

Bayesian Forecasting using an Extended Nelson-Siegel Model

Nikolaus Hautsch

Humboldt-Universität zu Berlin, Institute for Statistics and Econometrics

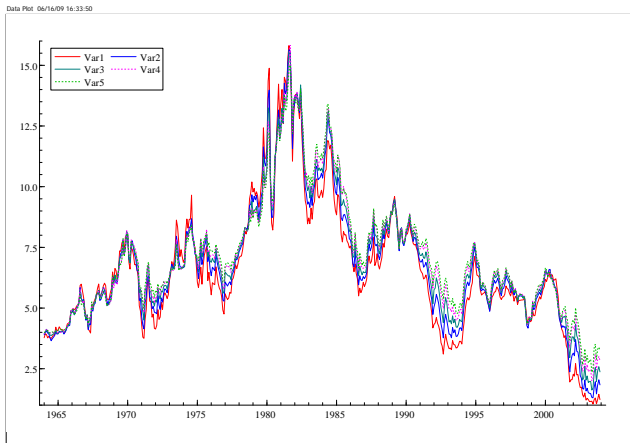
Fuyu Yang

Humboldt-Universität zu Berlin, Institute for Statistics and Econometrics



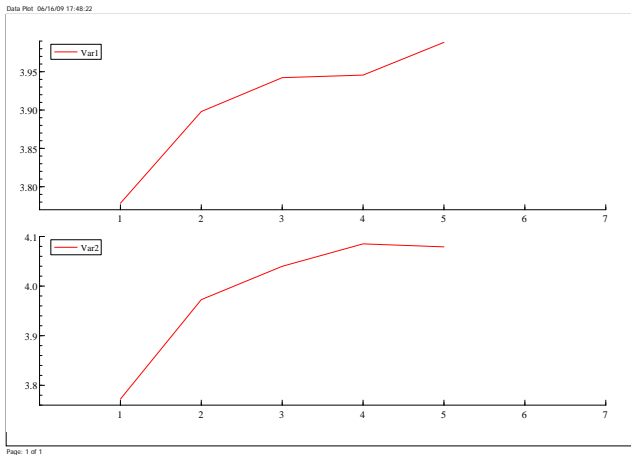
1. Motivation and Model Specification
2. Potential problems in the existing literature
3. An efficient MCMC approach to estimating the latent variables
4. Empirical Results
 - 4.1 Estimates
 - 4.2 Algorithm Evaluation
 - 4.3 In-Sample forecast
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Plots of the Spot rates 1964:1-2003:12



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Plots of the yield curve for 5 maturities



Motivations to Study Term Structure

- ▶ The yield curve carries information about prospective evolution of economic activity, inflation etc.
- ▶ Interest rate spreads (difference between 10 year and 3 month rates, or 10 year and 2 year rates) are predictive indicators of recession and inflation
- ▶ Since the yield curve assumes similar shape over time, we can explain the cross-sectional variation of interest rates through 3 factors: level, slope, and curvature.

The original NS model

The spot rate (yield)curve is expressed as:

$$y_t(n) = f_{1,t} + f_{2,t} \left[\frac{1 - e^{-\lambda_t \cdot n}}{\lambda_t \cdot n} \right] + f_{3,t} \left[\frac{1 - e^{-\lambda_t \cdot n}}{\lambda_t \cdot n} - e^{-\lambda_t \cdot n} \right]$$

- ▶ n : n period to maturity
- ▶ $\left[1, \frac{1 - e^{-\lambda_t \cdot n}}{\lambda_t \cdot n}, \frac{1 - e^{-\lambda_t \cdot n}}{\lambda_t \cdot n} - e^{-\lambda_t \cdot n} \right]$: long term component, short term component and medium term component
- ▶ $[f_{1,t}, f_{2,t}, f_{3,t}]$: level, slope, curvature
- ▶ λ_t : governs the speed of decay in the short term component

