ISSN 1518-3548

BANCO CENTRAL DO BRASIL

Working Paper Series 247

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August, 2011

ISSN 1518-3548
CGC 00.038.166/0001-05

Working Paper Series	Brasília	n. 247	Aug.	2011	p. 1-14

Working Paper Series

Edited by Research Department (Depep) – E-mail: workingpaper@bcb.gov.br

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Forecasting the Yield Curve for the Euro Region

Benjamin M. Tabak[1] Daniel O. Cajueiro[2] Alexandre B. Sollaci[3]

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Abstract

This paper compares the forecast precision of the Functional Signal plus Noise (FSN), the Dynamic Nelson-Siegel (DL), and a random walk model. The empirical results suggest that both outperform the random walk at short horizons (one-month) and that the the FSN model outperforms the DL at the one-month forecasting horizon. The conclusions provided in this paper are important for policy makers, fixed income portfolio managers, financial institutions and academics.

Key Words: European yield curve, Dynamic Nelson-Siegel, Functional Signal plus Noise, forecasting, term structure of interest rates.

JEL Classification: E43, G12.

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1 Introduction

The accurate forecast of the yield curve has gained significant importance in the last few years. The yield curve has proved to be a leading indicator for economic activity and inflation. It also has a massive influence over the development of macroeconomic scenarios, which are employed by large companies, financial institutions, regulators and institutional investors.

The main purpose of this paper is to evaluate the forecast performance of the two leading models presented in the literature for the yield curve denominated in Euros, namely the dynamic version of the parametrically parsimonious Nelson and Siegel [1987] model presented by Diebold and Li [2006] (DL) and the Functional Signal plus Noise time series model (FSN) introduced by Bowsher and Meeks [2008]. Therefore, we will compare both these models, as well as report their comparative results against a random walk (RW) forecast for one, three and six months forecasting horizon. It is worth mentioning that while the DL model has been already tested, the only information (due to the authors) that we have about the FSN model is that it is competitive for short-term horizon forecasting. In particular, Vicente and Tabak [2008] have shown that the DL model is very superior for forecasting purposes than the models with affine term structure.

We contribute to the literature in two main ways. First we compare different methods to forecast the Euro yield curve and find evidence that the Functional Signal plus Noise (FSN) model performs better in the short run than Dynamic Nelson-Siegel (DL) . Second, we employ a recent data-set that includes the last few years, in which yields have declined substantially due to the crisis that hit the US and global markets in 2007 and 2008. Therefore, the forecasting properties of these models are tested within a period in which substantial changes in the yield curve have taken place.

The remainder of the paper is structured as follows. Section 2 provides a description of the methods used to construct yield curve forecasts. Section 3 describes the data-set employed in the analysis. The empirical results are presented in section 4. Section 5 concludes the paper.

2 Methodology

2.1 The Diebold-Li Model

The Diebold and Li [2006] method follows the Nelson and Siegel [1987] exponential components framework to distill the entire yield curve, period-by-period, into a three-dimensional parameter that evolves dynamically. The corresponding yield curve is

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

where t is the date and τ is the maturity.

The parameter λ governs the exponential decay rate: small values of λ produce slow decay and can better fit the curve at long maturities, while large values of λ produce fast decay and can better fit the curve at short maturities. We follow Diebold and Li [2006] and adopt λ as a constant given by the value that maximizes the loading on the medium-term factor, as shown in equation (1). Therefore, we use the value $\lambda = 0.1$.

The terms β_{1t}, β_{2t} and β_{3t} are interpreted as three latent dynamic factors. The loading on β_{1t} is a constant, 1, that does not decay to 0 at the limit, hence, it is viewed as a long-term factor. The loading on β_{2t} is a function that starts at 1 and decays monotonically and quickly to 0, hence it may be viewed as a short-term factor. Finally, the loading on β_{3t} starts at 0, increases, and then decays to zero, hence it may be viewed as a medium-term factor. These three factors may also be interpreted in terms of level, slope and curvature respectively.

