FORECASTING TERM STRUCTURE OF GOVERNMENT BOND YIELDS IN THAILAND: NELSON-SIEGEL MODEL AND SVENSSON MODEL

BY

MR. SIWAPON THAMVIRIYAPORN

AN INDEPENDENT STUDY SUBMITTED IN PARTIAL FULFILLMENT OF THE REQUIREMENTS FOR THE DEGREE OF MASTER OF SCIENCE PROGRAM IN FINANCE (INTERNATIONAL PROGRAM)

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ABSTRACT

The yield curve is the benchmark for investors. Change in yield curve will affect to the other market index. The primary focus of this paper is forecasting the yield curve in Thailand. There are many ways to predict the yield curve. One of the famous paper which outperformed many models is Diebold and Li (2006). They suggested using fixed lambda parameter in Nelson-Sigel (1987) for out-of-sample forecasting. In this paper, I compare fixed lambda parameter method and time-varying method. Moreover, this independent study is adopted fixed lambda method into Svensson (1994) model which is the extension model of Nelson-Siegel. The results show that fixed lambda method can apply to Svensson model. It improves out-of-sample forecasting of the yield curve at 5-10 years to maturities. Finally, I added inflation variable to improve forecasting model. Inflation can increase the accuracy of predicting model that have time to maturities more than five years.

Keywords: Yield Curve, Forecasting, Nelson-Siegel model, Svensson model

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CHAPTER 1
INTRODUCTION

There are many market indexes in financial markets. One of the major market indexes is yield curve. Yield curve or term structure is a return on a zero-coupon bond issued by the government at the different maturities. Because of trustworthy and reliable in government, investors consider these treasury securities as risk-free. Yield curve becomes the minimum requirement of return or benchmark in debt market for the investor. The change in yield curve affects directly to fixed-income market. Spot curve also contains the information about the economic condition. The yield curve shape can be interpreted market condition such as the recession.

The popular method for construction the yield curve are interpolation and regression. First, spline interpolation is the acceptable method for plotting yield curve. This method is about connecting point-to-point with spline line. In earlier, linear spline and quadratic spline have a significant error. McCulloch (1975) improved the model to the 3^{rd} order called cubic spline interpolation. Cubic spline interpolation can fit the yield curve smoothly. However, cubic spline method generates downward sloping at long maturities when the discount shape is flat. This lead to a significant error at long maturities.

Another type for plotting the yield curve is the regression. The acceptable regression model for yield curve is Nelson-Siegel (1987) model. Nelson-Siegel model is known as a best fitting model for yield curve and easy to use for the ordinary investor. Svensson (1994) improved this model by adding hump parameter to the formula to allow the model to be able to generate more than one hump shape in the yield curve. Therefore, Svensson model enhances flexibility in medium and long maturity.

Forecasting of the yield curve in Thailand is the primary focus of this paper. The data come from ThaiBMA from July 2001 to December 2015. One of the famous paper which outperformed many models is Diebold and Li (2006). They studied the forecast model and found that fixed lambda in Nelson-Siegel model can significantly use for forecasting yield curve. Lorenčič (2016) compared between cubic spline interpolation and Nelson-Siegel model. Lorenčič (2016) found that Nelson-Siegel model gives more accurate result in long maturity. Ullah (2013) found that fixed lambda in Nelson-Siegel model can apply in Japan. Pongpit (2007) also predicted the yield curve in Thailand with fixed lambda in Nelson-Siegel model. He found that fixed lambda method in Nelson-Siegel model works very well in Thailand.

Since Nelson-Siegel model can apply in Thailand, I will study based on Nelson-Siegel model and Svensson model. First, I compare between time-varying lambda parameter method and fixed lambda parameter method. In in-sample estimation model, lambda (decay time) in Nelson-Siegel can vary to get the least sum of squared errors. Fixing the lambda in in-sample estimation model lead to higher error. However, Diebold and Li (2006) suggested using fixed lambda method instead of time-varying lambda in out-of-sample forecasting model to enhance simplicity. The first question of this paper is whether fixed lambda method is better than time varying lambda in the case of the forecasting model. I found that time-varying lambda parameter method is not the appropriate method for forecasting model.

Second, I compare between Nelson-Siegel model and Svensson model (extension of Nelson-Siegel model). In in-sample estimation model, Svensson model has less sum square error than Nelson-Siegel model. Svensson model is a better model than Nelson-Siegel model in terms of estimation model but there is not a conclusion that it is the better model in terms of the out-of-sample forecasting model. The second question is whether Svensson model is better than Nelson-Siegel model in the case of the forecasting model. I applied fixed lambda method with Svensson model. I found that Svensson model has the sum of squared errors of entire curve less than Nelson-Siegel model. However, Nelson-Siegel model is better at some specific maturities.

Finally, I aim to improve the forecasting power of the model by adding control variable. The yield curve comes from government's Treasury securities so there is no credit risk. Treasury securities are the most active product in debt market, so their liquidity is very high. The risk that will drive the yield curve is the domestic economic risk. For domestic economic, the yield curve will change directly from policy rate. However, I avoid using policy rate because there is mismatch about the frequency of data. Typically, Policy rate in Thailand announce every 6-7 weeks or 8 times per year. Error from interpolation frequency of data to monthly will lead to error in predicting yield curve. I used inflation to capture the change in domestic economic. Policymaker usually announces policy rate to slow down or stimulate the economy and their decision depends on inflation. The addition benefit from using inflation is the information of purchasing power in the country. The bond market will act and force the long-term yields due to inflation. I concern the global economic risk such as the spread of U.S Treasury securities and VIX index. According to Table 14, I found that these two variables are not significant and do not correlate with the yield curve in Thailand. I use month-to-month CPI in Thailand as the proxy for domestic inflation. The third question is whether this variable can significantly improve forecasting power. This data is at the end of the month from July 2001 to December 2015. I found that inflation increases the accuracy of the out-of-sample forecasting model for the long maturities.

CHAPTER 2
THEORETICAL FRAMEWORK

Yield curve or term structure show the relation between zero-coupon bond and time to maturity. The zero-coupon bond is treasury securities issued by the government, so it is considered as risk-free. We will use the latest Treasury or on-the-run Treasury securities to construct the yield curve. Stripped bond or coupon Treasury securities can be used to plot the yield of long maturities.

