

# Calibration of the Svensson model to simulated yield curves

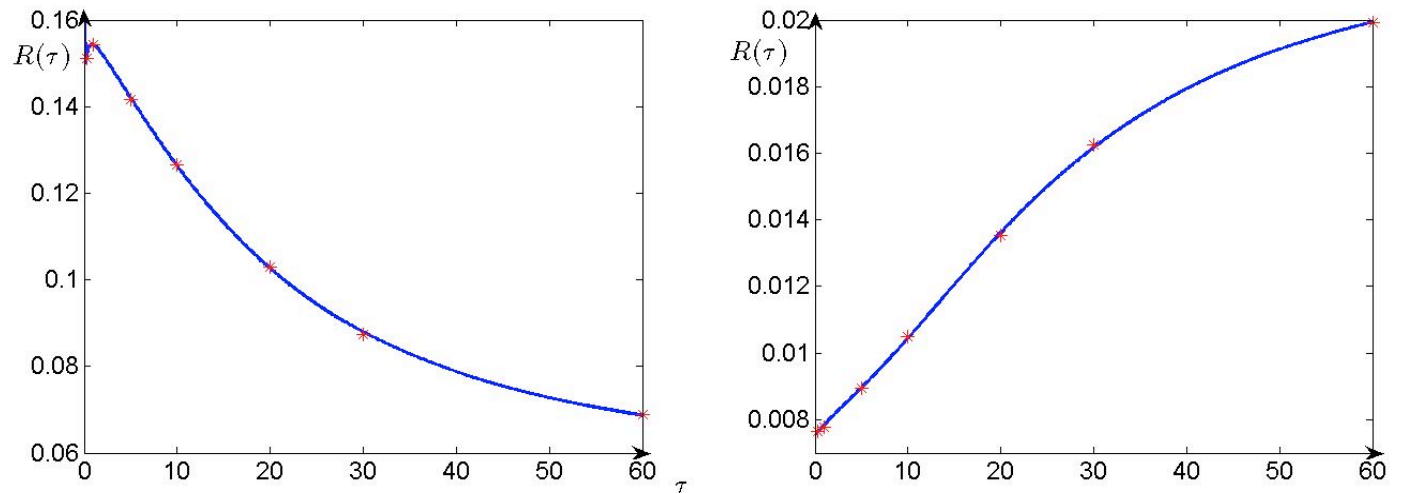
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# Calibration of the Svensson model to simulated yield curves

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# Introduction

## Notation



- $T$  is the time of maturity,  $t$  is the current time,  $\tau = T - t$  the time to maturity.
- $P(t, T)$  is the price of a zero coupon bond at time  $t$  with maturity  $T$ .
- $R(t, T) = -\frac{1}{\tau} \ln(P(t, T))$  is the zero rate.
- $f(t, T) = -\frac{\partial}{\partial T} \ln(P(t, T))$  is the instantaneous forward rate.

# Introduction

## Problem formulation

*Aim: approximate the given discrete yield curve by a continuous function, which is defined over the entire maturity domain ( $\tau \geq 0$ ).*

⇒ Parametric models, which assume for the instantaneous forward rate:

$$\hat{f}(\tau) = \sum_{i=1}^K \alpha_i \varphi_i(\beta_i, \tau).$$

By integration this gives the approximation of the zero rates:

$$\hat{R}(\tau) = \frac{1}{\tau} \left( \sum_{i=1}^K \alpha_i \int_t^T \varphi_i(\beta_i, s) ds \right).$$

The corresponding parameters  $\alpha_i$  and  $\beta_i$  can be determined by solving the following minimization problem:

$$\sum_{j=1}^J \left( R(\tau_j) - \hat{R}(\tau_j) \right)^2 \longrightarrow \min.$$

Where  $R(\tau_j)$  are the given zero rates for  $\tau_j$ , with  $j = \{1, \dots, J\}$ .