Because we have fixed the value of λ, we are able to compute the values of the two regressors and estimate the factors (betas) for each period t by Ordinary Least Squares. By doing so, we create a time series estimates of $\left\{\hat{\beta_{1t}}, \hat{\beta_{2t}}, \hat{\beta_{3t}}\right\}$. We now forecast the values of the factors using a univariate AR(1). The yield forecasts $\hat{y}_{t+h/t}(\tau)$ based on the AR(1) factor specifications are given by equation (1) with β_{it} replaced by $\hat{\beta}_{i,t+h/t}$, for $i = 1, 2, 3$, where

$$\hat{\beta}_{1,t+h/t} = \hat{c}_\imath + \hat{\gamma}_\imath \hat{\beta}_{\imath t}, \quad \imath = 1, 2, 3$$

and h is the forecast horizon.

2.2 The Bowsher-Meeks Model

The FSN model consists of a dynamically evolving natural cubic spline signal function denoted by $S_{\gamma_t}(\boldsymbol{\tau})$, plus a noise process. A cubic spline is essentially a piecewise cubic function with pieces that join to form a smooth function. The spline signal function, $S_{\gamma_t}(\boldsymbol{\tau}) := (S_{\gamma_t}(\tau_1), \ldots, S_{\gamma_t}(\tau_N))'$, has m knots, positioned at the maturities $k = (1, k_2, \ldots, k_m)$, which are deterministic and fixed over time. The notation $S_{\gamma_t}(\boldsymbol{\tau})$ is used to imply that the spline interpolates to the latent yields $\gamma_t = (\gamma_{1t}, \ldots, \gamma_{mt})'$ - i.e. $S_{\gamma_t}(k_\jmath) = \gamma_{\jmath t}$ for $\jmath = 1, \ldots, m$. We refer to the vector γ_t as the *knot yields* of the spline.

The model for the time series of N-dimensional observed yield curves, $\{y_t(\boldsymbol{\tau})\}$, is given by

$$\begin{aligned} y_t(\boldsymbol{\tau}) =& S_{\gamma_t}(\boldsymbol{\tau}) + \epsilon_t \\ =& W(k;\boldsymbol{\tau})\gamma_t + \epsilon_t, \\ \Delta\gamma_{t+1} =& \alpha(\beta'_{\gamma_t} - \mu_s) + \Psi\Delta\gamma_t + \nu_t \end{aligned}$$

Here $S_{\gamma_t}(\boldsymbol{\tau})$ is a natural cubic spline on $(k;\gamma_t)$, the $N \times m$ deterministic matrix $W(k;\boldsymbol{\tau})$ is defined as $S_{\gamma_t}(\boldsymbol{\tau})/\gamma_t$, the $m \times (m-1)$ matrix α has full rank, and the matrix β is defined uniquely by $\beta'_{\gamma_t} = (\gamma_{j+1,t} - \gamma_{jt})_{j=1}^{m-1}$. The initial state $(\gamma'_1, \gamma'_0)'$ has finite first and second moments given by μ^* and Ω^* respectively. The Gaussian FSN has the additional condition that $(\gamma'_1, \gamma'_0)'$ have multivariate Normal distributions.

The parameters of the various FSN models are estimated by maximizing the likelihood of the corresponding Gaussian FSN model, computed using the Kalman filter. The FSN forecasts are the 1-step ahead point predictions given by the Kalman filter, $[\hat{y}_t(\boldsymbol{\tau})|y_{t-1}(\boldsymbol{\tau}), \ldots, y_1(\boldsymbol{\tau}); \theta]_{KF}$, with the parameter vector of the model set equal to some estimated value, θ. In this case, $[\hat{y}_t(\boldsymbol{\tau})|y_{t-1}(\boldsymbol{\tau}), \ldots, y_1(\boldsymbol{\tau}); \theta]_{KF}$ is a linear function of the past observations $(y_{t-1}(\boldsymbol{\tau}), \ldots, y_1(\boldsymbol{\tau}))$ and has minimum MSFE amongst the class of such linear predictors when θ is equal to the true parameter vector.

The forecasts are defined by a vector $\varphi_t := Q\gamma_t$ consisting of the (latent) short rate and inter-knot (latent) yield spreads:

$$\varphi_t := (\gamma_{1t}, \gamma_{2t} - \gamma 1t, \ldots, \gamma_{mt} - \gamma_{m-1,t})' = \begin{pmatrix} 1 & 0_{1\times(m-1)} \\ \beta' & \end{pmatrix} \gamma_t = Q\gamma_t,$$

The state equation may then be written equivalently as the VAR

$$\Delta\varphi_{t+1} = Q\alpha(\beta' Q^{-1}\varphi_t - \mu_s) + Q\Psi Q^{-1}\Delta\varphi_t + \eta_t$$

where $\eta_t = Q\nu_t$.