The NS-DL model

$$\mathbf{y}_t = \mathbf{A}\mathbf{f}_t + \varepsilon_t \quad (1)$$

$$\mathbf{A} = \begin{pmatrix} 1 & \frac{1-e^{-\lambda_t \cdot 1}}{\lambda_t \cdot 1} & \frac{1-e^{-\lambda_t \cdot 1}}{\lambda_t \cdot 1} - e^{-\lambda_t \cdot 1} \\ 1 & \frac{1-e^{-\lambda_t \cdot 2}}{\lambda_t \cdot 2} & \frac{1-e^{-\lambda_t \cdot 2}}{\lambda_t \cdot 2} - e^{-\lambda_t \cdot 2} \\ \vdots & \vdots & \vdots \\ 1 & \frac{1-e^{-\lambda_t \cdot n}}{\lambda_t \cdot n} & \frac{1-e^{-\lambda_t \cdot n}}{\lambda_t \cdot n} - e^{-\lambda_t \cdot n} \end{pmatrix} : N \times 3$$

$$\mathbf{f}_t - \mu_{\mathbf{f}} = \Phi_{\mathbf{f}}(\mathbf{f}_{t-1} - \mu_{\mathbf{f}}) + \mathbf{u}_t \quad (2)$$

where $\varepsilon_t \stackrel{i.i.d}{\sim} f_{MN}(0_N, H_{\varepsilon})$. $\mathbf{y}_t = \{y_t(1), y_t(2), \dots, y_t(N)\}'$.
 $\mu_{\mathbf{f}} = \{\mu_{1,f}, \mu_{2,f}, \mu_{3,f}\}'$, $\Phi_{\mathbf{f}} = \{\phi_{1,f}, \phi_{2,f}, \phi_{3,f}\}'$

The NS-DL model

- ▶ $[f_{1,t}, f_{2,t}, f_{3,t}]$ are interpreted as latent dynamic factors
- ▶ NS-DL is able to capture the characteristics of term structure of interest rates over time

Can we learn about the volatilities of the dynamic factors?

The NS-SV model (Hautsch and Ou 2008)

Instead of assuming a constant variance-covariance matrix of \mathbf{u}_t
The NS-DL model is generalized to NS-SV to accommodate
Stochastic Volatilities

$$\mathbf{u}_t = \begin{pmatrix} \sqrt{\exp h_{1,t}} & 0 & 0 \\ 0 & \sqrt{\exp h_{2,t}} & 0 \\ 0 & 0 & \sqrt{\exp h_{3,t}} \end{pmatrix} \times \zeta_{j,t} \quad (3)$$

$$f_{j,t} - \mu_{j,f} = \phi_{j,f} (f_{j,t-1} - \mu_{j,f}) + \exp\left(\frac{h_{j,t}}{2}\right) \zeta_{j,t} : j = 1, 2, 3 \quad (4)$$

$$h_{j,t} - \mu_{j,h} = \phi_{j,h} (h_{j,t-1} - \mu_{j,h}) + \sigma_j \epsilon_{j,t} : j = 1, 2, 3 \quad (5)$$

where $\zeta_{j,t} \stackrel{i.i.d}{\sim} f_N(0, 1)$ and $\epsilon_{j,t} \stackrel{i.i.d}{\sim} f_N(0, 1)$

Estimation the model is challenging In Hautsch and Ou (2008), the model is estimated element by element using WinBugs

- ▶ The latent loading factors f and SV h are highly correlated, little movement in the draws (Chib and Greenberg 1996)
- ▶ chain converges slow and long chain is needed
- ▶ The estimate of $f_t \mid f_0, f_1, \dots, f_{t-1}, f_{t+1}, \dots, f_T$, and $h_t \mid h_0, h_1, \dots, h_{t-1}, h_{t+1}, \dots, h_T$
- ▶ $2 \times T$ steps are needed for each sweep, very time consuming

MCMC is a Solution to the Estimation problem

Target: random draws from $p(\theta | y)$ The MCMC can be constructed as follows:

- ▶ Partition θ into θ_1 and θ_2
- ▶ The posterior densities $p(\theta_1 | \theta_2, y)$ and $p(\theta_2 | \theta_1, y)$ have known analytical form
- ▶ generate random draws as the following:

$$\theta_1^n \sim p(\theta_1 | \theta_2^{n-1}, y)$$

$$\theta_2^n \sim p(\theta_2 | \theta_1^n, y)$$

Blocking the highly correlated latent variables

$$\begin{aligned}\mathbf{y}_t &= \mathbf{A}\mathbf{f}_t + \varepsilon_t \\ \mathbf{f}_t - \mu_{\mathbf{f}} &= \Phi_{\mathbf{f}}(\mathbf{f}_{t-1} - \mu_{\mathbf{f}}) + \mathbf{u}_t \\ f_{j,t}^* &= h_{j,t} + z_{j,t} \\ h_{j,t+1} - \mu_{j,h} &= \phi_{j,h}(h_{j,t} - \mu_{j,h}) + \sigma_j \epsilon_{j,t} : j = 1, 2, 3\end{aligned}$$