# Fitting of yield curves

## The Nelson and Siegel method (1987)

Assume the following functional form for the instantaneous forward rate:

$$\hat{f}(\tau) = \alpha_0 + \alpha_1 \exp\left(-\frac{\tau}{\beta_1}\right) + \alpha_2 \left(\frac{\tau}{\beta_1} \exp\left(-\frac{\tau}{\beta_1}\right)\right).$$

Integration leads to:

$$\hat{R}(\tau) = \alpha_0 + \alpha_1 \left(\frac{1 - \exp\left(-\frac{\tau}{\beta_1}\right)}{\frac{\tau}{\beta_1}}\right) + \alpha_2 \left(\frac{1 - \exp\left(-\frac{\tau}{\beta_1}\right)}{\frac{\tau}{\beta_1}} - \exp\left(-\frac{\tau}{\beta_1}\right)\right).$$

- $\alpha_0 > 0$  is the long term zero rate.
- $\alpha_0 + \alpha_1 > 0$  is the short rate.  
Hence  $\alpha_1$  represents the deviation from the asymptote  $\alpha_0$ .
- $\alpha_2$  determines the height and direction of the hump.
- $\beta_1 > 0$  determines the position of the hump.

# Fitting of yield curves

## The Svensson method (1994)

Extension of the Nelson and Siegel model, which improves the flexibility of the curves.

$$\hat{f}(\tau) = \alpha_0 + \alpha_1 \exp\left(-\frac{\tau}{\beta_1}\right) + \alpha_2 \left(\frac{\tau}{\beta_1} \exp\left(-\frac{\tau}{\beta_1}\right)\right) + \alpha_3 \left(\frac{\tau}{\beta_2} \exp\left(-\frac{\tau}{\beta_2}\right)\right).$$

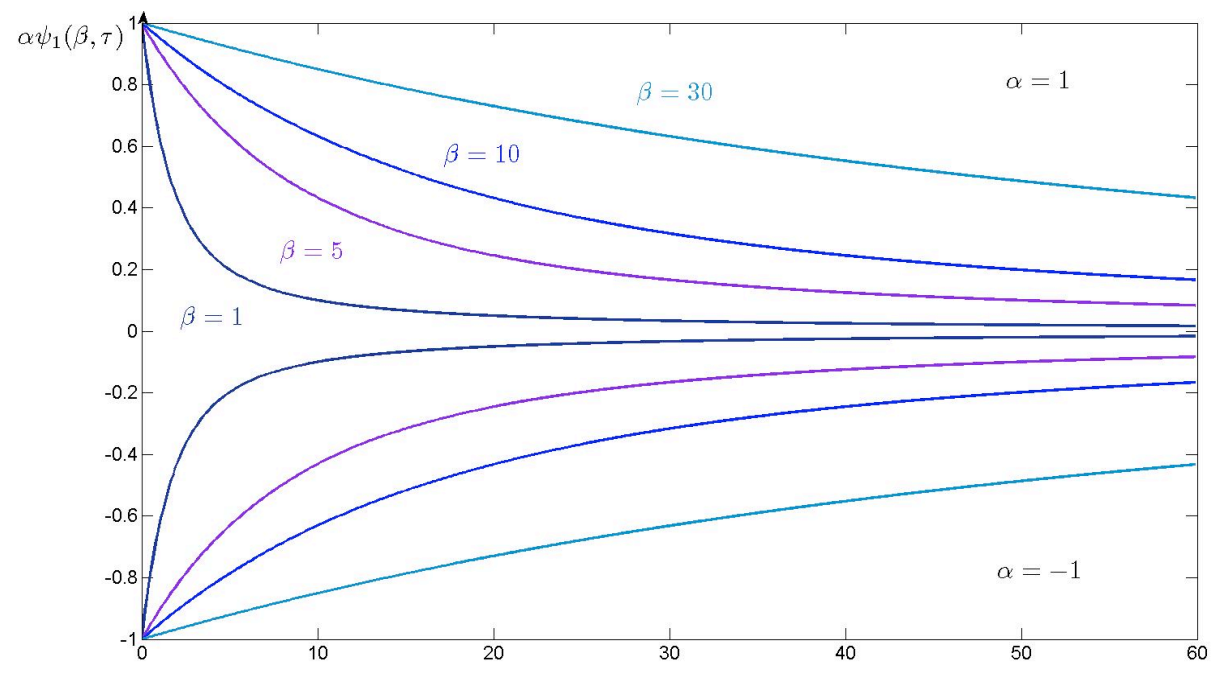
$$\begin{aligned} \hat{R}(\tau) = & \alpha_0 + \alpha_1 \left( \frac{1 - \exp\left(-\frac{\tau}{\beta_1}\right)}{\frac{\tau}{\beta_1}} \right) + \\ & \alpha_2 \left( \frac{1 - \exp\left(-\frac{\tau}{\beta_1}\right)}{\frac{\tau}{\beta_1}} - \exp\left(-\frac{\tau}{\beta_1}\right) \right) + \alpha_3 \left( \frac{1 - \exp\left(-\frac{\tau}{\beta_2}\right)}{\frac{\tau}{\beta_2}} - \exp\left(-\frac{\tau}{\beta_2}\right) \right). \end{aligned}$$

The new parameters  $\alpha_3$  and  $\beta_2 > 0$  determine the height, direction and position of the second hump.