3 Data Sampling

Our data consists of Zero Coupon Government Bond yields ranging from January $1^{\underline{st}}$, 1999 to July $31^{\underline{st}}$, 2009, and in 20 different maturities, equally spaced, starting at 6 months and ending in 10 years. This data was obtained in Thomson Reuters Datastream.

4 Empirical Results

We have forecast the bond yields for the Eurozone using the Diebold-Li (DL), the Bowsher-Meeks (FSN), and a Random-Walk (RW) models. The estimation window for all models is of 60 months and the out-of-sample forecast will be for 1, 3 and 6 months ahead. We compare the first two models with the Random-Walk as a "control" test to provide a minimum standard on predictive accuracy for each model. Once both models show better forecasts than the Random-Walk, we compare the Diebold-Li and the Bowsher-Meeks models in order to elect which has the best forecast power.

Table 1 presents the Diebold and Mariano [1995] Diebold-Mariano statistics for the DL against RW models. For medium-term maturities, the DL model does predict much better than the RW, although this is not the case in short and long-term maturities.

Place Table 1 About Here

Table 2 has the results for the comparison between the FSN model against the RW. In this case, there is a clear superiority of the FSN model for short-term forecasts (one and three months ahead) especially in lower maturities. As forecasts move further ahead, the FSN loses its relative forecasting power, and we can no longer point a better forecasting ability.

Place Table 2 About Here

As shown in tables 1 and 2, there is no statistically significant different forecast between the Random-Walk and both other models in which the Random-Walk has a better forecast, and the opposite is not true. This leads us to conclude that both DL and FSN predict at least as well as the Random-Walk, and most likely better.

In table 3 we present results for the DL against the FSN. Results imply that, at least for short-term forecasts, the FSN outperforms the DL model.

Place Table 3 About Here

5 Final Considerations

This paper compares the forecasting accuracy of the Diebold-Li (DL) and Bowsher-Meeks (FSN) models. We also compare both these models with the Random-Walk. The results for the Eurozone point a superior forecasting capacity of the FSN and DL models relatively to the Random-Walk, although the difference in predictive ability is tenuous in some cases. When comparing the DL and the FSN models, we find that the FSN has a better forecasting ability for short-term forecasts.

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Table 1: Diebold-Mariano statistic results for the comparison between the Diebold-Li against the Random-Walk models

Model	maturity	Diebold-Mariano Statistic					
		1 month	p-value	3 month	p-value	6 month	p-value
DL	6	-0.2962	0.7671	-0.8802	0.3788	-0.3839	0.701
DL	12	2.313	0.0207	-0.1941	0.8461	0.1948	0.8456
DL	18	0.3087	0.7576	-0.2119	0.8322	0.223	0.8235
DL	24	-2.512	0.012	-1.235	0.2168	0.2587	0.7959
DL	30	-2.41	0.016	-1.52	0.1285	0.2443	0.807
DL	36	-1.45	0.147	-1.237	0.2162	0.1497	0.881
DL	42	-0.7507	0.4528	-1.053	0.2923	0.09202	0.9267
DL	48	-0.3759	0.707	-1.056	0.2911	0.08112	0.9353
DL	54	-0.3467	0.7288	-1.109	0.2674	0.04617	0.9632
DL	60	-0.6429	0.5203	-1.204	0.2287	-0.03038	0.9758
DL	66	-1.208	0.2272	-1.377	0.1685	-0.1238	0.9015
DL	72	-2.024	0.043	-1.626	0.104	-0.225	0.822
DL	78	-2.988	0.0028	-1.883	0.0597	-0.3494	0.7268
DL	84	-3.899	0.0001	-2.076	0.0379	-0.4953	0.6204
DL	90	-4.312	0	-2.167	0.0302	-0.6305	0.5284
DL	96	-3.917	0.0001	-2.15	0.0316	-0.7324	0.4639
DL	102	-2.749	0.006	-2.025	0.0429	-0.8017	0.4227
DL	108	-1.179	0.2383	-1.821	0.0686	-0.8366	0.4028
DL	114	0.3782	0.7053	-1.582	0.1136	-0.8369	0.4027
DL	120	1.758	0.0788	-1.333	0.1826	-0.8092	0.4184

