAR(1)	**0.25***	**0.31***	**0.44***	**0.55**	**0.57**	**0.57***	**0.56***	**0.54***	**0.53***	**0.52***	**0.51***	**0.51***	**0.48**
BVAR(1)	**0.29***	**0.25***	**0.23***	**0.18***	**0.19***	**0.26***	**0.30***	**0.34***	**0.36***	**0.39***	**0.40***	**0.42***	**0.31***
AR(1)-RWD-RWD	1.01	1.05	1.10	1.10	1.06	**0.99**	**0.94**	**0.91**	**0.88**	**0.87**	**0.86**	**0.85**	**0.98**
AR(1)-NC	1.02	1.06	1.12	1.12	1.09	1.01	**0.96**	**0.92**	**0.89**	**0.88**	**0.87**	**0.86**	**0.99**
VAR(1)-NC	**0.15***	**0.24***	**0.39***	**0.51**	**0.54**	**0.57***	**0.56***	**0.55***	**0.55***	**0.55***	**0.55***	**0.55***	**0.48**
BVAR(1)-NC	**0.14***	**0.22***	**0.29***	**0.28***	**0.23***	**0.25***	**0.23***	**0.22***	**0.21***	**0.21***	**0.20***	**0.20***	**0.23***
AR(1)-RWD-NC	1.02	1.06	1.12	1.12	1.09	1.01	**0.96**	**0.92**	**0.89**	**0.88**	**0.87**	**0.86**	**0.99**
VAR(1)-P	**0.28***	**0.33***	**0.45**	**0.57**	**0.59**	**0.59***	**0.57***	**0.56***	**0.54***	**0.53***	**0.53***	**0.52***	**0.50**
BVAR(1)-P	**0.34**	**0.42**	**0.54**	**0.63**	**0.64**	**0.62***	**0.59***	**0.57***	**0.55***	**0.54***	**0.53***	**0.53***	**0.54**

Table 15: (T)RMSPE, 2016:10 - 2019:2, 12-month forecast horizon

6.4.2 China

Model	3M	6M	1Y	2Y	3Y	4Y	5Y	6Y	7Y	8Y	9Y	10Y	Entire YC
RW	0.26*	0.20*	0.17*	0.17*	0.17*	0.16*	0.15*	0.13*	0.12*	0.11*	0.11*	0.11*	0.16*
AR(1)	**0.97***	1.12*	1.25*	1.18*	1.00*	**0.96***	**0.95***	1.07*	1.13	1.09*	1.08*	1.10*	1.07
VAR(1)	1.03*	1.04*	1.10*	1.05*	**0.94***	**0.92***	**0.92***	**0.96***	1.00*	1.00*	1.03*	1.06*	1.01
BVAR(1)	1.02*	1.06*	1.13*	1.07*	**0.95***	**0.92***	**0.91***	1.01*	1.09	1.06*	1.06*	1.07*	1.03
RWD	**0.97***	1.03*	1.08*	1.03*	**0.98***	**0.97***	**0.96***	1.00*	1.05*	1.05*	1.06*	1.08*	1.01
VAR(2)	1.00*	**0.96***	1.00*	**0.95***	**0.87***	**0.87***	**0.89***	**0.91***	**0.96***	**0.96***	1.00*	1.03*	**0.95***
BVAR(2)	**0.97***	1.01*	1.08*	1.02*	**0.92***	**0.90***	**0.91***	**0.96***	1.01*	1.00*	1.02*	1.05*	**0.98***
AR(1)-NC	**0.97***	1.13*	1.39*	1.47*	1.63	1.64	1.70	1.64	1.62	1.67	1.70	1.64	1.42
VAR(1)-NC	**0.99***	1.14*	1.43*	1.52*	1.69	1.70	1.76	1.69	1.65	1.71	1.75	1.69	1.47
BVAR(1)-NC	1.01*	1.17*	1.44*	1.46*	1.54	1.50	1.51	1.45	1.45	1.46	1.45	1.43	1.35
AR(2)-RWD-NC	**0.96***	1.11*	1.39*	1.49*	1.66	1.68	1.74	1.69	1.67	1.72	1.75	1.69	1.45
VAR(2)-NC	1.01*	1.15*	1.44*	1.55*	1.73	1.75	1.81	1.75	1.72	1.78	1.82	1.76	1.50
BVAR(2)-NC	**0.98***	1.13*	1.41*	1.50*	1.66	1.67	1.73	1.66	1.63	1.68	1.71	1.66	1.44
VAR(1)-P	1.03*	1.06*	1.13*	1.08*	**0.96***	**0.93***	**0.93***	**0.99***	1.03*	1.02*	1.04*	1.08*	1.03
BVAR(1)-P	**0.97***	1.06*	1.16*	1.10*	**0.97***	**0.94***	**0.95***	1.00*	1.05*	1.04*	1.05*	1.08*	1.03

Table 16: (T)RMSPE, 2016:3 - 2019:2, 1-month forecast horizon

Model	3M	6M	1Y	2Y	3Y	4Y	5Y	6Y	7Y	8Y	9Y	10Y	Entire YC
RW	0.59	0.51	0.47	0.44	0.44	0.44*	0.42*	0.38	0.35	0.34	0.34*	0.34*	0.43
AR(1)	1.07*	1.23*	1.31	1.29	1.15*	1.04*	1.00*	1.02*	1.04*	1.01	1.00*	1.01	1.12
VAR(1)	**0.55***	**0.55***	**0.56***	**0.52***	**0.41***	**0.37***	**0.38***	**0.36***	**0.37***	**0.39***	**0.42***	**0.46***	**0.47**
BVAR(1)	**0.55***	**0.56***	**0.57***	**0.55***	**0.43***	**0.38***	**0.36***	**0.36***	**0.36***	**0.35***	**0.36***	**0.39***	**0.47***
RWD	**0.98***	1.03	1.06	1.06	1.02	**0.98***	**0.98***	1.02*	1.08	1.08	1.08*	1.10*	1.03
VAR(2)	**0.51***	**0.48***	**0.49***	**0.46***	**0.43***	**0.45***	**0.50***	**0.48***	**0.51***	**0.56***	**0.61***	**0.66***	**0.51**
BVAR(2)	**0.49***	**0.48***	**0.48***	**0.45***	**0.37***	**0.35***	**0.35***	**0.37***	**0.40***	**0.38***	**0.38***	**0.40***	**0.43***
AR(1)-NC	1.00	1.04	1.01	**0.99**	1.02	1.02	1.06	1.03	1.05	1.09	1.11	1.13	1.04
VAR(1)-NC	**0.56***	**0.58***	**0.61***	**0.68***	**0.78***	**0.80***	**0.85***	**0.80***	**0.80**	**0.83**	**0.86***	**0.86***	**0.73**
BVAR(1)-NC	**0.56***	**0.57***	**0.61***	**0.59***	**0.59***	**0.56***	**0.56***	**0.53***	**0.55***	**0.53**	**0.52***	**0.53***	**0.56**
AR(2)-RWD-NC	**0.94**	**0.98**	**0.98**	1.01	1.07	1.08*	1.12*	1.08	1.10	1.14	1.17	1.18	1.05
VAR(2)-NC	**0.50***	**0.51***	**0.60***	**0.72***	**0.86***	**0.89***	**0.95***	**0.91***	**0.92**	**0.96**	**0.99***	**0.99***	**0.78**
BVAR(2)-NC	**0.52***	**0.52***	**0.54***	**0.58***	**0.68***	**0.70***	**0.75***	**0.69***	**0.69**	**0.71**	**0.73***	**0.73***	**0.63**
VAR(1)-P	**0.62***	**0.66***	**0.68***	**0.65***	**0.52***	**0.46***	**0.44***	**0.43***	**0.44***	**0.43***	**0.45***	**0.49***	**0.56**
BVAR(1)-P	**0.62***	**0.67***	**0.70***	**0.67***	**0.54***	**0.47***	**0.45***	**0.44***	**0.45***	**0.42***	**0.42***	**0.45***	**0.56**