# The Svensson method

The different components of  $\hat{R}(\tau) = \sum_{i=0}^4 \alpha_i \psi_i(\beta_i, \tau)$  are:

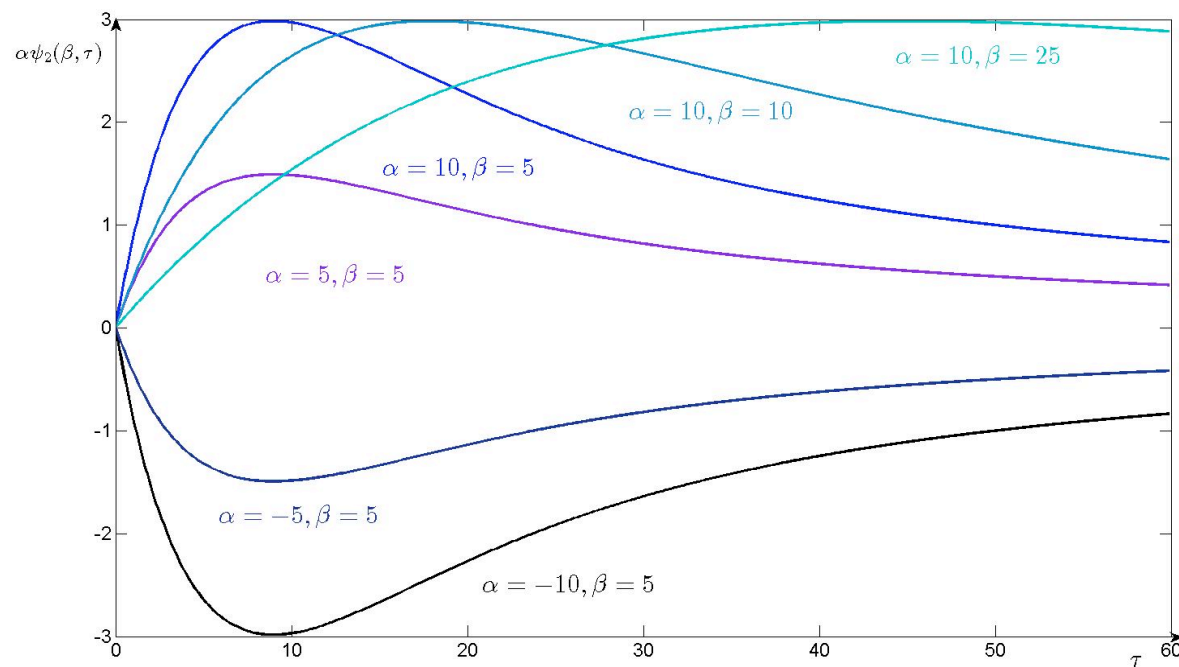
- $\alpha \psi_0(\beta, \tau) = \alpha$
- $\alpha \psi_1(\beta, \tau) = \alpha \left( \frac{1 - \exp(-\frac{\tau}{\beta})}{\frac{\tau}{\beta}} \right)$



# The Svensson method

The different components of  $\hat{R}(\tau) = \sum_{i=0}^4 \alpha_i \psi_i(\beta_i, \tau)$  are:

- $\alpha \psi_2(\beta, \tau) = \alpha \left( \frac{1 - \exp\left(-\frac{\tau}{\beta}\right)}{\frac{\tau}{\beta}} - \exp\left(-\frac{\tau}{\beta}\right) \right)$





# Calibration of the Svensson model

## Formulation of the optimization problem

We determine the parameters  $\alpha \in \mathbb{R}^4$  and  $\beta \in \mathbb{R}^2$  by minimization of the objective function

$$F(\alpha, \beta) = \sum_{j=1}^J \left( R(\tau_j) - \hat{R}(\tau_j) \right)^2.$$