There are many ways to construct the yield curve. As mention in the introduction, this paper will focus on Nelson-Siegel model and Svensson model. I use a formula that factorizes from nominal forward rate Nelson-Siegel (1987).

$$Y_t(T) = \beta_{1,t} + \beta_{2,t}\left(\frac{1 - e^{-T.\lambda_{1,t}}}{T.\lambda_{1,t}}\right) + \beta_{3,t}\left(\frac{1 - e^{-T.\lambda_{1,t}}}{T.\lambda_{1,t}} - e^{-T.\lambda_{1,t}}\right) \quad (1)$$

Where

Y_t = Spot rate

λ_1 = Decay time or partial adjusted of time

T = Time to maturity

I vary the time of maturity as follow to analysis the beta of Nelson-Siegel model.

$$\lim_{T\to\infty} Y(t) = \beta_1 \quad (2)$$

$$\lim_{T\to 0} Y(t) = \beta_1 + \beta_2 \quad (3)$$

$$Y_\infty(t) - Y_0(t) = -\beta_2 \quad (4)$$

I vary time to maturity into infinity to see the long-term effect and zero to see a short-term effect. When the time to maturity approach to infinity in Nelson-Siegel model, there is only β_1 left. If the time to maturity is close to zero in Nelson-Siegel model, there are β_1 and β_2 left. Therefore, β_1 will determine the level of the entire yield curve. β_2 is a difference between long term and short term effect so that β_2 can be identified as the slope. β_3 will determine the curvature of the yield curve which affects only the medium term.

In sum,

β_1= Level of yield curve

β_2= Slope of yield curve

β_3= Curvature of yield curve

Nelson-Siegel model is simplicity model and can best fit with the various shape of the yield curve. However, Nelson-Siegel can produce only one hump shape in the yield curve. Svensson (1995) improved Nelson-Siegel model to enhance flexibility.

$$Y_t(T) = \beta_{1,t} + \beta_{2,t}\left(\frac{1 - e^{-T.\lambda_{1,t}}}{T.\lambda_{1,t}}\right) + \beta_{3,t}\left(\frac{1 - e^{-T.\lambda_{1,t}}}{T.\lambda_{1,t}} - e^{-T.\lambda_{1,t}}\right) + \beta_{4,t}\left(\frac{1 - e^{-T.\lambda_{2,t}}}{T.\lambda_{2,t}} - e^{-T.\lambda_{2,t}}\right) \tag{5}$$

Where

Y_t = Spot rate

λ_1 = First decay time

λ_2 = Second decay time

T = Time to maturity

β_1= Level of yield curve

β_2= Slope of yield curve

β_3= Curvature of yield curve

β_4= Hump of yield curve

Svensson added parameters to improve flexibility in medium maturities. Therefore, his model can generate more than one hump. Nowadays, the central bank of many countries such as Germany, France, Switzerland, and etcetera use Svensson model.

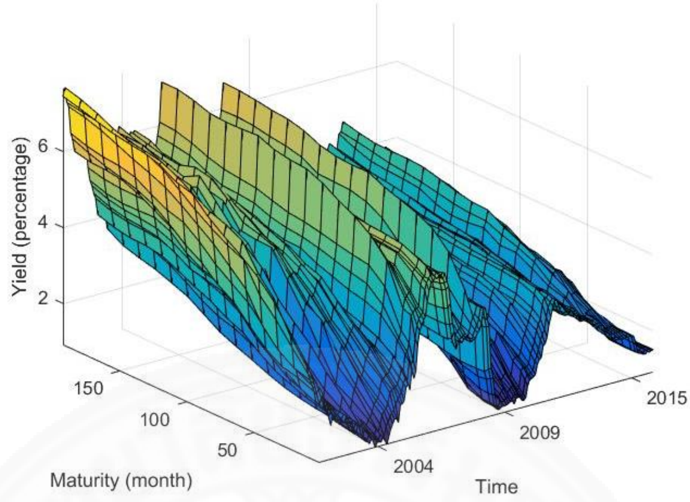
CHAPTER 3
METHODOLOGY

The data is end-of-month yield curve provided by ThaiBMA since July 2001 to December 2015. The time to maturity of the yield curve in each period is 1 month to 16 years.

Table 3.1: Descriptive statistics, yield curve from July 2001–December 2015

Maturity	Mean	Std. dev.	Minimum	Maximum
1	2.357	1.043	0.901	5.007
3	2.417	1.033	1.024	5.029
6	2.502	1.027	1.057	5.192
12	2.603	1.033	1.069	5.288
24	2.862	1.045	1.214	5.478
36	3.089	1.007	1.434	5.625
48	3.339	0.946	1.514	5.933
60	3.549	0.936	1.617	6.151
72	3.772	0.909	1.769	6.417
84	3.964	0.901	1.947	6.600
96	4.096	0.929	2.112	6.635
108	4.199	0.954	2.293	6.716
120	4.328	0.983	2.565	6.888
132	4.479	1.013	2.550	6.966
144	4.576	0.999	2.741	7.029
156	4.649	0.991	2.912	7.174
168	4.712	1.001	2.965	7.383
180	4.785	1.004	3.070	7.551
192	4.875	0.989	3.206	7.671

Figure 3.1: Monthly Yield Curve in Thailand during July 2001–December 2015



I forecast yield curve based on Nelson-Siegel and Svensson model. First, we must regress yield curve with Nelson-Siegel and Svenson model to get parameters for predicting.

Nelson-Siegel model:

$$Y_t(T) = \beta_{1,t} + \beta_{2,t}\left(\frac{1 - e^{-T.\lambda_{1,t}}}{T.\lambda_{1,t}}\right) + \beta_{3,t}\left(\frac{1 - e^{-T.\lambda_{1,t}}}{T.\lambda_{1,t}} - e^{-T.\lambda_{1,t}}\right) \quad (6)$$

Svensson model:

$$Y_t(T) = \beta_{1,t} + \beta_{2,t}\left(\frac{1 - e^{-T.\lambda_{1,t}}}{T.\lambda_{1,t}}\right) + \beta_{3,t}\left(\frac{1 - e^{-T.\lambda_{1,t}}}{T.\lambda_{1,t}} - e^{-T.\lambda_{1,t}}\right) + \beta_{4,t}\left(\frac{1 - e^{-T.\lambda_{2,t}}}{T.\lambda_{2,t}} - e^{-T.\lambda_{2,t}}\right) \quad (7)$$

Normally, these 2 model can be estimated with nonlinear least squares so that all parameters from estimation will vary over the time. Diebold and Li (2006) suggested using fixed lambda to enhance simplicity. They apply fixed lambda because they can use ordinary least square (OLS) instead of nonlinear least squares.

The fixed lambda come from trial several numbers to find the minimum sums of squared error. Diebold and Li (2006) set the lambda to 0.0609 which determine from maximized medium term $\left(\frac{1-e^{-T.\lambda_{1,t}}}{T.\lambda_{1,t}} - e^{-T.\lambda_{1,t}}\right)$ at the 30-month time to maturity.

I apply the same practical to find the appropriated lambda for Svensson model. I fix λ_1 = 0.0609 and trial λ_2 to optimize square error in estimation model. I discover that λ_1 = 0.0609 $and\, \lambda_2$ = 0.03985 give the best fit in estimation. λ_2 = 0.03985 is determined from maximized medium term $\left(\frac{1-e^{-T.\lambda_{1,t}}}{T.\lambda_{1,t}} - e^{-T.\lambda_{1,t}}\right)$ at the 45-month time to maturity.