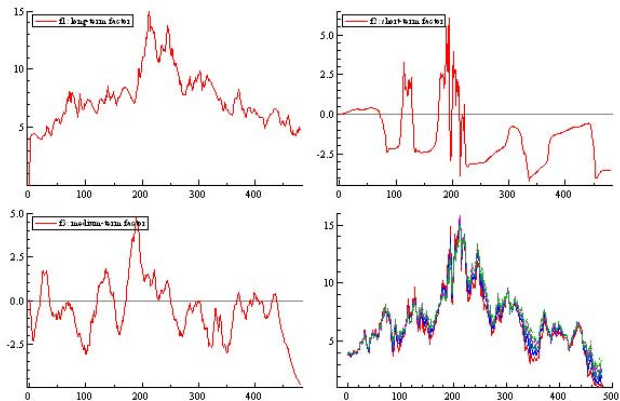
where

$$\begin{aligned}f_{j,t}^* &= \ln \left\{ [f_{j,t} - \mu_{j,f} - \phi_{j,f}(f_{j,t-1} - \mu_{j,f})]^2 + c \right\} \\ z_{j,t} &= \ln \left(\zeta_{j,t}^2 \right)\end{aligned}$$

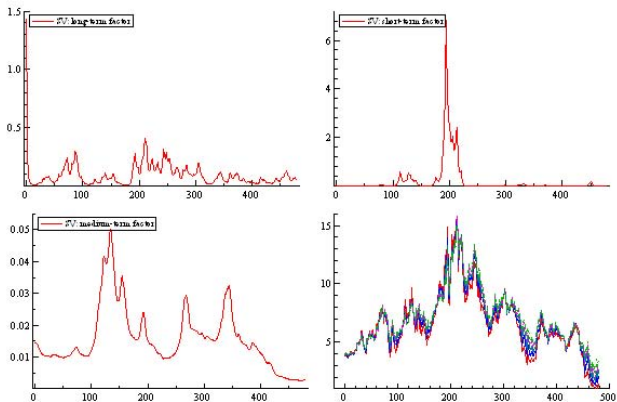
The improved method works

- ▶ Chain moves fast and algorithm is efficient according to the Relative Numerical Efficiency (RNE)
- ▶ Correlation among the draws are smaller
- ▶ latent variables are drawn in 6 blocks, only 6 steps are need in each iteration