Table 2: Diebold-Mariano statistic results for the comparison between the Bowsher-Meeks against the Random-Walk models

Model	maturity	Diebold-Mariano Statistic					
		1 month	p-value	3 month	p-value	6 month	p-value
FSN	6	-3.318	0.0009	-2.224	0.0262	-0.3918	0.6952
FSN	12	-3.177	0.0015	-1.889	0.0588	-0.1699	0.8651
FSN	18	-2.359	0.0183	-1.6	0.1095	-0.1559	0.8761
FSN	24	-3.019	0.0025	-1.608	0.1079	-0.008621	0.9931
FSN	30	-2.881	0.004	-1.642	0.1007	0.01818	0.9855
FSN	36	-2.96	0.0031	-1.521	0.1282	-0.08126	0.9352
FSN	42	-3.06	0.0022	-1.405	0.1599	-0.1537	0.8779
FSN	48	-3.292	0.001	-1.419	0.1559	-0.174	0.8619
FSN	54	-3.492	0.0005	-1.39	0.1644	-0.2049	0.8377
FSN	60	-3.602	0.0003	-1.298	0.1944	-0.2578	0.7966
FSN	66	-3.663	0.0002	-1.223	0.2214	-0.3076	0.7584
FSN	72	-3.762	0.0002	-1.187	0.2352	-0.3486	0.7274
FSN	78	-3.828	0.0001	-1.155	0.248	-0.3967	0.6916
FSN	84	-3.866	0.0001	-1.117	0.2639	-0.4558	0.6485
FSN	90	-3.838	0.0001	-1.085	0.278	-0.5071	0.6121
FSN	96	-3.781	0.0002	-1.051	0.293	-0.542	0.5878
FSN	102	-3.687	0.0002	-1.019	0.3081	-0.57	0.5687
FSN	108	-3.577	0.0003	-0.9918	0.3213	-0.5958	0.5513
FSN	114	-3.47	0.0005	-0.9716	0.3312	-0.6151	0.5385
FSN	120	-3.396	0.0007	-0.9611	0.3365	-0.6281	0.5299

Table 3: Diebold-Mariano statistic results for the comparison between the Diebold-Li against the Bowsher-Meeks models

Model	maturity	Diebold-Mariano Statistic					
		1 month	p-value	3 month	p-value	6 month	p-value
DL	6	2.411	0.0159	2.65	0.008	0.2279	0.8198
DL	12	4.642	0	1.856	0.0635	0.7993	0.4241
DL	18	4.241	0	1.814	0.0697	0.897	0.3697
DL	24	1.2	0.2303	1.231	0.2185	0.71	0.4777
DL	30	0.4111	0.681	0.8627	0.3883	0.7044	0.4812
DL	36	1.363	0.1729	0.7747	0.4385	0.8391	0.4014
DL	42	1.878	0.0604	0.6583	0.5103	0.8933	0.3717
DL	48	2.207	0.0273	0.5411	0.5885	0.8982	0.3691
DL	54	2.222	0.0263	0.423	0.6723	0.8913	0.3728
DL	60	1.887	0.0592	0.2677	0.7889	0.8557	0.3921
DL	66	1.321	0.1865	0.05251	0.9581	0.7763	0.4376
DL	72	0.5474	0.5841	-0.2053	0.8374	0.642	0.5209
DL	78	-0.3933	0.6941	-0.45	0.6527	0.4484	0.6538
DL	84	-1.216	0.2238	-0.6255	0.5317	0.2412	0.8094
DL	90	-1.339	0.1804	-0.7132	0.4757	0.06684	0.9467
DL	96	-0.6188	0.5361	-0.7202	0.4714	-0.05808	0.9537
DL	102	0.504	0.6143	-0.6541	0.513	-0.1351	0.8925
DL	108	1.695	0.09	-0.5289	0.5969	-0.1723	0.8632
DL	114	2.788	0.0053	-0.3719	0.7099	-0.1839	0.8541
DL	120	3.767	0.0002	-0.1942	0.846	-0.1767	0.8597

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