Table 3.2: Summary of estimation method

Model	Parameters for Estimating	Estimation Method
Time-varying lambda in Nelson-Siegel	$\beta_{1,t}, \beta_{2,t}, \beta_{3,t}, \lambda_{1,t}$	Non-linear least square
Time-varying lambda in Svensson	$\beta_{1,t}, \beta_{2,t}, \beta_{3,t}, \beta_{4,t}$, $\lambda_{1,t}, \lambda_{2,t}$	Non-linear least square
Fixed lambda in Nelson-Siegel	$\beta_{1,t}, \beta_{2,t}, \beta_{3,t}$ $\lambda_{1,t} = 0.0609$	OLS
Fixed lambda in Nelson-Siegel	$\beta_{1,t}, \beta_{2,t}, \beta_{3,t}, \beta_{4,t}$ $\lambda_{1,t} = 0.0609$ $\lambda_{2,t} = 0.03985$	OLS

After regression, I obtain the parameters as the same as Table (2) and use it for forecasting. I predict out-of-sample with AR (1) for 1-month-ahead forecasting and VAR (1) for 6-month-ahead forecasting and 12-month-ahead forecasting. The forecast period is January 2013 to December 2015 (36 months). The forecasting horizon is 1 month, 6 months and 12 months.

Where AR (1) process

$$\hat{\beta}_{i,t+h/t} = \hat{\alpha}_i + \widehat{\Theta}\hat{\beta}_{i,t} \qquad \text{i = 1,2,3,} \qquad (8)$$

The example for AR (1) of Time-varying lambda in Nelson-Siegel is below.

$$\hat{\beta}_{1,t} = \hat{\alpha}_1 + \widehat{\Theta}\hat{\beta}_{1,t-1} \tag{9}$$

$$\hat{\beta}_{2,t} = \hat{\alpha}_2 + \widehat{\Theta}\hat{\beta}_{2,t-1} \tag{10}$$

$$\hat{\beta}_{3,t} = \hat{\alpha}_3 + \widehat{\Theta}\hat{\beta}_{3,t-1} \tag{11}$$

$$\hat{\lambda}_{1,t} = \hat{\alpha}_4 + \widehat{\Theta}\hat{\lambda}_{1,t-1} \tag{12}$$

Where VAR (1) process

$$\hat{\beta}_{t+h/t} = \hat{\alpha} + \widehat{\Theta}\hat{\beta}_t \tag{13}$$

The example for VAR (1) of Time-varying lambda in Svenson is below.

$$\begin{bmatrix} \hat{\beta}_{1,t} \\ \hat{\beta}_{2,t} \\ \hat{\beta}_{3,t} \\ \hat{\beta}_{4,t} \\ \lambda_{1,t} \\ \lambda_{2,t} \end{bmatrix} = \begin{bmatrix} \hat{\alpha}_1 \\ \hat{\alpha}_2 \\ \hat{\alpha}_3 \\ \hat{\alpha}_4 \\ \hat{\alpha}_5 \\ \hat{\alpha}_6 \end{bmatrix} + \begin{bmatrix} \widehat{\Theta}_{1,1} & \cdots & \widehat{\Theta}_{1,6} \\ \vdots & \ddots & \vdots \\ \widehat{\Theta}_{6,1} & \cdots & \widehat{\Theta}_{6,6} \end{bmatrix} \begin{bmatrix} \hat{\beta}_{1,t-1} \\ \hat{\beta}_{2,t-1} \\ \hat{\beta}_{3,t-1} \\ \hat{\beta}_{4,t-1} \\ \lambda_{1,t-1} \\ \lambda_{2,t-1} \end{bmatrix} \tag{14}$$

After forecasting, I obtain forecasting parameters for 36 months. I substitute the forecasting parameters back into Nelson-Siegel and Svensson model to get the forecasting yields. This paper will be used the root mean square error (RMSE) to test the forecasting. The model that have the RMSE value lower is more accurate.

$$RMSE = \sqrt{\frac{\sum_{t=1}^{n}(\hat{Y}_t(T) - Y_t(T))^2}{n}} \tag{15}$$

Table 3.3: RMSE for entire yield curve at 1-month forecasting horizon

Model	RMSE
Fixed lambda in Nelson-Siegel with AR (1)	0.0418
Time-Varying lambda in Nelson-Siegel with AR (1)	0.1443

Fixed lambda in Svensson with AR (1)	0.0390
Time-Varying lambda in Svensson with AR (1)	443.9416

Table 3.4: RMSE for major maturities of yield curve at 1-month forecasting horizon

Maturities	Mean	Std. Dev.	RMSE
Fixed lambda in Nelson-Siegel with AR (1)			
1 Year	2.1641	0.4375	0.0081
2 Years	2.3441	0.4569	0.0210
3 Years	2.5947	0.4610	0.0290
5 Years	3.0456	0.4589	0.0474
10 Years	3.6377	0.4595	0.0713
Time-Varying lambda in Nelson-Siegel with AR (1)			
1 Year	2.3474	0.3994	0.0642
2 Years	2.5381	0.4357	0.0995
3 Years	2.7459	0.4540	0.1026
5 Years	3.1363	0.4627	0.1075
10 Years	3.8146	0.4154	0.2109
Fixed lambda in Svensson with AR (1)			
1 Year	2.2550	0.4223	0.0251
2 Years	2.4174	0.4323	0.0421
3 Years	2.6062	0.4448	0.0359
5 Years	2.9733	0.4682	0.0338
10 Years	3.6000	0.4574	0.0603
Time-Varying lambda in Svensson with AR (1)			
1 Year	-9.9286	4.2775	161.6067
2 Years	-16.7471	4.7825	382.8518
3 Years	-20.3889	4.0197	538.0470
5 Years	-22.7029	2.3745	662.6881
10 Years	-19.3354	4.8295	542.4400

Table 3.5: RMSE for entire yield curve at 6-month forecasting horizon

Model	RMSE
Fixed lambda in Nelson-Siegel with VAR (1)	0.0428
Time-Varying lambda in Nelson-Siegel with VAR (1)	0.1912
Fixed lambda in Svensson with VAR (1)	0.0398
Time-Varying lambda in Svensson with VAR (1)	6.7454

Table 3.6: RMSE for major maturities of yield curve at 6-month forecasting horizon