This can be written as the following minimization problem:

$$\min_{(\alpha, \beta) \in \mathbb{R}^4 \times \mathbb{R}^2} F(\alpha, \beta)$$

$$s.t. \quad \alpha_0, \beta_1, \beta_2 \geq \epsilon$$

$$\alpha_0 + \alpha_1 \geq \epsilon.$$

To ensure reasonable solutions one can introduce box-constraints:

$$(\alpha, \beta) \in G = \{(\alpha, \beta) \in \mathbb{R}^6 : lb \leq (\alpha, \beta) \leq ub\}.$$

For example:

$$lb = [\epsilon, -1, -10, -10, \epsilon, \epsilon]$$

$$ub = [1, 10, 10, 10, 50, 50].$$

# Calibration of the Svensson model

Traditional method to solve the optimization problem

To solve the following nonlinear optimization problem:

$$\begin{aligned} \min_{(\alpha, \beta) \in \mathbb{R}^4 \times \mathbb{R}^2} \quad & F(\alpha, \beta) \\ \text{s.t.} \quad & A\alpha \leq b \\ & lb \leq (\alpha, \beta) \leq ub \end{aligned}$$

one can use `fmincon` in Matlab which is local convergent.

- we need a good starting point.
- the solution might be a local minimum.

Therefore we will improve bad solutions by using a global method.

1. Which are “bad” solutions?
2. Which global method is appropriate?

# Calibration of the Svensson model

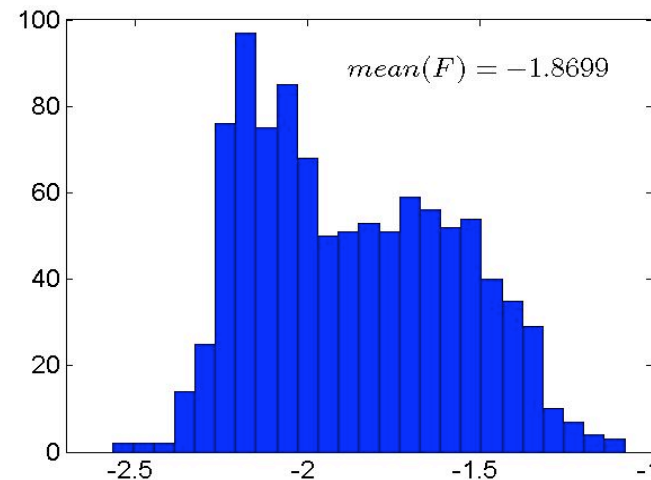
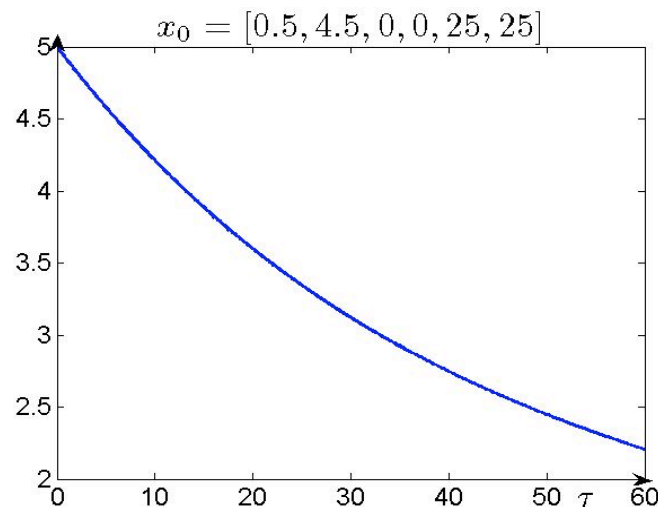
Traditional method to solve the optimization problem

Some thoughts about the starting point:

1st idea:

$$x_0 = \frac{lb + ub}{2} = (0.5, 4.5, 0, 0, 25, 25)$$

this leads to the following yield curve and solutions of `fmincon` over 1000 scenarios with 7 given times to maturity:

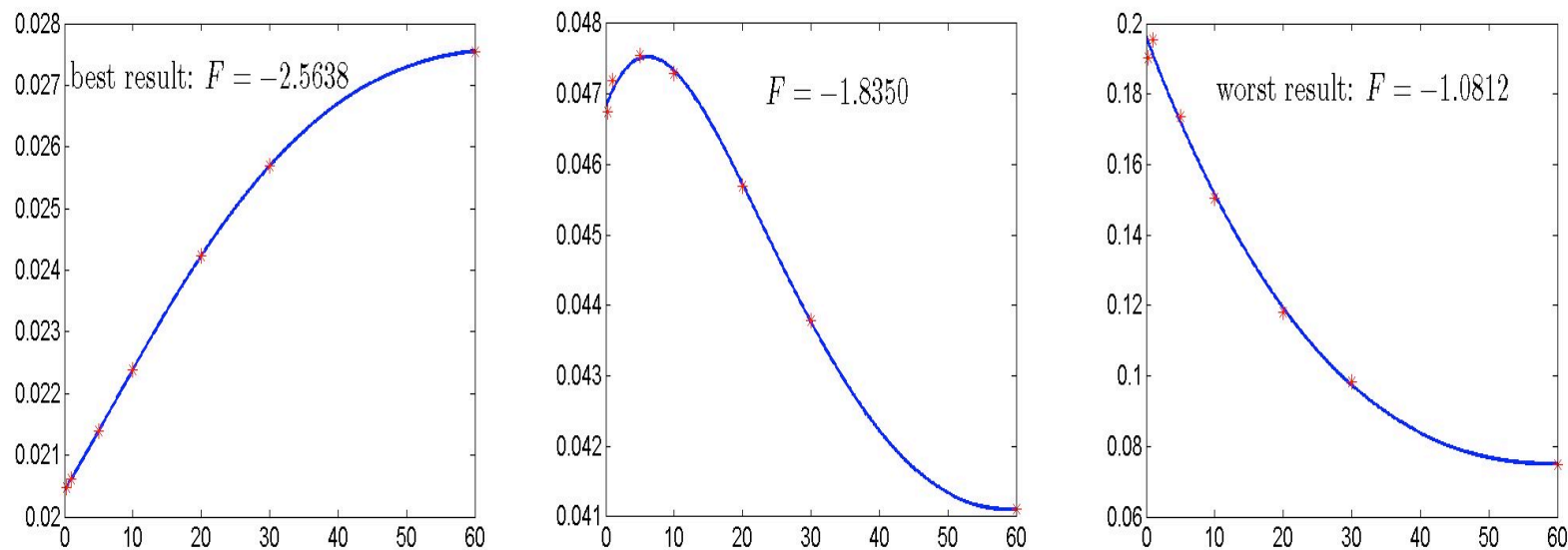


The objective value is  $F = \log_{10}(\sqrt{f})$ , where  $f = \sum_{j=1}^J \left( R(\tau_j) - \hat{R}(\tau_j) \right)^2$ .

# Calibration of the Svensson model

Traditional method to solve the optimization problem

Some examples of the solutions with this starting point:



The 1st figure shows the best result, the 2nd shows one with an average objective value and the 3rd shows the worst result.

# Calibration of the Svensson model

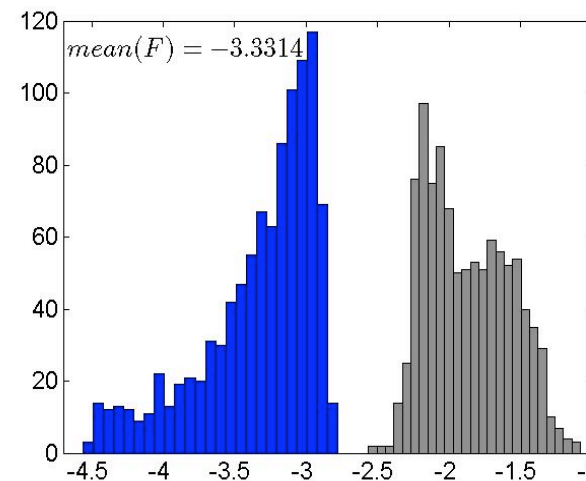
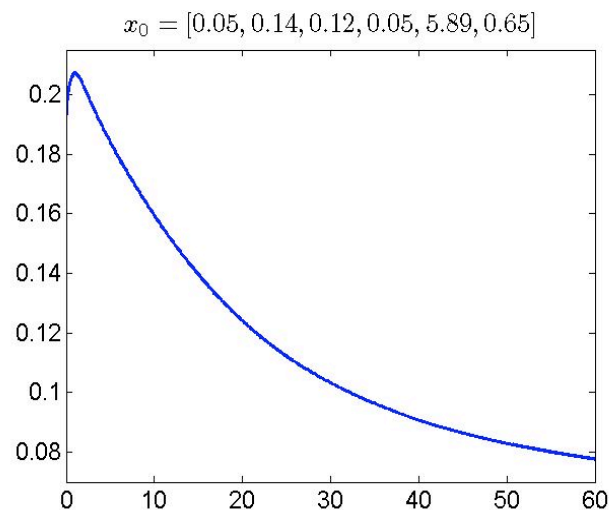
Traditional method to solve the optimization problem