Table 17: (T)RMSPE, 2016:3 - 2019:2, 6-month forecast horizon

Model	3M	6M	1Y	2Y	3Y	4Y	5Y	6Y	7Y	8Y	9Y	10Y	Entire YC
RW	0.86	0.81	0.76	0.70	0.69	0.69	0.68	0.63	0.60	0.59	0.59	0.59	0.69
AR(1)	**0.95***	1.02*	1.08	1.07	**0.97***	**0.90***	**0.88***	**0.89**	**0.91***	**0.91**	**0.91**	**0.91**	**0.96**
VAR(1)	**0.44***	**0.44***	**0.45***	**0.42***	**0.33***	**0.29***	**0.29***	**0.28***	**0.29***	**0.31***	**0.34***	**0.37***	**0.37**
BVAR(1)	**0.45***	**0.46***	**0.47***	**0.44***	**0.34***	**0.29***	**0.27***	**0.25***	**0.25***	**0.24***	**0.26***	**0.28***	**0.36***
RWD	1.03	1.05	1.06	1.06	1.04	1.01*	1.01*	1.05	1.10*	1.10*	1.10	1.10	1.05
VAR(2)	**0.44***	**0.42***	**0.42***	**0.41***	**0.39***	**0.41***	**0.44***	**0.43***	**0.45***	**0.49***	**0.53***	**0.55***	**0.44**
BVAR(2)	**0.38***	**0.36***	**0.37***	**0.36***	**0.30***	**0.28***	**0.28***	**0.28***	**0.30***	**0.28***	**0.28***	**0.29***	**0.33***
AR(1)-NC	**0.88**	**0.88**	**0.88**	**0.89**	**0.93**	**0.95***	**0.98***	**0.98**	1.02*	1.04*	1.05	1.05	0.95
VAR(1)-NC	**0.49***	**0.46***	**0.47***	**0.52***	**0.60***	**0.62***	**0.65***	**0.62**	**0.62***	**0.64***	**0.66**	**0.66**	**0.57**
BVAR(1)-NC	**0.49***	**0.47***	**0.46***	**0.44***	**0.41***	**0.39***	**0.38***	**0.38***	**0.41***	**0.39***	**0.38***	**0.39***	**0.43**
AR(2)-RWD-NC	**0.83**	**0.83**	**0.84**	**0.89**	**0.96**	**0.98***	1.01*	1.01	1.05*	1.07*	1.09	1.08	0.95
VAR(2)-NC	**0.42***	**0.40***	**0.44***	**0.54***	**0.65***	**0.68***	**0.72***	**0.69***	**0.71***	**0.73***	**0.75**	**0.75**	**0.61**
BVAR(2)-NC	**0.40***	**0.36***	**0.34***	**0.36***	**0.42***	**0.44***	**0.46***	**0.42***	**0.41***	**0.43***	**0.44***	**0.43***	**0.41**
VAR(1)-P	**0.53***	**0.55***	**0.57**	**0.54***	**0.43***	**0.38***	**0.35***	**0.34***	**0.34***	**0.34***	**0.36***	**0.38***	**0.45**
BVAR(1)-P	**0.53***	**0.56***	**0.57**	**0.55***	**0.44***	**0.38***	**0.34***	**0.33***	**0.32***	**0.31***	**0.31***	**0.33***	**0.45**

Table 18: (T)RMSPE, 2016:3 - 2019:2, 12-month forecast horizon

6.4.3 India

Model	3M	6M	1Y	2Y	3Y	4Y	5Y	6Y	7Y	8Y	9Y	10Y	Entire YC
RW	0.20*	0.17*	0.16*	0.17*	0.18*	0.19*	0.19*	0.19*	0.20*	0.20*	0.20*	0.20*	0.19*
AR(1)	**0.99***	1.00*	1.03*	**0.98***	**0.98***	**0.99***	**0.99***	1.00*	1.00*	**0.99***	**0.99***	1.00*	**0.99***
VAR(1)	1.04*	**0.94***	**0.99***	1.00*	**0.99***	1.00*	1.00*	1.01*	1.01*	1.01*	1.01*	1.01*	1.00*
BVAR(1)	1.04*	**0.94***	**0.99***	1.00*	**0.99***	**0.99***	1.00*	1.01*	1.01*	1.02*	1.02*	1.03*	1.01*
RWD-RWD-ARIMA(1,1,1)	1.05*	1.02*	1.07*	1.06*	1.04*	1.03*	1.03*	1.03*	1.02*	1.01*	1.01*	1.01*	1.03
AR(1)-NC	1.18*	1.74	2.47	2.78	2.63	2.37	2.12	1.94	1.77	1.64	1.53	1.46	1.98
VAR(1)-NC	1.15*	1.69	2.40	2.72	2.57	2.32	2.08	1.89	1.73	1.60	1.49	1.42	1.93
BVAR(1)-NC	1.32	1.91	2.59	2.78	2.56	2.27	2.00	1.80	1.63	1.49	1.38	1.31	1.92
RWD-NC	1.19	1.68	2.36	2.64	2.46	2.20	1.95	1.76	1.60	1.47	1.37	1.30	1.84
VAR(1)-P	1.04*	**0.94***	1.00*	1.01*	1.00*	1.00*	1.01*	1.02*	1.01*	1.01*	1.01*	1.02*	1.01*
BVAR(1)-P	1.05*	**0.94***	1.00*	1.04*	1.03*	1.01*	1.01*	1.01*	1.00*	1.00*	1.01*	1.01*	1.01*