Maturities	Mean	Std. Dev.	RMSE
Fixed lambda in Nelson-Siegel with VAR (1)			
1 Year	2.0531	0.4931	0.0176
2 Years	2.2599	0.4997	0.0162
3 Years	2.5362	0.4901	0.0178
5 Years	3.0267	0.4660	0.0412
10 Years	3.6663	0.4405	0.0858
Time-Varying lambda in Nelson-Siegel with VAR (1)			
1 Year	2.2388	0.4624	0.0261
2 Years	2.4651	0.4691	0.0602
3 Years	2.7067	0.4664	0.0753
5 Years	3.1555	0.4532	0.1090
10 Years	3.9230	0.4060	0.3003
Fixed lambda in Svensson with VAR (1)			
1 Year	2.1193	0.4799	0.0100
2 Years	2.3179	0.4818	0.0188
3 Years	2.5372	0.4757	0.0163
5 Years	2.9493	0.4666	0.0311
10 Years	3.6319	0.4330	0.0740
Time-Varying lambda in Svensson with VAR (1)			
1 Year	5.2041	0.9806	10.7788
2 Years	5.2479	0.9817	10.3038
3 Years	5.2625	0.9821	9.2374
5 Years	5.2742	0.9824	7.2616
10 Years	5.2830	0.9826	5.1714

Table 3.7: RMSE for entire yield curve at 12-month forecasting horizon

Model	RMSE
Fixed lambda in Nelson-Siegel with VAR (1)	0.0439
Time-Varying lambda in Nelson-Siegel with VAR (1)	0.1974
Fixed lambda in Svensson with VAR (1)	0.0412
Time-Varying lambda in Svensson with VAR (1)	6.6872

Table 3.8: RMSE for major maturities of yield curve at 12-month forecasting horizon

Maturities	Mean	Std. Dev.	RMSE
Fixed lambda in Nelson-Siegel with VAR (1)			
1 Year	2.0517	0.4900	0.0174
2 Years	2.2605	0.4963	0.0162
3 Years	2.5385	0.4875	0.0181
5 Years	3.0312	0.4652	0.0429
10 Years	3.6732	0.4421	0.0888
Time-Varying lambda in Nelson-Siegel with VAR (1)			
1 Year	2.2376	0.4651	0.0266
2 Years	2.4659	0.4725	0.0594
3 Years	2.7099	0.4696	0.0761
5 Years	3.1631	0.4548	0.1122
10 Years	3.9368	0.4041	0.3116
Fixed lambda in Svensson with VAR (1)			
1 Year	2.1174	0.4759	0.0096
2 Years	2.3192	0.4782	0.0189
3 Years	2.5401	0.4729	0.0170
5 Years	2.9539	0.4661	0.0317
10 Years	3.6396	0.4367	0.0771
Time-Varying lambda in Svensson with VAR (1)			
1 Year	5.1933	1.0041	10.6942
2 Years	5.2370	1.0052	10.2127
3 Years	5.2516	1.0056	9.1492
5 Years	5.2633	1.0059	7.1982
10 Years	5.2720	1.0061	5.1238

According to the Table (3) – (8), it can be concluded that fixed lambda parameter in the model is the better method than varying lambda parameter in the model. Varying in lambda parameters is not the appropriate method for Svensson model. Because the lambda also affects to the slope and curvature factor in Nelson-Siegel formula. Error from forecasting in lambda will impact to the entire yield curve. Therefore, fixed lambda method is more appropriate in the case of prediction.

I compare Nelson-Siegel and Svensson that fix lambda parameter due to result in the last paragraph. RMSE for the entire yield curve from Svensson model less than Nelson-Siegel so that Svensson model is a better model in the overall term. However, Nelson-Siegel model is the better model for 2 years to maturity and 12-15 years to maturities. Svensson model has hump parameter. This parameter makes model more flexibility and less error in term of forecasting at overall.

I add more variables to increase forecasting power. The variable that I select for this study must affect the yield curve movement in the future. The movement of the yield curve can change by the risk associated with Treasury securities. Government issue treasury securities. Treasury securities are the most active in debt market. Therefore, there is no proxy for credit risk and liquidity risk. The remainder of risk associated is the domestic economic risk. I select Thailand's inflation to control variable. If expected inflation is upward, the market will force yield of long-term bond to increase. Therefore, the level of yield curve should have the positive correlation with inflation. Policymaker will increase policy rate to slow down the economic and prevent hyperinflation. Increasing the policy rate will step up the short-term interest rate so that slope and inflation should have the opposite sign of correlation. The model for forecasting is fixed lambda parameters in Nelson-Siegel and Svensson model due to the result of the first and second question. The forecasting method is VAR because VAR method can be added the other variables. The out-of-sample forecasting horizons is 6 months and 12 months.

$$\begin{bmatrix}\hat{\beta}_{1,t}\\ \hat{\beta}_{2,t}\\ \hat{\beta}_{3,t}\\ \hat{\beta}_{4,t}\end{bmatrix} = \begin{bmatrix}0.707\\ -0.693\\ -0.209\\ -0.888\end{bmatrix} + \begin{bmatrix}0.842 & 0.035 & -0.040 & 0.282\\ 0.137 & 0.843 & 0.144 & 0.140\\ 0.216 & 0.121 & 0.928 & 0.151\\ -0.103 & -0.230 & 0.010 & 0.797\end{bmatrix}\begin{bmatrix}\hat{\beta}_{1,t-1}\\ \hat{\beta}_{2,t-1}\\ \hat{\beta}_{3,t-1}\\ \hat{\beta}_{4,t-1}\end{bmatrix} + \begin{bmatrix}0.282\\ -0.245\\ 0.234\\ -0.085\end{bmatrix} Inflation_{t-1} \tag{16}$$

The equation (14) is the result of Svensson model with VAR (1). The period of data for regression is June 2003 to June 2015. The signs of coefficient among inflation, level, and slope parameter are the same as expected.

Table 3.9: RMSE for entire yield curve at 6-month forecasting horizon with VAR (1) and control variable

Model	RMSE
Nelson-Siegel with VAR (1) + control variable	0.0352
Svensson with VAR (1) + control variable	0.0322

Table 3.10: RMSE for major maturities of yield curve at 6-month forecasting horizon with VAR (1) and control variable

Maturities	Mean	Std. Dev.	RMSE
Nelson-Siegel with VAR (1) + control variable			
1 Year	2.0272	0.4995	0.0242
2 Years	2.2252	0.5096	0.0206
3 Years	2.4972	0.5026	0.0178
5 Years	2.9845	0.4819	0.0295
10 Years	3.6231	0.4597	0.0642
Svensson with VAR (1) + control variable			
1 Year	2.0891	0.4826	0.0118
2 Years	2.2779	0.4872	0.0176
3 Years	2.4928	0.4836	0.0152
5 Years	2.9019	0.4778	0.0263
10 Years	3.5836	0.4475	0.0544

Table 3.11: RMSE for entire yield curve at 12-month forecasting horizon with VAR (1) and control variable

Model	RMSE
Nelson-Siegel with VAR (1) + control variable	0.0351
Svensson with VAR (1) + control variable	0.0327