Some thoughts about the starting point:

2nd idea:

$$x_0 = (0.0512, 0.1422, 0.1217, 0.0538, 5.8940, 0.6510)$$

this leads to the following yield curve and solutions of `fmincon` over 1000 scenarios:

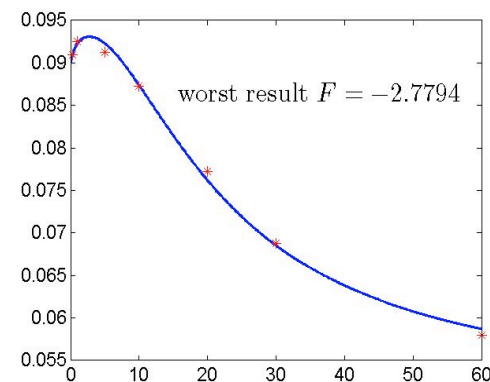
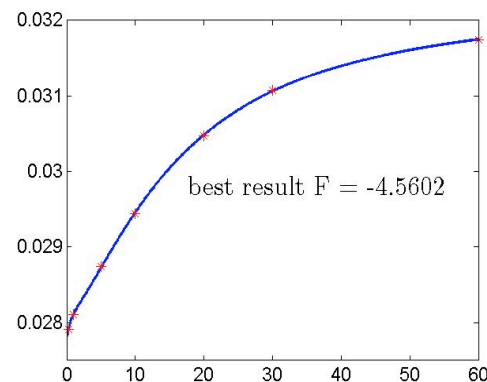


The computation time is reduced by 80%, the average objective value is improved by 1.46.

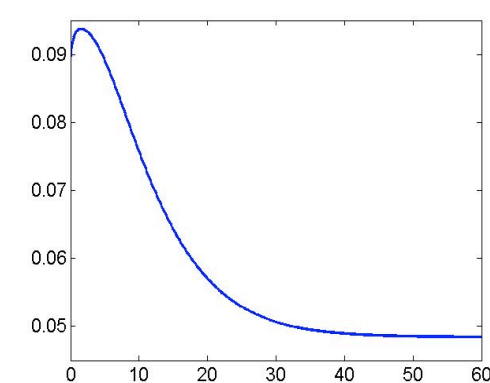
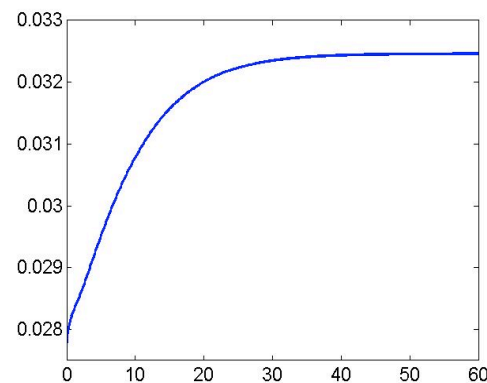
# Calibration of the Svensson model

Results of the optimization with `fmincon`.

The best and worst solutions of the optimization with the 2nd starting point are:



The corresponding instantaneous forward rates are:



# Calibration of the Svensson model

## Improvement by global optimization

We use an adaptive, iterative method which is based on the HCP algorithm (Novak, Ritter 1995) and uses sparse grids.

Advantages and disadvantages of this method:

- converges to the global minimum of the objective function.
- the objective function must (only) be in  $C^0(G)$ .
- slow for difficult objective functions and high dimensional problems.

As this method is too slow for our application we have to reformulate the optimization problem.