Table 19: (T)RMSPE, 2015:2 - 2019:2, 1-month forecast horizon

Model	3M	6M	1Y	2Y	3Y	4Y	5Y	6Y	7Y	8Y	9Y	10Y	Entire YC
RW	0.47	0.52	0.53	0.53	0.56	0.58	0.59	0.59	0.59	0.59	0.58	0.57	0.56
AR1	**0.82**	**0.74**	**0.78**	**0.86**	**0.90**	**0.92**	**0.93**	**0.94**	**0.95**	**0.96**	**0.98**	**0.99**	**0.91**
VAR(1)	**0.59**	**0.47***	**0.44***	**0.37***	**0.35***	**0.35***	**0.35***	**0.35***	**0.35***	**0.35***	**0.35***	**0.36***	**0.39***
BVAR(1)	**0.42***	**0.49**	**0.50**	**0.45***	**0.42***	**0.40***	**0.41***	**0.41***	**0.42***	**0.43***	**0.44***	**0.45***	**0.44**
RWD-ARIMA(1,1,1)	1.05	**0.87**	**0.87**	**0.94**	**0.96**	**0.95**	**0.95**	**0.97**	**0.96**	**0.97**	**0.98**	**0.99**	**0.96**
AR(1)-NC	**0.91**	**0.92**	1.10	1.30	1.31	1.27	1.22	1.20	1.17	1.15	1.15	1.14	1.17
VAR(1)-NC	**0.40***	**0.51**	**0.68**	**0.84**	**0.85**	**0.80**	**0.74**	**0.70**	**0.65**	**0.62**	**0.59**	**0.57**	**0.68**
BVAR(1)-NC	**0.67**	**0.78**	**0.89**	**0.92**	**0.83**	**0.73**	**0.64**	**0.58**	**0.53**	**0.48***	**0.45***	**0.42***	**0.67**
RWD-RWD-NC	1.09	**0.96**	1.04	1.15	1.12	1.07	1.03	1.01	**0.99**	**0.99**	**0.99**	1.00	1.03
VAR(1)-P	**0.66**	**0.53**	**0.51**	**0.45***	**0.41***	**0.39***	**0.39***	**0.38***	**0.38***	**0.37***	**0.37***	**0.38***	**0.43**
BVAR(1)-P	**0.50***	**0.34***	**0.33***	**0.35***	**0.35***	**0.35***	**0.34***	**0.35***	**0.35***	**0.35***	**0.35***	**0.35***	**0.36***

Table 20: (T)RMSPE, 2015:2 - 2019:2, 6-month forecast horizon

Model	3M	6M	1Y	2Y	3Y	4Y	5Y	6Y	7Y	8Y	9Y	10Y	Entire YC
RW	0.78	0.85	0.84	0.81	0.83	0.86	0.87	0.87	0.88	0.87	0.86	0.84	0.85
AR(1)	**0.75**	**0.70**	**0.75**	**0.87**	**0.91**	**0.92**	**0.92**	**0.94**	**0.94**	**0.96**	**0.97**	1.00	**0.89**
VAR(1)	**0.53**	**0.45***	**0.42***	**0.35***	**0.32***	**0.30***	**0.29***	**0.28***	**0.27***	**0.26***	**0.25***	**0.25***	**0.34***
BVAR(1)	**0.35***	**0.39***	**0.39***	**0.36**	**0.35***	**0.35***	**0.34***	**0.33***	**0.33***	**0.32***	**0.31***	**0.31***	**0.34**
RWD-ARIMA(1,1,1)	1.02	**0.86**	**0.87**	**0.95**	**0.96**	**0.95**	**0.94**	**0.95**	**0.94**	**0.95**	**0.97**	**0.99**	**0.95**
AR(1)-NC	**0.82**	**0.83**	**0.98**	1.19	1.23	1.21	1.17	1.15	1.13	1.13	1.12	1.14	1.10
VAR(1)-NC	**0.28***	**0.33***	**0.42***	**0.56**	**0.59**	**0.58**	**0.55**	**0.52**	**0.50**	**0.48**	**0.46**	**0.45**	**0.49**
BVAR(1)-NC	**0.34***	**0.42***	**0.50***	**0.56**	**0.53**	**0.48**	**0.43**	**0.39**	**0.36**	**0.34**	**0.31**	**0.30***	**0.42**
RWD-NC	1.07	**0.96**	1.01	1.13	1.11	1.07	1.02	1.01	**0.99**	1.00	1.00	1.03	1.03
VAR(1)-P	**0.61**	**0.52***	**0.48***	**0.41**	**0.36***	**0.33***	**0.32***	**0.30***	**0.29***	**0.28***	**0.27***	**0.27***	**0.38**
BVAR(1)-P	**0.34***	**0.23***	**0.23***	**0.27***	**0.27***	**0.27***	**0.26***	**0.26***	**0.25***	**0.25***	**0.25***	**0.25***	**0.26***

Table 21: (T)RMSPE, 2015:2 - 2019:2, 12-month forecast horizon

6.4.4 Indonesia

Model	3M	6M	1Y	2Y	3Y	4Y	5Y	6Y	7Y	8Y	9Y	10Y	Entire YC
RW	0.44*	0.45*	0.40*	0.38*	0.35*	0.37*	0.36*	0.37*	0.35*	0.34*	0.35*	0.35*	0.38*
AR(1)	**0.93***	**0.93***	1.02*	**0.97***	**0.96***	**0.98***	1.09*	1.00*	1.06*	1.05*	1.02*	1.19	1.01
VAR(1)	1.10*	1.01*	1.07*	1.00*	1.00*	1.07*	1.26	1.02*	**0.99***	1.06*	1.08*	1.38	1.09
BVAR(1)	1.02*	1.00*	1.09*	**0.96***	**0.97***	1.01*	1.13*	1.00*	1.05*	1.04*	1.00*	1.13	1.03
RWD-IMA(1,1)-AR(1)	**0.94***	**0.97***	1.09*	1.11*	1.08*	1.03*	1.04*	1.09*	1.21*	1.19*	1.07*	1.10*	1.07
AR(1)-NC	1.01*	1.10	1.39	1.37	1.53	1.53	1.64	1.43	1.41	1.36	1.33	1.49	1.37
VAR(1)-NC	1.04*	1.13	1.42	1.39	1.55	1.54	1.64	1.44	1.42	1.37	1.33	1.48	1.38
BVAR(1)-NC	1.10	1.19	1.46	1.39	1.51	1.49	1.57	1.38	1.38	1.31	1.26	1.38	1.36
RWD-IMA(1,1)-NC	1.01*	1.13*	1.41	1.39	1.50	1.45	1.50	1.39	1.43	1.36	1.28	1.33	1.34
VAR(1)-P	**0.93***	**0.83***	**0.91***	**0.91***	**0.88***	**0.93***	1.10*	**0.92***	**0.91***	**0.96***	**0.98***	1.26	**0.96***
BVAR(1)-P	1.05*	1.03*	1.13*	**0.99***	1.00*	1.04*	1.16*	1.01*	1.04*	1.04*	1.00*	1.15	1.05