Table 3.12: RMSE for major maturities of yield curve at 6-month forecasting horizon with VAR (1) and control variable

Maturities	Mean	Std. Dev.	RMSE
Nelson-Siegel with VAR (1) + control variable			
1 Year	2.0231	0.5004	0.0247
2 Years	2.2222	0.5112	0.0205
3 Years	2.4954	0.5053	0.0171
5 Years	2.9846	0.4865	0.0300
10 Years	3.6254	0.4662	0.0641

Table 3.12: (Continued)

Maturities	Mean	Std. Dev.	RMSE
Svensson with VAR (1) + control variable			
1 Year	2.0841	0.4824	0.0119
2 Years	2.2752	0.4882	0.0172
3 Years	2.4913	0.4854	0.0147
5 Years	2.9021	0.4812	0.0266
10 Years	3.5866	0.4549	0.0551

The result in the Table (5) - (12) interpret that this inflation improves the forecasting power of Nelson-Siegel and Svensson model in the overall term. Adding inflation in Nelson-Siegel model does not improve accuracy when predicting yields of 1 year and 2 years to maturities. This control variable also does not help when predicting with Svensson model at 1 year and 4 years to maturities. Inflation variable can improve the forecasting power of yield curve when time to maturity is more than 5 years. In sum, the inflation contains information about bond market's force in long-term interest and can be used to increase forecasting power of both models.

CHAPTER 4
CONCLUSION

I predict the out-of-sample forecasting yield curve with Nelson-Siegel and Svensson model. I adopt dynamic formula of Nelson-Siegel model and fix lambda parameter method from Diebold and Li (2006). The benefit from using fixed lambda method are simplicity and stability. Typically, Nelson-Siegel can be varied lambda parameter, and its results are more accurate than results from fixed lambda method in term of in-sample estimation. I compare these two methods and found that fixed lambda parameter is more accurate in the case of out-of-sample forecasting. Error from forecasting lambda spread to other parameters such as level, slope, and curvature. I adapted fixed lambda method into the Svensson model. Svensson model is an extension model from original Nelson-Siegel model by adding hump parameter. The yield curve that plot with Svensson model can have more hump shape. Svensson model also has fewer sums of squared errors in term of in-sample estimation. I compared Nelson-Siegel model and Svensson model with fixed lambda method in the case of out-of-sample forecasting. Svensson model is more accurate than Nelson model in the overall term. For 6-month to 2-years of time to maturities, Nelson-Siegel is more accurate than Svensson model. In sum, Nelson-Siegel is better at some particular points of maturities, but Svensson model is better in the overall term. Hump parameter in Svensson model improves forecasting in the medium term of the yield curve. I added inflation as a control variable to forecasting model. Inflation variable can improve the forecasting power of yield curve when time to maturity is more than 5 years for Nelson-Siegel and Svensson model. Generally, yields of the long-term bond vary depending on market's perspective. The market will force yield higher if inflation is high, so inflation improves the accuracy of yield in long maturities.

In sum, the movement of the yield curve is not a random walk. We can forecast the yield curve with its lagged term. We can apply Nelson-Siegel and Svensson model with fixed lambda method to predict the yield curve. Policymaker can implement this forecasting to see the movement of long maturities. They can use this forecasting and fundamental data to manipulate policy rate which affects to fund flow in the country.

For the further research, I suggest finding a method that allows lambda to change over the time without losing stability of beta, adding control variable that increases the accuracy of forecasting model in short maturities and applying this method to the investment strategies.

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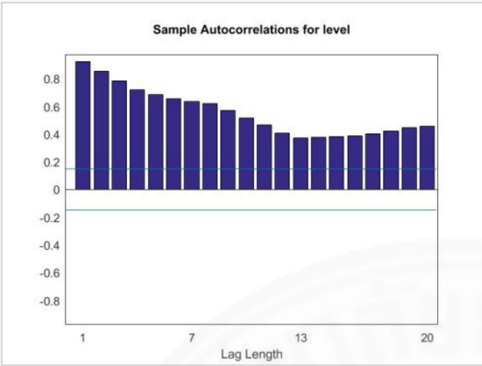
APPENDICES

APPENDIX A
OUT-OF-SAMPLE FORECASTING WITH AUTOREGRESSIVE MODEL

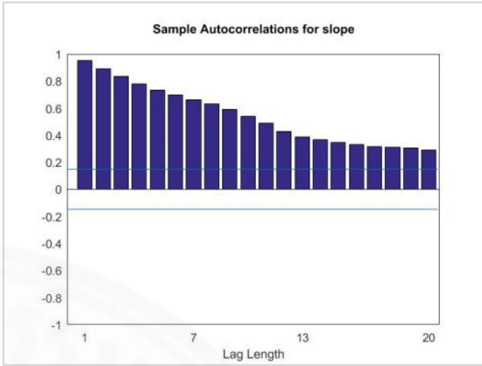
In this study is applied autoregressive model (AR) to forecast the yield curve. First, check the serial correlation among their lag term with autocorrelation function in figure (A.1). After that, identifying the number of lagging time for the autoregressive model with partial autocorrelation function in figure (A.2). Finally, plotting the forecasting result with 95% confidential interval and reality which is useful to determine suitable horizontal.

Figure A.1: Autocorrelation function for level, slope, curvature, hump, lambda1 and lambda2

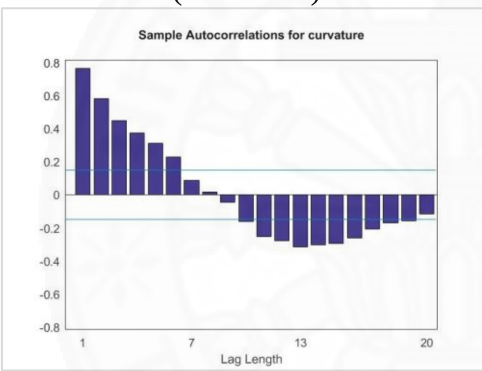
(level)



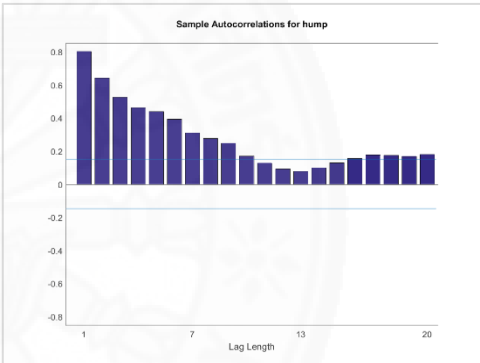
(Slope)



