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Forecasting the yield curve using a dynamic natural cubic spline model

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HIGHLIGHTS

- A dynamic NCS model for the prediction of yield curves.
- Data-driven selection of the number and positions of knots.
- Relatively strong performance in forecasting the Chinese yield curves.

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ABSTRACT

We propose a dynamic natural cubic spline model with a two-step procedure for the forecasting of the entire yield curve. We apply our method to the monthly Chinese yield-curve data and evaluate the out-of-sample forecast performance. We find that our method compares favourably with its competitors, especially in the medium and long-term forecasts.

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1. Introduction

The accurate forecast of the yield curve is crucial in many scenarios including bond portfolio management, asset pricing, and risk management. Diebold and Li (2006) use the framework of Nelson and Siegel (1987) to develop a dynamic Nelson–Siegel (DNS) model for the yield curve. They propose a two-step procedure for the estimation and forecasting of the entire yield curve. For the same purpose, Bowsher and Meeks (2008) use the natural cubic spline to develop the functional signal plus noise (FSN) model of the yield curve, which can be written in the linear state-space form and be estimated by MLE. Tabak et al. (2012) compare the performance of FSN and DNS in forecasting the Euro yield curve and find that both models outperform the random walk model.

In this paper, we propose a dynamic natural cubic spline (DNCS) model for the yield curve with a simple two-step estimation and forecasting procedure similar with Diebold and Li (2006). Following Bowsher and Meeks (2008), Jungbacker et al. (2014) and Almeida et al. (2018), we use the natural cubic spline to fit the yield curves. Note that Almeida et al. (2018) is based on the preferred habitat theory for the term structure (Vayanos and Vila, 2009) and that the natural cubic spline is employed to achieve the segmentation of the yield curve at some predetermined knot positions. In contrast, we select the set of knot positions in a data-driven approach with the single aim of improving out-of-sample forecasts.

Our empirical study is based on the monthly yield curve data of the Chinese Treasury from January 2002 to December 2017. We compare the out-of-sample forecasting performance of our method with those of AAKSV (Almeida et al., 2018), FSN, DNS, and the random walk. We find that our method compares favourably with its competitors, especially in the medium and long-term forecasts.

The rest of the paper is organized as follows. Section 2 introduces the model and methodology. In Section 3 we first describe the data we use, then we present the empirical results. Section 4 concludes.

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Table 1
Descriptive statistics for the Chinese yield rates.

Maturity (months)	Mean	Std. dev.	Minimum	Maximum	$\hat{\rho}(1)$	ADF	N. Obs.
3	2.0993	0.6422	0.7317	3.5276	0.7596	−3.7370***	192
6	2.2469	0.6461	0.8119	3.6374	0.8508	−3.6979***	192
9	2.3944	0.6785	0.8894	3.8063	0.9075	−2.6940*	192
12	2.5420	0.7357	0.9605	4.2189	0.9261	−2.7291*	192
15	2.5895	0.7265	1.0189	4.2486	0.9308	−2.7042*	192
18	2.6370	0.7184	1.0773	4.2784	0.9349	−2.6877*	192
21	2.6845	0.7116	1.1356	4.3081	0.9383	−2.6786*	192
24	2.7320	0.7059	1.1674	4.3378	0.9409	−2.6755*	192
30	2.8141	0.6756	1.2452	4.3770	0.9423	−2.7820*	192
36	2.8963	0.6503	1.3230	4.4162	0.9417	−2.8928**	192
48	3.0425	0.6188	1.5584	4.5129	0.9428	−2.9804**	192
60	3.1527	0.5877	1.8084	4.4583	0.9378	−2.9266**	192
72	3.2882	0.5857	2.0006	4.6571	0.9381	−2.9151**	192
84	3.3760	0.5650	2.1692	4.7438	0.9339	−2.9512**	192
96	3.4571	0.5650	2.2805	4.9632	0.9343	−3.9930***	192
108	3.5188	0.5661	2.3320	5.1625	0.9334	−3.9930***	192
120	3.5717	0.5675	2.3810	5.3419	0.9305	−2.5852*	192

Note: $\hat{\rho}(1)$ represents the first-order sample autocorrelation coefficients, ADF represents the Augmented Dickey–Fuller unit root test statistics.
* Indicate significance of the unit root test at the 10% level.
** Indicate significance of the unit root test at the 5% level.
*** Indicate significance of the unit root test at the 1% level.