Table 22: (T)RMSPE, 2016:1 - 2019:2, 1-month forecast horizon

Model	3M	6M	1Y	2Y	3Y	4Y	5Y	6Y	7Y	8Y	9Y	10Y	Entire YC
RW	0.83*	0.91*	1.00*	0.97	1.00	1.02	1.03*	0.98	0.93	0.89	0.87	0.86*	0.94
AR1	**0.84***	**0.83***	**0.82***	**0.79**	**0.83**	**0.89**	**0.96**	**0.95**	**0.97**	1.03	1.10	1.23	**0.94**
VAR(1)	1.06*	**0.82***	**0.64***	**0.54***	**0.55***	**0.64**	**0.75***	**0.70**	**0.69**	**0.78**	**0.89**	1.07	**0.76**
BVAR(1)	1.20	**0.96***	**0.75***	**0.58***	**0.52***	**0.54**	**0.60***	**0.50**	**0.46***	**0.50***	**0.57***	**0.71***	**0.67**
RWD-IMA(1,1)-AR(1)	**0.84***	**0.93***	**0.97***	1.01*	**0.99***	**0.97**	**0.93***	**0.99**	1.03	1.04	1.01	**0.98***	**0.98**
AR(1)-NC	**0.97***	1.00*	1.04	1.07	1.12	1.18	1.24	1.20	1.20	1.25	1.32	1.44	1.17
VAR(1)-NC	**0.84***	**0.77***	**0.77***	**0.76***	**0.79***	**0.84**	**0.89***	**0.82**	**0.79**	**0.82**	**0.88**	1.01*	**0.83**
BVAR(1)-NC	1.09	**0.96***	**0.85***	**0.72***	**0.68***	**0.67**	**0.69***	**0.60**	**0.55**	**0.54***	**0.58***	**0.67***	**0.73**
RWD-IMA(1,1)-NC	**0.90***	**0.98***	1.00	**0.96**	**0.94**	**0.95**	**0.95**	**0.95**	**0.97**	**0.99**	**0.99**	1.00*	**0.96**
VAR(1)-P	**0.73***	**0.55***	**0.47***	**0.41***	**0.36***	**0.40***	**0.51***	**0.47***	**0.46***	**0.54***	**0.65**	**0.82***	**0.53***
BVAR(1)-P	**0.56***	**0.44***	**0.41***	**0.38***	**0.36***	**0.40***	**0.48***	**0.44***	**0.44***	**0.47***	**0.55***	**0.70***	**0.47***

Table 23: (T)RMSPE, 2016:1 - 2019:2, 6-month forecast horizon

Model	3M	6M	1Y	2Y	3Y	4Y	5Y	6Y	7Y	8Y	9Y	10Y	Entire YC
RW	1.18*	1.17*	1.26	1.29	1.34	1.33	1.34	1.32	1.28	1.19	1.22	1.19	1.26
AR(1)	**0.95***	**0.93***	**0.90**	**0.86**	**0.90**	**0.99**	1.09	1.06	1.08*	1.18	1.23	1.36	1.05
VAR(1)	**0.90***	**0.79***	**0.66**	**0.55**	**0.57**	**0.66**	**0.77**	**0.71**	**0.71***	**0.81**	**0.87**	1.01	**0.75**
BVAR(1)	1.09	**0.97**	**0.79**	**0.59**	**0.51**	**0.52**	**0.55***	**0.44**	**0.40***	**0.42***	**0.46***	**0.56***	**0.63**
RWD-IMA(1,1)-AR(1)	**0.83***	**0.88***	**0.92**	**0.96**	**0.96**	**0.96**	**0.94**	**0.98**	1.01*	1.03	1.00	1.00	**0.96**
AR(1)-NC	1.06	1.12	1.15	1.18	1.22	1.30	1.37	1.31	1.31	1.40	1.43	1.55	1.29
VAR(1)-NC	**0.83***	**0.84***	**0.84**	**0.81**	**0.84**	**0.90**	**0.96**	**0.87**	**0.85***	**0.91**	**0.94**	1.06	**0.89**
BVAR(1)-NC	1.14	1.08	**0.94**	**0.73**	**0.65**	**0.63**	**0.65**	**0.53**	**0.47***	**0.47***	**0.49***	**0.56***	**0.72**
RWD-IMA(1,1)-NC	**0.88***	**0.94***	**0.96**	**0.93**	**0.92**	**0.93**	**0.94**	**0.94**	**0.96***	**0.98**	**0.97**	**0.99**	**0.94**
VAR(1)-P	**0.56***	**0.46***	**0.40***	**0.33***	**0.34***	**0.42***	**0.54***	**0.49***	**0.49***	**0.57**	**0.64**	**0.79**	**0.51***
BVAR(1)-P	**0.56***	**0.47***	**0.41***	**0.33***	**0.34***	**0.42***	**0.53***	**0.48***	**0.48***	**0.55**	**0.62**	**0.77**	**0.50***