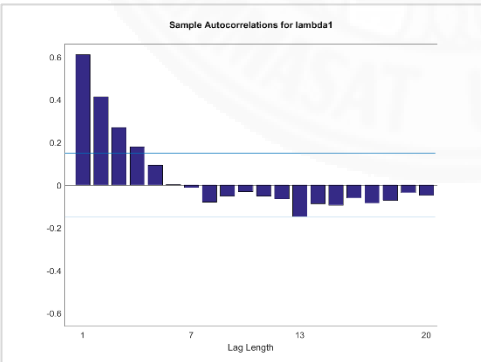
(Curvature)



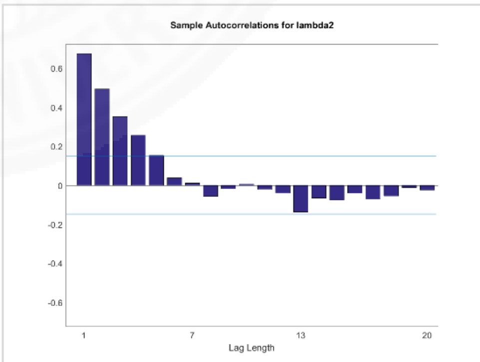
(Hump)



(lambda1)



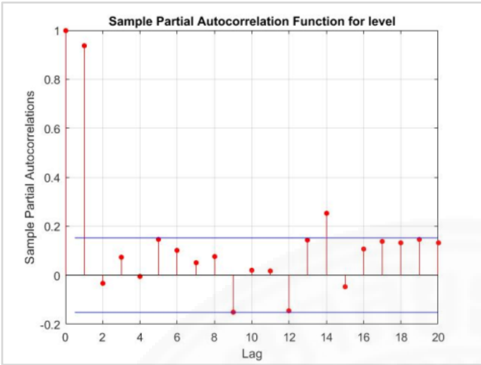
(lambda2)



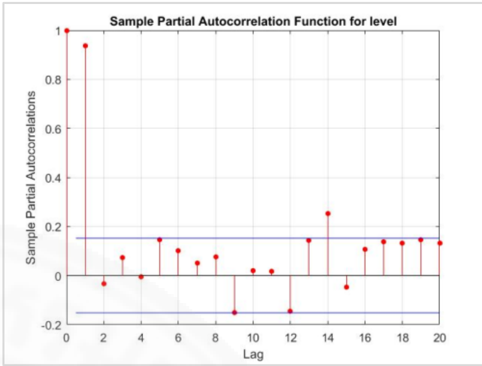
According to Figure (A.1), There are the dynamic correlation with their lagging term.

Figure A.2: Partial autocorrelation function for level, slope, curvature, hump, lambda1 and lambda2.

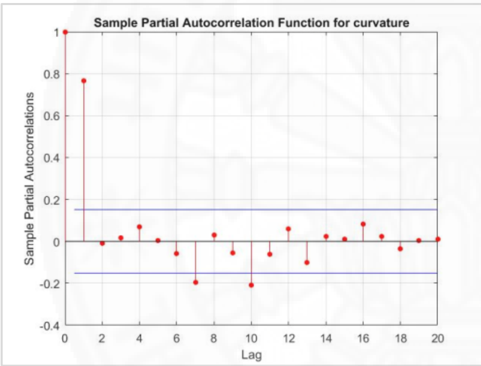
(level)



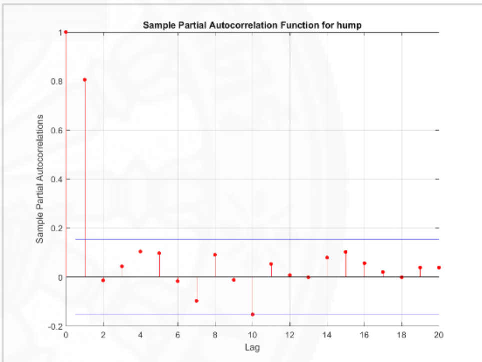
(Slope)



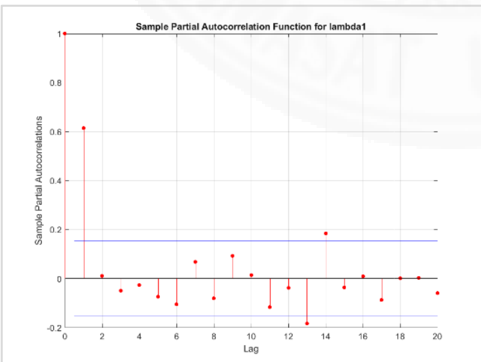
(Curvature)



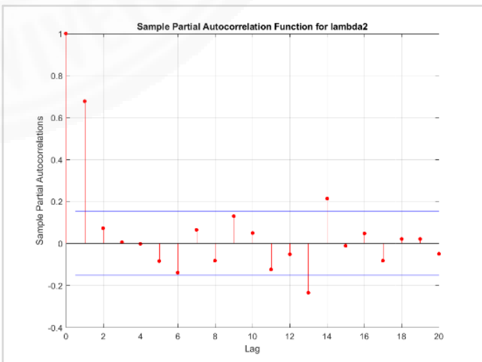
(Hump)



(lambda1)



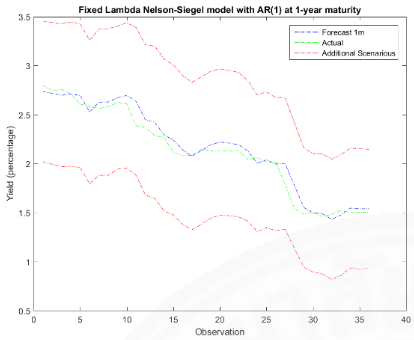
(lambda2)



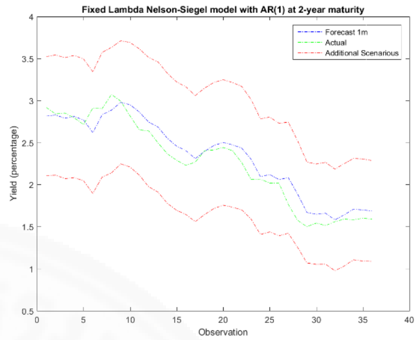
According to Figure (A.2), 1-period lagging term is appropriate.