Estimated yield factors

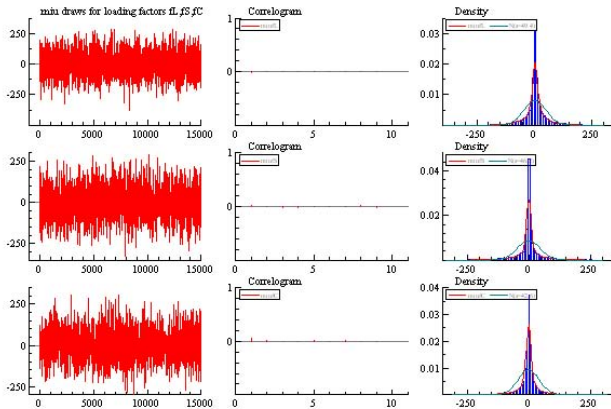


Filtered Stochastic Volatilities



MCMC draws, Correlogram and Histogram for μ_f

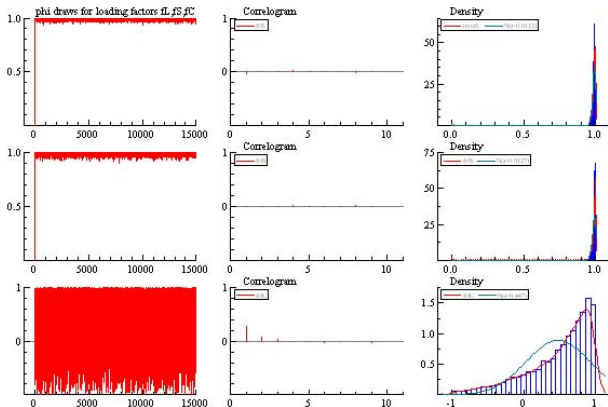
μ_f



Efficient MCMC for NS-SV



MCMC draws, Correlogram and Histogram for

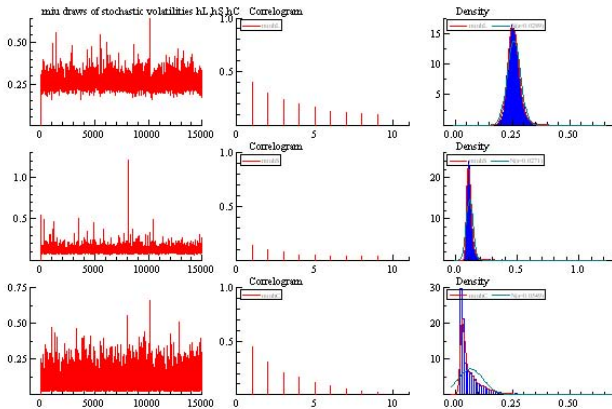
 ϕ_f


Efficient MCMC for NS-SV



MCMC draws, Correlogram and Histogram for μ_h

μ_h

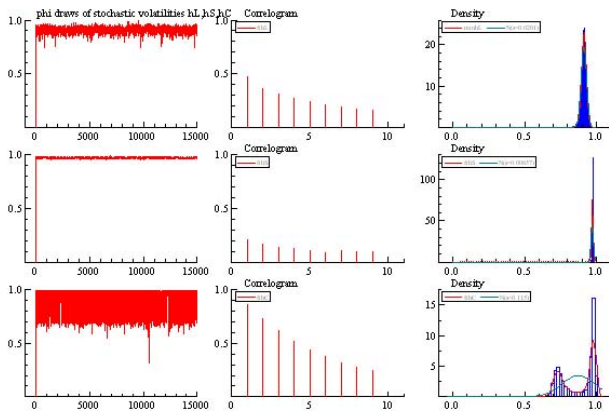


Efficient MCMC for NS-SV



MCMC draws, Correlogram and Histogram for ϕ_h

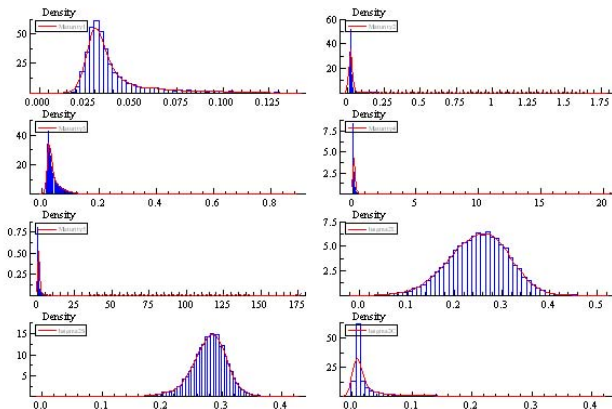
ϕ_h



Efficient MCMC for NS-SV



MCMC draws, Correlogram and Histogram for σ^2



MCMC draws, Correlogram and Histogram for λ

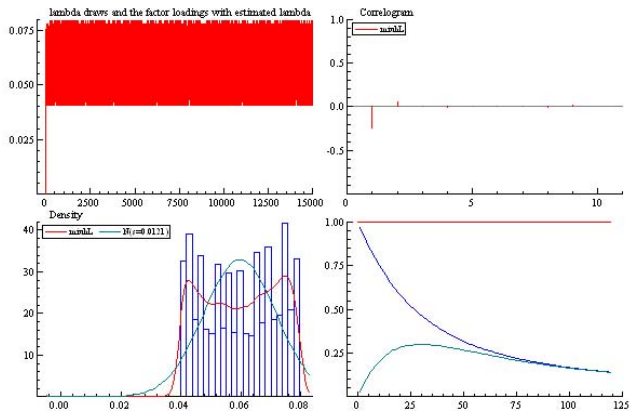


Table 1: Estimation results from MCMC

	$\phi_{f,L}$	$\phi_{f,S}$	$\phi_{f,C}$	$\mu_{h,L}$	$\mu_{h,S}$	$\phi_{h,L}$	$\phi_{h,S}$	$\phi_{h,C}$
<i>mean</i>	0.9954	0.9949	0.8647	0.2566	0.1123	0.9125	0.9738	0.8742
<i>MCse</i>	0.0066	0.0081	0.3020	0.0288	0.0271	0.0187	0.0032	0.1148
<i>HPIV_{lo}</i>	0.9818	0.9782	0.2071	0.2160	0.0848	0.8818	0.9680	0.7031
<i>HPIV_{up}</i>	0.9999	0.9999	0.9995	0.3030	0.1561	0.9412	0.9785	0.9905
	$\sigma_{1,\varepsilon}^2$	$\sigma_{4,\varepsilon}^2$	$\sigma_{5,\varepsilon}^2$	$\sigma_{1,h}^2$	$\sigma_{2,h}^2$	$\sigma_{3,h}^2$	λ	
<i>mean</i>	0.0386	0.0930	0.9758	0.2509	0.2789	0.0324	0.0598	
<i>MCse</i>	0.0163	0.2572	3.1646	0.0619	0.0298	0.0490	0.0121	
<i>HPIV_{lo}</i>	0.0243	0.0217	0.1417	0.1460	0.2268	0.0055	0.0407	
<i>HPIV_{up}</i>	0.0756	0.2524	3.3381	0.3480	0.3228	0.1468	0.0780	