Table 24: (T)RMSPE, 2016:1 - 2019:2, 12-month forecast horizon

6.4.5 Russia

Model	3M	6M	1Y	2Y	3Y	4Y	5Y	6Y	7Y	8Y	9Y	10Y	Entire YC
RW	0.37*	0.36*	0.32*	0.27*	0.28*	0.31*	0.34*	0.32*	0.32*	0.31*	0.32*	0.31*	0.32*
AR(1)	1.51*	1.56*	1.64*	1.61*	1.62*	1.54*	1.52*	1.51*	1.45*	1.48*	1.50*	1.51*	1.54
VAR(1)	1.04*	**0.99***	**0.97***	1.11*	1.18*	1.26*	1.31*	1.40*	1.49*	1.58*	1.62*	1.67*	1.32
BVAR(1)	**0.97***	**0.94***	**0.94***	1.11*	1.21*	1.30*	1.36*	1.43*	1.49*	1.58*	1.62*	1.66	1.31
ARI(1,1)-IMA(1,1)-MA(3)	1.39*	1.33*	1.29*	1.35*	1.21*	1.13*	1.08*	1.05*	1.03*	1.04*	1.03*	1.01*	1.17*
VAR(2)	**0.97***	**0.95***	**0.96***	1.04*	1.03*	1.06*	1.08*	1.11*	1.16*	1.21*	1.23*	1.26*	1.09*
BVAR(2)	**0.94***	**0.92***	**0.95***	1.10*	1.11	1.14	1.16	1.19	1.22	1.28	1.30	1.32	1.13*
AR(1)-NC	1.53*	1.61*	1.78*	1.98*	2.01*	1.87*	1.81*	1.77*	1.68*	1.68*	1.67*	1.67*	1.74
VAR(1)-NC	1.06*	1.15*	1.44*	2.14	2.26	2.23	2.23	2.28	2.29	2.35	2.36	2.40	2.03
BVAR(1)-NC	1.04*	1.07*	1.18*	1.24*	1.24*	1.17*	1.11*	1.10*	1.08*	1.08*	1.06*	1.08*	1.11*
ARI(1,1)-IMA(1,1)-NC	1.46*	1.46*	1.54*	1.78*	1.63*	1.46*	1.35*	1.27*	1.18*	1.15*	1.12*	1.09*	1.38
VAR(2)-NC	1.12*	1.17*	1.38*	1.87	1.87	1.81	1.78	1.77	1.75	1.78	1.78	1.79	1.65
BVAR(2)-NC	**0.99***	**0.98***	1.09*	1.38*	1.40*	1.38*	1.37*	1.36*	1.36*	1.39*	1.39*	1.40*	1.29
VAR(1)-P	**0.95***	**0.93***	**0.95***	1.14*	1.21*	1.29*	1.34*	1.45*	1.56*	1.65*	1.69*	1.76*	1.34
BVAR(1)-P	1.07*	1.05*	1.03*	**0.98***	1.01*	1.08*	1.13*	1.22*	1.32*	1.41*	1.45*	1.50*	1.20
VAR(2)-P	**0.97***	**0.96***	**0.97***	1.03*	**0.99***	1.00*	1.01*	1.05*	1.12*	1.17*	1.19*	1.23*	1.06*
BVAR(2)-P	**0.93***	**0.92***	**0.95***	1.12*	1.12*	1.15*	1.17*	1.21*	1.26*	1.31*	1.34*	1.36*	1.15*

Table 25: (T)RMSPE, 2016:5 - 2019:2, 1-month forecast horizon

Model	3M	6M	1Y	2Y	3Y	4Y	5Y	6Y	7Y	8Y	9Y	10Y	Entire YC
RW	1.00*	1.00*	1.00	0.98	0.96	0.97	0.98	0.95*	0.93*	0.91*	0.90*	0.88*	0.96
AR(1)	1.24*	1.18*	1.06*	**0.88***	**0.90**	**0.92***	**0.96**	**0.98***	**0.99***	1.04*	1.09*	1.12*	1.04
VAR(1)	**0.62***	**0.54***	**0.38***	**0.32***	**0.48***	**0.63***	**0.75***	**0.83***	**0.90***	**0.97***	1.04*	1.09*	**0.74**
BVAR(1)	1.07*	1.01*	**0.87***	**0.59**	**0.52***	**0.46***	**0.43***	**0.47***	**0.51***	**0.55***	**0.57***	**0.61***	**0.68***
ARI(1,1)-IMA(1,1)-MA(3)	1.10*	1.02*	**0.93***	**0.88**	**0.82**	**0.81***	**0.82***	**0.83***	**0.86***	**0.90***	**0.93***	**0.95***	**0.91**
VAR(2)	**0.51***	**0.47***	**0.40***	**0.38***	**0.47***	**0.56***	**0.63***	**0.66***	**0.69***	**0.73***	**0.78***	**0.81***	**0.60***
BVAR(2)	**0.92***	**0.84***	**0.68***	**0.39***	**0.33***	**0.32***	**0.35***	**0.37***	**0.40***	**0.45***	**0.48***	**0.51***	**0.55***
AR(1)-NC	1.23*	1.16*	1.04*	**0.91**	**0.95**	**0.98***	1.02*	1.05*	1.05*	1.09*	1.14*	1.17*	1.07
VAR(1)-NC	**0.69***	**0.68***	**0.68***	**0.80**	**0.94**	1.04	1.12	1.17	1.21	1.26	1.32	1.36	1.03
BVAR(1)-NC	1.14	1.11	1.03*	**0.86**	**0.85**	**0.82***	**0.79***	**0.84***	**0.89***	**0.92***	**0.93***	**0.97***	**0.94**
ARI(1,1)-IMA(1,1)-NC	1.12*	1.06*	**0.99***	**0.97**	**0.90**	**0.87**	**0.87***	**0.87***	**0.90***	**0.93***	**0.95***	**0.98***	**0.96**
VAR(2)-NC	**0.52***	**0.54***	**0.60***	**0.76**	**0.86**	**0.94**	1.00	1.03	1.05	1.09	1.14	1.17	**0.90**
BVAR(2)-NC	**0.51***	**0.46***	**0.41***	**0.42***	**0.50***	**0.59***	**0.66***	**0.68***	**0.72***	**0.76***	**0.80***	**0.83***	**0.62***
VAR(1)-P	**0.53***	**0.47***	**0.35***	**0.31***	**0.45***	**0.59***	**0.71***	**0.79***	**0.87***	**0.95***	1.02*	1.07*	**0.70***
BVAR(1)-P	1.03*	**0.95***	**0.79***	**0.46***	**0.37***	**0.36***	**0.40***	**0.45***	**0.50***	**0.57***	**0.62***	**0.66***	**0.64***
VAR(2)-P	**0.55***	**0.51***	**0.42***	**0.27***	**0.30***	**0.37***	**0.43***	**0.45***	**0.49***	**0.53***	**0.57***	**0.60***	**0.46***
BVAR(2)-P	**0.53***	**0.50***	**0.44***	**0.45***	**0.53***	**0.62***	**0.70***	**0.73***	**0.77***	**0.82***	**0.87***	**0.90***	**0.66***