Figure A.3: Forecasting result of fixed lambda parameter in Nelson-Siegel model for 1-month forecasting horizon

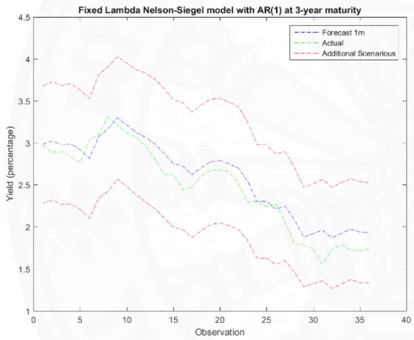
(1-year maturity)



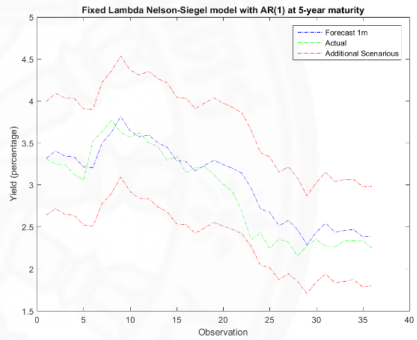
(2-year maturity)



(3-year maturity)



(5-year maturity)



(10-year maturity)

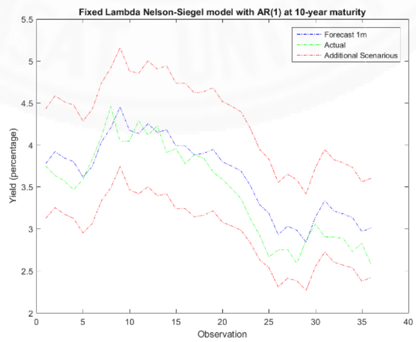
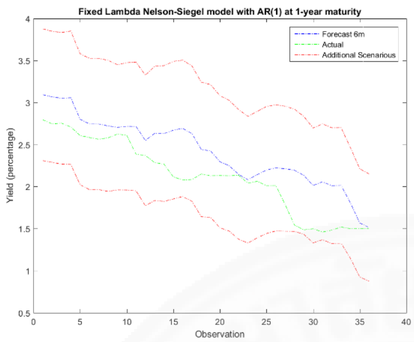
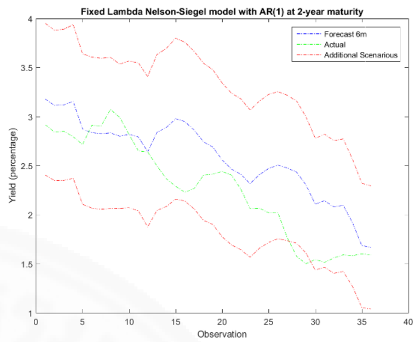


Figure A.4: Forecasting result of fixed lambda parameter in Nelson-Siegel model for 6-month forecasting horizon

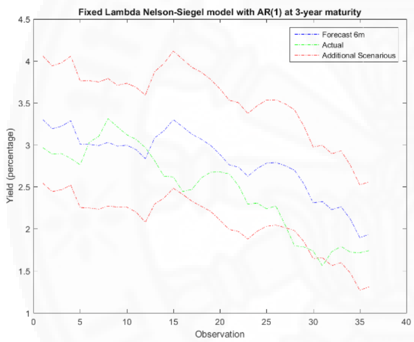
(1-year maturity)



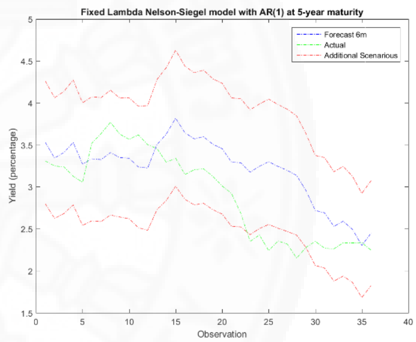
(2-year maturity)



(3-year maturity)



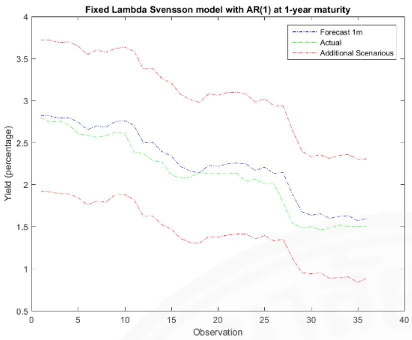
(5-year maturity)



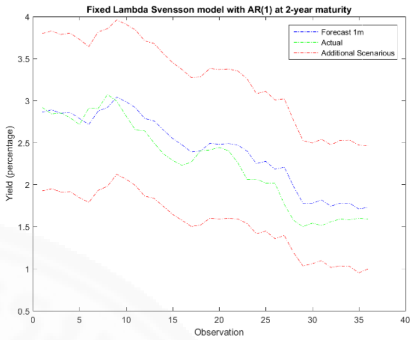
(10-year maturity)

Figure A.5: Forecasting result of fixed lambda parameter in Svensson model for 1-month forecasting horizon

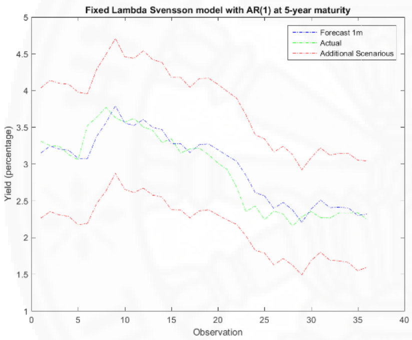
(1-year maturity)



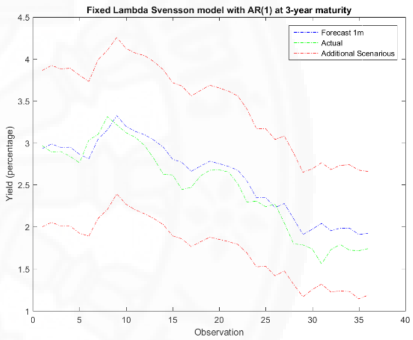
(2-year maturity)



(3-year maturity)



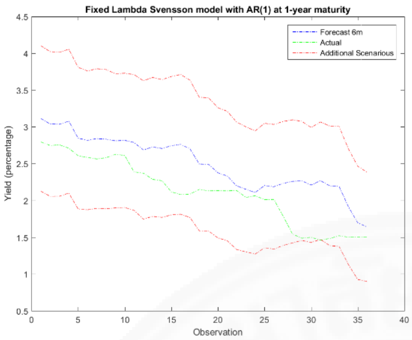
(5-year maturity)



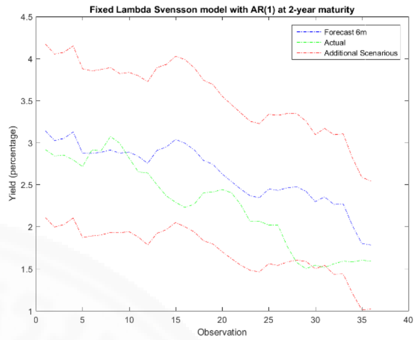
(10-year maturity)

Figure A.6: Forecasting result of fixed lambda parameter in Svensson model for 6-month forecasting horizon

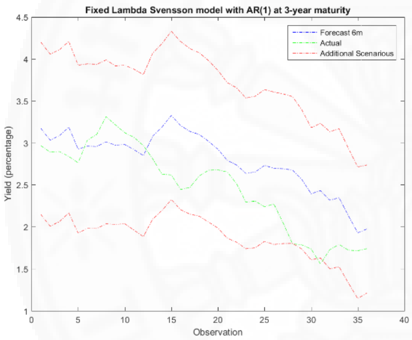
(1-year maturity)