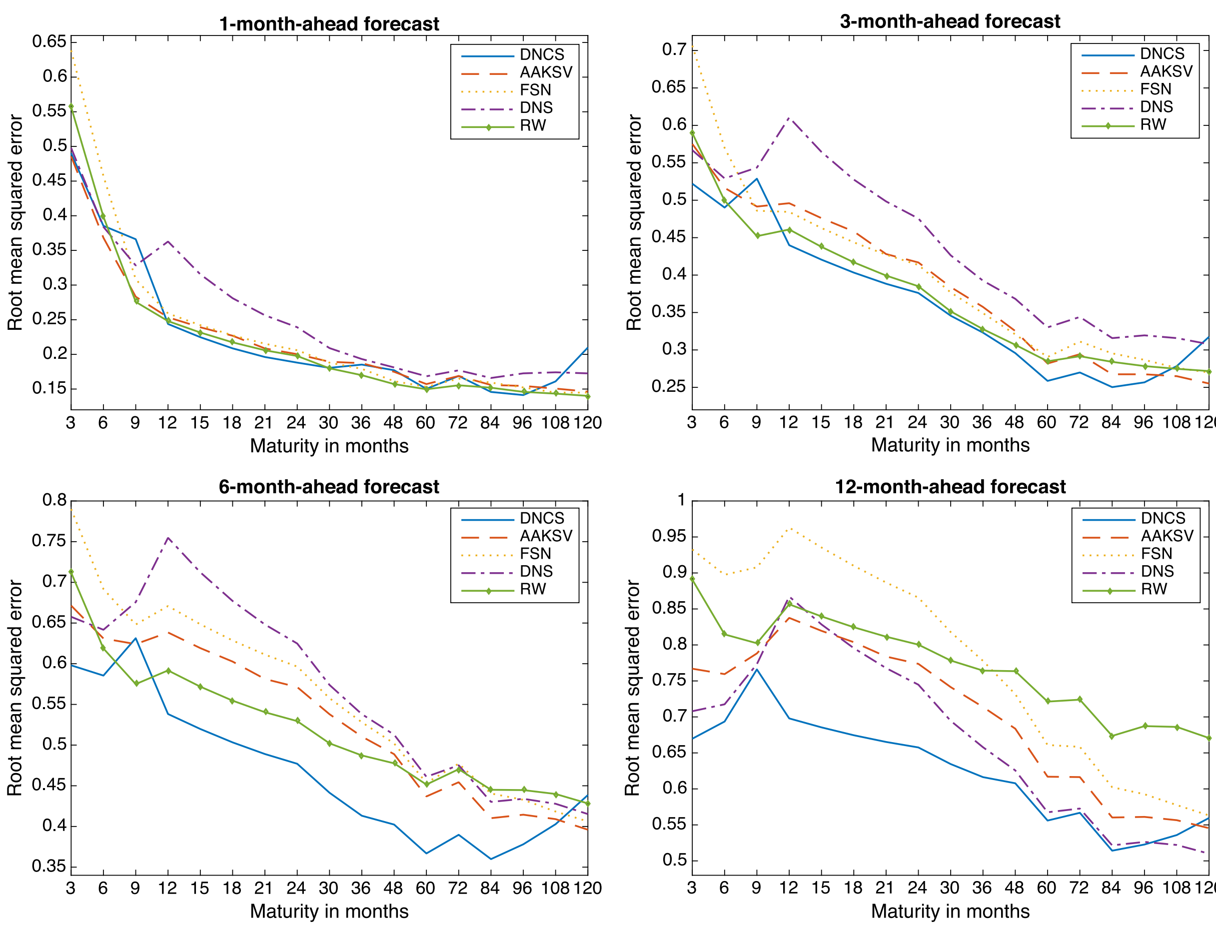

Fig. 1. Forecasting performance of different models.

2. Model and methodology

2.1. Dynamic natural cubic spline model

Let $\boldsymbol{\tau} = (\tau_1, \ldots, \tau_N)'$ be the vector of observed maturities and suppose that we observe a time series of N-dimensional yield vector $\boldsymbol{y}_t(\boldsymbol{\tau}) = (y_t(\tau_1), y_t(\tau_2), \ldots, y_t(\tau_N))'$, $t = 1, \ldots, T$. We follow Bowsher and Meeks (2008) and assume that the yield curve consists of a time-varying signal $S_{\gamma_t}(\boldsymbol{\tau})$ plus a noise process $\boldsymbol{\epsilon}_t(\boldsymbol{\tau})$,

$$\boldsymbol{y}_t(\boldsymbol{\tau}) = S_{\gamma_t}(\boldsymbol{\tau}) + \boldsymbol{\epsilon}_t(\boldsymbol{\tau}). \tag{1}$$

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