Table 26: (T)RMSPE, 2016:5 - 2019:2, 6-month forecast horizon

Model	3M	6M	1Y	2Y	3Y	4Y	5Y	6Y	7Y	8Y	9Y	10Y	Entire YC
RW	1.72	1.72	1.72	1.73	1.73	1.74	1.75	1.71	1.69	1.68	1.66	1.63	1.71
AR(1)	**0.80**	**0.76**	**0.67**	**0.54**	**0.53**	**0.54***	**0.57***	**0.57***	**0.58***	**0.60***	**0.62***	**0.64***	**0.62**
VAR(1)	**0.40***	**0.36***	**0.28***	**0.23***	**0.30***	**0.38***	**0.45***	**0.48***	**0.51***	**0.55***	**0.58***	**0.61***	**0.44***
BVAR(1)	**0.85**	**0.81**	**0.73**	**0.54**	**0.48**	**0.43***	**0.39***	**0.40***	**0.41***	**0.41***	**0.41***	**0.42***	**0.55**
ARI(1,1)-IMA(1,1)-MA(3)	1.20	1.14	1.06	1.01	**0.95**	**0.94**	**0.94**	**0.95***	**0.97***	**0.99***	1.01*	1.03*	1.02
VAR(2)	**0.43***	**0.40***	**0.35***	**0.30***	**0.35***	**0.40***	**0.44***	**0.46***	**0.47***	**0.50***	**0.53***	**0.55***	**0.44***
BVAR(2)	**0.78**	**0.72**	**0.60**	**0.38***	**0.30***	**0.24***	**0.22***	**0.21***	**0.21***	**0.23***	**0.24***	**0.25***	**0.42***
AR(1)-NC	**0.79**	**0.74**	**0.65**	**0.54**	**0.55**	**0.57***	**0.60***	**0.61***	**0.61***	**0.63***	**0.65***	**0.67***	**0.64**
VAR(1)-NC	**0.55***	**0.53**	**0.50***	**0.48**	**0.53**	**0.57**	**0.61**	**0.63***	**0.63***	**0.65***	**0.68***	**0.70***	**0.59**
BVAR(1)-NC	**0.55***	**0.53**	**0.50***	**0.48**	**0.53**	**0.57**	**0.61**	**0.63***	**0.63***	**0.65***	**0.68***	**0.70***	**0.59**
ARI(1,1)-IMA(1,1)-NC	1.22	1.17	1.11	1.07	1.01	**0.99**	**0.99**	**0.99**	1.00*	1.01	1.03*	1.05*	1.06
VAR(2)-NC	**0.41***	**0.41***	**0.42***	**0.48***	**0.54**	**0.59**	**0.63**	**0.65**	**0.66***	**0.69***	**0.72**	**0.73***	**0.59**
BVAR(2)-NC	**0.50***	**0.44**	**0.35***	**0.23***	**0.25***	**0.30***	**0.35***	**0.37***	**0.39***	**0.41***	**0.44***	**0.46***	**0.38***
VAR(1)-P	**0.35***	**0.31***	**0.24***	**0.19***	**0.25***	**0.33***	**0.40***	**0.43***	**0.47***	**0.51***	**0.55***	**0.57***	**0.40***
BVAR(1)-P	**0.76**	**0.71**	**0.60***	**0.37***	**0.29***	**0.24***	**0.23***	**0.23***	**0.24***	**0.27***	**0.29***	**0.30***	**0.42***
VAR(2)-P	**0.46***	**0.42***	**0.34***	**0.22***	**0.22***	**0.26***	**0.30***	**0.32***	**0.33***	**0.36***	**0.39***	**0.40***	**0.34***
BVAR(2)-P	**0.54***	**0.50**	**0.42***	**0.26***	**0.24***	**0.26***	**0.29***	**0.30***	**0.31***	**0.34***	**0.37***	**0.38***	**0.36***

Table 27: (T)RMSPE, 2016:5 - 2019:2, 12-month forecast horizon

6.4.6 Turkey

Model	3M	6M	1Y	2Y	3Y	4Y	5Y	6Y	7Y	8Y	9Y	10Y	Entire YC
RW	1.51*	1.49*	1.38*	1.49*	1.55*	1.63*	1.42*	1.25*	1.16*	1.18*	1.11*	1.04*	1.36*
AR(1)	1.14*	**0.99***	1.00*	**0.98***	1.00*	**0.97***	**0.98***	**0.98***	1.00*	**0.98***	1.00*	1.00*	1.00*
VAR(1)	1.11*	1.01*	1.02*	**0.99***	1.02*	**0.99***	1.00*	1.04*	1.07*	1.02*	1.04*	1.06*	1.03
BVAR(1)	1.15*	1.00*	1.01*	**0.99***	1.02*	**0.98***	**0.99***	**0.99***	1.00*	**0.99***	1.00*	1.00*	1.01*
RWD	1.07*	**0.97***	1.00*	**0.99***	1.02*	**0.98***	1.00*	1.01*	1.03*	1.00*	1.02*	1.03*	1.01*
AR(1)-NC	1.29*	1.22*	1.37*	1.47*	1.42*	1.33*	1.29*	1.24*	1.20*	1.21*	1.18*	1.12*	1.30
VAR(1)-NC	1.20*	1.14*	1.24*	1.33*	1.30*	1.23*	1.17*	1.13*	1.10*	1.08*	1.05*	1.02*	1.19
BVAR(1)-NC	1.20*	1.14*	1.24*	1.33*	1.30*	1.23*	1.17*	1.13*	1.10*	1.09*	1.06*	1.02*	1.19
RWD-NC	1.18*	1.13*	1.26*	1.38*	1.36*	1.29*	1.24*	1.20*	1.17*	1.18*	1.16*	1.11*	1.24
VAR(1)-P	1.16*	1.07*	1.10*	1.04*	1.06*	1.01*	1.03*	1.05*	1.08*	1.03*	1.05*	1.06*	1.06
BVAR(1)-P	1.14*	1.00*	1.01*	**0.99***	1.02*	**0.98***	**0.99***	**0.99***	1.01*	**0.99***	1.01*	1.01*	1.02*

Table 28: (T)RMSPE, 2016:5 - 2019:2, 1-month forecast horizon

Model	3M	6M	1Y	2Y	3Y	4Y	5Y	6Y	7Y	8Y	9Y	10Y	Entire YC
RW	3.96*	3.93*	3.81	3.94	3.85	3.85	3.42	3.08	2.84	2.83	2.61	2.47	3.43
AR(1)	1.18*	1.09*	1.06*	1.01*	**0.97***	**0.93***	**0.93***	**0.93***	**0.93***	**0.93***	**0.94***	**0.93***	1.01
VAR(1)	**0.51***	**0.49***	**0.50***	**0.53***	**0.58***	**0.61***	**0.66***	**0.73***	**0.79***	**0.76***	**0.82***	**0.87***	**0.63**
BVAR(1)	**0.67***	**0.57***	**0.53***	**0.50***	**0.50***	**0.49***	**0.47***	**0.45***	**0.44***	**0.46***	**0.46***	**0.44***	**0.52***
RWD	1.04	1.00	1.03	1.04	1.04	1.01	1.02	1.03	1.04	1.04	1.06	1.05	1.03
AR(1)-NC	1.21*	1.15*	1.14*	1.08*	1.03*	**0.97***	**0.96***	**0.95***	**0.94***	**0.95***	**0.95***	**0.94***	1.05
VAR(1)-NC	**0.52***	**0.49***	**0.49***	**0.50***	**0.52***	**0.52***	**0.51***	**0.53***	**0.55***	**0.54***	**0.57***	**0.61***	**0.52***
BVAR(1)-NC	**0.52***	**0.49***	**0.53***	**0.59***	**0.61***	**0.60***	**0.57***	**0.55***	**0.54***	**0.56***	**0.55***	**0.53***	**0.56**
RWD-NC	1.04*	1.00*	1.02*	1.01*	1.00*	**0.96***	**0.97***	**0.97***	**0.98***	**0.99***	1.01*	1.00*	1.00
VAR(1)-P	**0.83***	**0.80***	**0.77***	**0.66***	**0.66***	**0.64***	**0.66***	**0.70***	**0.73***	**0.69***	**0.72***	**0.76***	**0.72**
BVAR(1)-P	**0.64***	**0.55***	**0.52***	**0.48***	**0.49***	**0.48***	**0.46***	**0.44***	**0.44***	**0.45***	**0.46***	**0.44***	**0.50***