CD, NSE, RNE

Table 2: Algorithm Evaluations 1

	$\mu_{f,L}$	$\mu_{f,S}$	$\mu_{f,C}$	$\phi_{f,L}$	$\phi_{f,S}$	$\mu_{h,L}$	$\mu_{h,S}$	$\mu_{h,C}$
<i>cd</i>	0.4583	-0.5092	-0.2334	0.4780	0.6622	0.3939	1.0604	0.0447
<i>nse</i>	0.4052	0.3776	0.3477	0.0001	0.0001	0.0002	0.0002	0.0004
<i>nse</i> _{.04}	0.3268	0.3830	0.3640	0.0001	0.0001	0.0007	0.0005	0.0008
<i>nse</i> _{.08}	0.2660	0.3845	0.3365	0.0001	0.0001	0.0007	0.0005	0.0007
<i>nse</i> _{.15}	0.2381	0.3518	0.2794	0.0001	0.0001	0.0007	0.0005	0.0006
<i>rne</i> _{.04}	1.5370	0.9720	0.9121	0.3538	0.3931	0.1072	0.1780	0.3111
<i>rne</i> _{.08}	2.3191	0.9643	1.0673	0.3941	0.4375	0.1300	0.1794	0.3805
<i>rne</i> _{.15}	2.8964	1.1520	1.5485	0.5450	0.3792	0.1238	0.2074	0.4856

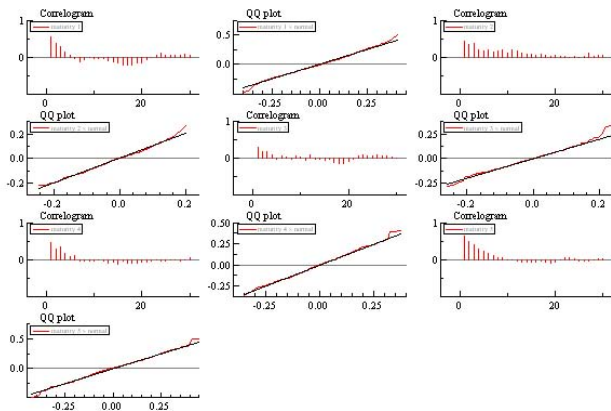
CD, NSE, RNE continue

Table 3: Algorithm Evaluations 2

	$\sigma_{1,\varepsilon}^2$	$\sigma_{3,\varepsilon}^2$	$\sigma_{4,\varepsilon}^2$	$\sigma_{5,\varepsilon}^2$	$\sigma_{1,h}^2$	$\sigma_{2,h}^2$	λ
<i>cd</i>	-0.4979	-0.6888	-0.8046	0.1797	-0.0070	-0.8839	1.0481
<i>nse</i>	0.0001	0.0002	0.0021	0.0259	0.0005	0.0002	0.0001
<i>nse</i> . ₀₄	0.0002	0.0002	0.0019	0.0286	0.0010	0.0006	0.0001
<i>nse</i> . ₀₈	0.0002	0.0002	0.0021	0.0272	0.0009	0.0005	0.0001
<i>nse</i> . ₁₅	0.0002	0.0002	0.0023	0.0242	0.0008	0.0004	0.0001
<i>rne</i> . ₀₄	0.5102	1.1849	1.1790	0.8210	0.2440	0.1636	1.9894
<i>rne</i> . ₀₈	0.5212	1.5643	0.9900	0.9087	0.3000	0.2394	2.6511
<i>rne</i> . ₁₅	0.6589	1.6099	0.8412	1.1508	0.4116	0.3651	3.3624

Model Fits check

Good model fits: Probability Integral Transforms (PIT) should be iid uniform.



Concluding Remarks

- ▶ Contributions:
 - ▷ Algorithm is efficient to estimate the NS-SV model
 - ▷ The iteration number in the MCMC can be reduced from 200,000,000 to 20,000.
 - ▷ NS-SV fits the data well

- ▶ Future research on the agenda:
 - ▷ Out-of-sample forecast with NS-SV
 - ▷ Term structure of interest rates and macrovariables
 - ▷ Model comparisons of NS class term structure model