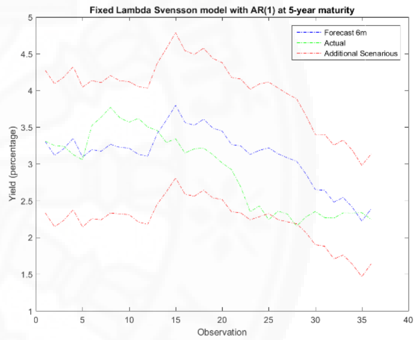
(2-year maturity)



(3-year maturity)



(5-year maturity)



(10-year maturity)

APPENDIX B
OUT-OF-SAMPLE FORECASTING WITH VECTOR AUTOREGRESSIVE MODEL

In this study is applied vector autoregressive model (VAR) to add more control variable into the forecasting model. As mention in the introduction, I add the proxy for the domestic economic risk in table (B.1). The global financial risks are included in table (B.2)

Table B.1: Example result from Svensson model with VAR (1). (1st parameter = level, 2nd parameter = slope, 3rd parameter = curvature, 4th parameter = hump, 5th parameter = inflation)

Parameter	Value	Std. Error	t-Statistic
Constant (1)	0.7067	0.2326	3.0385
Constant (2)	-0.6933	0.2397	-2.8921
Constant (3)	-0.2089	0.7828	-0.2669
Constant (4)	-0.8876	0.9436	-0.9407
Constant (5)	0.1416	0.0419	3.3809
1-Lag			
Coefficient (1,1)	0.8416	0.0547	15.3810
Coefficient (1,2)	0.0354	0.0491	0.7221
Coefficient (1,3)	-0.0403	0.0323	-1.2482
Coefficient (1,4)	-0.0546	0.0282	-1.9362
Coefficient (1,5)	0.2822	0.0868	3.2494
Coefficient (2,1)	0.1370	0.0564	2.4298
Coefficient (2,2)	0.8433	0.0506	16.6782
Coefficient (2,3)	0.1438	0.0333	4.3158
Coefficient (2,4)	0.1407	0.0291	4.8402
Coefficient (2,5)	-0.2460	0.0893	-2.7546
Coefficient (3,1)	0.2164	0.1842	1.1749
Coefficient (3,2)	0.1210	0.1651	0.7325
Coefficient (3,3)	0.9276	0.1088	8.5248
Coefficient (3,4)	0.1509	0.0949	1.5897
Coefficient (3,5)	0.2336	0.2905	0.8041
Coefficient (4,1)	-0.1027	0.2220	-0.4624
Coefficient (4,2)	-0.2299	0.1991	-1.1552
Coefficient (4,3)	0.0102	0.1312	0.0780
Coefficient (4,4)	0.7967	0.1144	6.9642
Coefficient (4,5)	-0.0851	0.3504	-0.2430
Coefficient (5,1)	0.0000		
Coefficient (5,2)	0.0000		
Coefficient (5,3)	0.0000		
Coefficient (5,4)	0.0000		
Coefficient (5,5)	0.3522	0.0818	4.3069

Table B.2: Example result from Svensson model with VAR (1). (1st parameter = level, 2nd parameter = slope, 3rd parameter = curvature, 4th parameter = hump, 5th parameter = inflation, 6th parameter = spread of 10 years and 2 years in US. Treasury, 7th parameter = VIX index)

Parameter	Value	Std. Error	t-Statistic
Constant (1)	0.7221	0.2842	2.5407
Constant (2)	-0.8898	0.3024	-2.9422
Constant (3)	-0.2221	1.0267	-0.2163
Constant (4)	-0.3161	1.2800	-0.2470
Constant (5)	0.1621	0.0430	3.7714
Constant (6)	0.0007	0.0173	0.0407
Constant (7)	-0.0374	0.4229	-0.0883
1-Lag			
Coefficient (1,1)	0.8713	0.0629	13.8473
Coefficient (1,2)	0.0499	0.0600	0.8317
Coefficient (1,3)	-0.0555	0.0350	-1.5853
Coefficient (1,4)	-0.0433	0.0275	-1.5763
Coefficient (1,5)	0.2697	0.1090	2.4748
Coefficient (1,6)	-0.1122	0.2502	-0.4485
Coefficient (1,7)	0.0059	0.0105	0.5587
Coefficient (2,1)	0.1223	0.0670	1.8265
Coefficient (2,2)	0.8208	0.0638	12.8624
Coefficient (2,3)	0.1468	0.0372	3.9439
Coefficient (2,4)	0.1116	0.0292	3.8195
Coefficient (2,5)	-0.2183	0.1155	-1.8893
Coefficient (2,6)	0.1817	0.2642	0.6875
Coefficient (2,7)	-0.0030	0.0111	-0.2717
Coefficient (3,1)	0.2977	0.2274	1.3090
Coefficient (3,2)	0.2873	0.2167	1.3259
Coefficient (3,3)	0.7456	0.1264	5.8966
Coefficient (3,4)	0.0493	0.0993	0.4971
Coefficient (3,5)	0.2636	0.3930	0.6708
Coefficient (3,6)	-0.1460	0.8876	-0.1645
Coefficient (3,7)	-0.0500	0.0374	-1.3359
Coefficient (4,1)	-0.3008	0.2835	-1.0609
Coefficient (4,2)	-0.3987	0.2701	-1.4757
Coefficient (4,3)	0.2701	0.1576	1.7134
Coefficient (4,4)	0.9377	0.1237	7.5779
Coefficient (4,5)	-0.0527	0.4902	-0.1076

Table A.14: (Continued)

Parameter	Value	Std. Error	t-Statistic
Coefficient (4,6)	0.3031	1.1058	0.2741
Coefficient (4,7)	0.0316	0.0466	0.6779
Coefficient (5,1)	0.0000		
Coefficient (5,2)	0.0000		
Coefficient (5,3)	0.0000		
Coefficient (5,4)	0.0000		
Coefficient (5,5)	0.3152	0.0814	3.8708
Coefficient (5,6)	0.0000		
Coefficient (5,7)	0.0000		
Coefficient (6,1)	0.0000		
Coefficient (6,2)	0.0000		
Coefficient (6,3)	0.0000		
Coefficient (6,4)	0.0000		
Coefficient (6,5)	0.0000		
Coefficient (6,6)	0.0942	0.0857	1.0989
Coefficient (6,7)	-0.0002	0.0036	-0.0685
Coefficient (7,1)	0.0000		
Coefficient (7,2)	0.0000		
Coefficient (7,3)	0.0000		
Coefficient (7,4)	0.0000		
Coefficient (7,5)	0.0000		
Coefficient (7,6)	0.2287	2.0740	0.1103
Coefficient (7,7)	0.0456	0.0864	0.5278

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