Table 29: (T)RMSPE, 2016:5 - 2019:2, 6-month forecast horizon

Model	3M	6M	1Y	2Y	3Y	4Y	5Y	6Y	7Y	8Y	9Y	10Y	Entire YC
RW	5.15	5.01	4.84	4.64*	4.31*	4.12*	3.68*	3.33*	3.09*	3.06*	2.85*	2.68*	3.99
AR(1)	1.11	1.05	1.02	**0.98***	**0.96***	**0.94***	**0.93***	**0.91***	**0.90***	**0.91***	**0.91***	**0.90***	**0.99**
VAR(1)	**0.47***	**0.48***	**0.52***	**0.61***	**0.71***	**0.78***	**0.86***	**0.95***	1.02*	**0.98***	1.05*	1.13*	**0.73**
BVAR(1)	**0.68***	**0.61***	**0.58***	**0.56***	**0.56***	**0.56***	**0.54***	**0.51***	**0.49***	**0.51***	**0.51***	**0.49***	**0.57***
RWD	1.06	1.04	1.06	1.08*	1.10*	1.09*	1.10*	1.09*	1.09*	1.10*	1.12*	1.12*	1.08
AR(1)-NC	1.13	1.09	1.07	1.04*	1.02*	**0.99***	**0.98***	**0.96***	**0.94***	**0.94***	**0.94***	**0.93***	1.03
VAR(1)-NC	**0.49***	**0.47***	**0.46***	**0.48***	**0.52***	**0.56***	**0.57***	**0.61***	**0.65***	**0.64***	**0.69***	**0.75***	**0.54***
BVAR(1)-NC	**0.46***	**0.44***	**0.47***	**0.55***	**0.60***	**0.61***	**0.59***	**0.56***	**0.55***	**0.57***	**0.57***	**0.55***	**0.53***
RWD-NC	1.05	1.02	1.02	1.04*	1.06*	1.05*	1.06*	1.06*	1.06*	1.08*	1.09*	1.10*	1.05
VAR(1)-P	1.34*	1.33*	1.27*	1.14*	1.12*	1.09*	1.12*	1.16*	1.19*	1.12*	1.17*	1.23*	1.21
BVAR(1)-P	**0.64***	**0.58***	**0.54***	**0.53***	**0.54***	**0.54***	**0.51***	**0.49***	**0.48***	**0.49***	**0.49***	**0.47***	**0.55***

Table 30: (T)RMSPE, 2016:5 - 2019:2, 12-month forecast horizon

6.4.7 The USA

Model	3M	6M	1Y	2Y	3Y	4Y	5Y	6Y	7Y	8Y	9Y	10Y	Entire YC
RW	0.07*	0.08*	0.08*	0.12*	0.15*	0.17*	0.19*	0.20*	0.20*	0.20*	0.20*	0.20*	0.16*
AR(1)	1.58*	1.14*	1.37*	1.09*	1.02*	1.06*	1.00*	1.00*	**0.97***	1.01*	1.05*	1.10*	1.05*
VAR(1)	1.65*	1.04*	1.38*	1.09*	**0.97***	1.01*	**0.97***	**0.97***	**0.96***	**0.99***	1.04*	1.11*	1.03*
BVAR(1)	1.58*	1.02*	1.38*	1.09*	0.97*	1.01*	**0.97***	**0.97***	**0.96***	**0.99***	1.04*	1.11*	1.03*
RWD-AR(1)-RWD	1.22*	1.40*	1.77	1.26	1.00*	**0.99***	**0.96***	**0.98***	1.00*	1.03*	1.08*	1.16*	1.07*
VAR(2)	1.53*	**0.94***	1.34*	1.11*	1.00*	1.03*	**0.99***	**0.99***	**0.99***	1.02*	1.06*	1.12*	1.05*
BVAR(2)	1.28*	1.03*	1.51*	1.17	**0.99***	1.00*	**0.97***	**0.98***	**0.99***	1.01*	1.06*	1.13*	1.04*
AR(1)-NC	3.49	1.86	1.81	2.84	2.39	1.84	1.24	1.00*	1.03*	1.21*	1.48	1.78	1.63
VAR(1)-NC	4.07	2.32	1.59*	2.65	2.27	1.76	1.19	**0.98***	1.04*	1.23*	1.50	1.81	1.63
BVAR(1)-NC	4.07	2.32	1.58*	2.64	2.27	1.75	1.19	**0.98***	1.05*	1.23*	1.50	1.81	1.63
RWD-AR(1)-NC	4.12	2.47	1.70	2.55	2.15	1.64	1.11	**0.98***	1.13	1.34	1.64	1.96	1.66
VAR(3)-NC	3.82	2.06	1.59*	2.71	2.31	1.78	1.22	1.00*	1.07*	1.25	1.53	1.84	1.64
BVAR(3)-NC	4.06	2.26	1.47*	2.59	2.23	1.71	1.18	**0.99***	1.10	1.29	1.57	1.89	1.64
VAR(1)-P	1.66*	1.05*	1.39*	1.09*	**0.98***	1.02*	**0.97***	**0.97***	**0.96***	**0.99***	1.04*	1.10*	1.03*
BVAR(1)-P	1.58*	1.02*	1.39*	1.09*	**0.98***	1.02*	**0.97***	**0.97***	**0.96***	**0.99***	1.04*	1.10*	1.03*
VAR(2)-P	1.57*	**0.94***	1.35*	1.12*	1.01*	1.05*	1.00*	1.01*	**0.99***	1.03*	1.07*	1.13*	1.06
BVAR(2)-P	1.36*	1.00*	1.46*	1.14	**0.99***	1.02*	**0.98***	**0.98***	**0.98***	1.01*	1.06*	1.12*	1.04*

Table 31: (T)RMSPE, 2013:3 - 2019:2, 1-month forecast horizon

Model	3M	6M	1Y	2Y	3Y	4Y	5Y	6Y	7Y	8Y	9Y	10Y	Entire YC
RW	0.29*	0.30*	0.31*	0.33*	0.36*	0.38*	0.41	0.43	0.45	0.45	0.45	0.46	0.39
AR(1)	1.26*	1.19*	1.20	1.12*	1.08	1.09	1.01	1.02	**0.98**	1.03	1.06	1.09	1.08
VAR(1)	1.43*	1.06*	**0.79***	**0.57***	**0.57***	**0.60***	**0.57***	**0.54**	**0.49***	**0.50***	**0.51***	**0.51***	**0.66***
BVAR(1)	1.27*	**0.93***	**0.70***	**0.53***	**0.55***	**0.58***	**0.56***	**0.53***	**0.49***	**0.50***	**0.50***	**0.51***	**0.62***
RWD-AR(1)-RWD	1.29*	1.43*	1.54	1.41*	1.22*	1.16*	1.09	1.10	1.12	1.14	1.18	1.22	1.21
VAR(2)	1.32*	**0.93***	**0.66***	**0.50***	**0.56***	**0.59***	**0.56***	**0.53***	**0.47***	**0.47***	**0.46***	**0.46***	**0.61***
BVAR(2)	**0.96***	**0.71***	**0.59***	**0.46***	**0.44***	**0.47***	**0.48***	**0.47***	**0.46***	**0.46***	**0.46***	**0.48***	**0.52***
AR(1)-NC	**0.94***	**0.95***	1.19	1.48	1.40	1.24	1.02	**0.95**	**0.93**	**0.99**	1.06	1.15	1.10
VAR(1)-NC	1.00*	**0.62***	**0.49***	1.04*	1.09*	**0.93***	**0.68***	**0.53***	**0.46***	**0.49***	**0.56***	**0.66***	**0.71***
BVAR(1)-NC	1.00*	**0.62***	**0.48***	1.03*	1.08*	**0.92***	**0.68***	**0.52***	**0.46***	**0.49***	**0.56***	**0.67***	**0.70***
RWD-AR(1)-NC	1.83	1.64	1.41*	1.26*	1.13*	1.07*	1.01*	1.09	1.21	1.31	1.42	1.53	1.32
VAR(3)-NC	**0.64***	**0.32***	**0.64***	1.21*	1.20	1.00*	**0.73**	**0.56**	**0.48***	**0.51***	**0.58***	**0.68***	**0.73***
BVAR(3)-NC	1.10*	**0.69***	**0.34***	**0.89***	**0.95***	**0.80***	**0.60***	**0.49***	**0.50***	**0.56***	**0.66***	**0.78***	**0.70***
VAR(1)-P	1.43*	1.06*	**0.81***	**0.61***	**0.61***	**0.65***	**0.61***	**0.58***	**0.52***	**0.53***	**0.53***	**0.53***	**0.68***
BVAR(1)-P	1.36*	1.02*	**0.79***	**0.62***	**0.63***	**0.65***	**0.60***	**0.56***	**0.50***	**0.51***	**0.50***	**0.50***	**0.66***
VAR(2)-P	1.34*	**0.96***	**0.71***	**0.59***	**0.64***	**0.69***	**0.64***	**0.61**	**0.54**	**0.55***	**0.53***	**0.52***	**0.67***
BVAR(2)-P	**0.97***	**0.72***	**0.60***	**0.46***	**0.45***	**0.49***	**0.49***	**0.48***	**0.46***	**0.46***	**0.47***	**0.48***	**0.53***

Table 32: (T)RMSPE, 2013:3 - 2019:2, 6-month forecast horizon

Model	3M	6M	1Y	2Y	3Y	4Y	5Y	6Y	7Y	8Y	9Y	10Y	Entire YC
RW	0.53*	0.55*	0.56*	0.54*	0.54*	0.54*	0.57	0.59	0.61	0.61	0.62	0.63	0.58
AR(1)	1.23*	1.18	1.15	1.14	1.13	1.15	1.07	1.07	1.03	1.08	1.11	1.12	1.12
VAR(1)	1.11*	**0.86***	**0.65***	**0.53***	**0.57***	**0.60***	**0.58***	**0.55***	**0.50**	**0.52**	**0.52***	**0.51***	**0.64**
BVAR(1)	1.04*	**0.80***	**0.60***	**0.50***	**0.54***	**0.58***	**0.56***	**0.54***	**0.48**	**0.50***	**0.50***	**0.49***	**0.60***
RWD-AR(1)-RWD	1.32*	1.42*	1.48	1.49	1.40	1.36	1.26	1.26	1.27	1.28	1.30	1.33	1.34
VAR(2)	1.09*	**0.83***	**0.62***	**0.53***	**0.57***	**0.60***	**0.56***	**0.53***	**0.47***	**0.47***	**0.46***	**0.44***	**0.61***
BVAR(2)	**0.78***	**0.61***	**0.46***	**0.35***	**0.36***	**0.40***	**0.42***	**0.42***	**0.41***	**0.41***	**0.43***	**0.44***	**0.47***
AR(1)-NC	**0.88***	**0.93***	1.04	1.20	1.19	1.12	**0.97**	**0.92**	**0.88**	**0.92**	**0.97**	1.01	1.00
VAR(1)-NC	**0.58***	**0.38***	**0.31***	**0.69***	**0.82***	**0.77***	**0.61***	**0.49***	**0.40***	**0.40***	**0.42***	**0.46***	**0.54***
BVAR(1)-NC	**0.58***	**0.37***	**0.30***	**0.68***	**0.81***	**0.76***	**0.60***	**0.48***	**0.39***	**0.39***	**0.42***	**0.46***	**0.53***
RWD-AR(1)-NC	1.67	1.57	1.37	1.21	1.13*	1.16*	1.16	1.26	1.35	1.44	1.52	1.60	1.39
VAR(3)-NC	**0.21***	**0.20***	**0.52***	**0.91**	**0.98**	**0.89***	**0.69**	**0.55***	**0.44***	**0.42***	**0.44***	**0.48***	**0.60***
BVAR(3)-NC	**0.56***	**0.33***	**0.21***	**0.60***	**0.71***	**0.65***	**0.52***	**0.44***	**0.43***	**0.46***	**0.52***	**0.59***	**0.52***
VAR(1)-P	1.13*	**0.89***	**0.69***	**0.60***	**0.64***	**0.69***	**0.65***	**0.62***	**0.56**	**0.58***	**0.57***	**0.56***	**0.69**
BVAR(1)-P	1.25	1.02	**0.81**	**0.69***	**0.70***	**0.70***	**0.64***	**0.59***	**0.51***	**0.52***	**0.50***	**0.48***	**0.71**
VAR(2)-P	1.13*	**0.88***	**0.69***	**0.62***	**0.67***	**0.71***	**0.66***	**0.63***	**0.55**	**0.56***	**0.54***	**0.53***	**0.69**
BVAR(2)-P	**0.80***	**0.62***	**0.47***	**0.36***	**0.38***	**0.43***	**0.45***	**0.44***	**0.42***	**0.43***	**0.44***	**0.45***	**0.48***

Table 33: (T)RMSPE, 2013:3 - 2019:2, 12-month forecast horizon.

7 References

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