# Calibration of the Svensson model

## Reformulation of the problem: splitting

The original optimization problem

$$\begin{aligned} \min_{(\alpha, \beta) \in \mathbb{R}^4 \times \mathbb{R}^2} \quad & F(\alpha, \beta) \\ \text{s.t.} \quad & A\alpha \leq b \\ & lb \leq (\alpha, \beta) \leq ub. \end{aligned}$$

is equivalent to the nondifferentiable problem

$$\begin{aligned} \min_{\beta \in \mathbb{R}^2} \quad & H(\beta) \\ \text{s.t.} \quad & lb \leq \beta \leq ub. \end{aligned}$$

Where H is the following optimization problem:

$$\begin{aligned} H(\beta) = \min_{\alpha \in \mathbb{R}^4} \quad & F(\alpha, \beta) \\ \text{s.t.} \quad & A\alpha \leq b \\ & lb \leq \alpha \leq ub. \end{aligned}$$



# Calibration of the Svensson model

## Reformulation of the problem: splitting

We solve

$$\begin{aligned} \min_{\beta \in \mathbb{R}^2} \quad & H(\beta) \\ \text{s.t.} \quad & lb \leq \beta \leq ub \end{aligned}$$

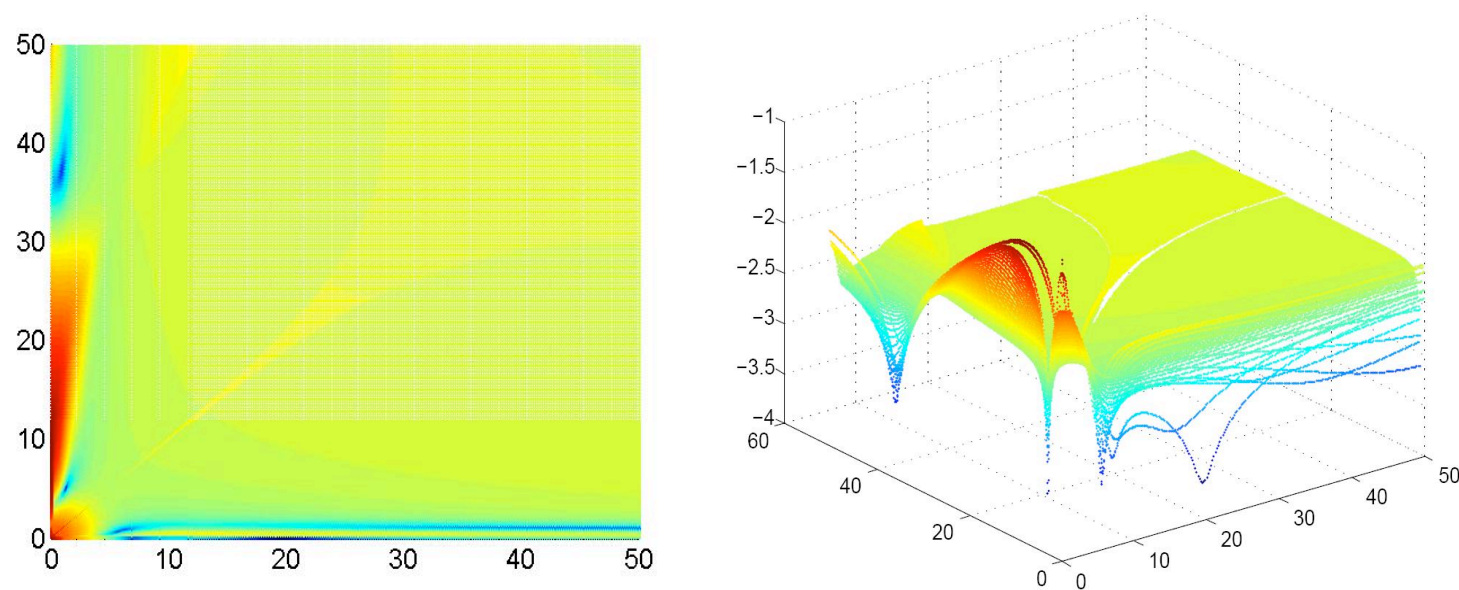
where  $lb = [\epsilon, \epsilon]$  and  $ub = [50, 50]$  with the global optimization algorithm.

- global optimization on two parameters is much faster than in six parameters.
- the evaluation of the objective function takes longer (one easy minimization problem per evaluation).

# Calibration of the Svensson model

## Reformulation of the problem: splitting

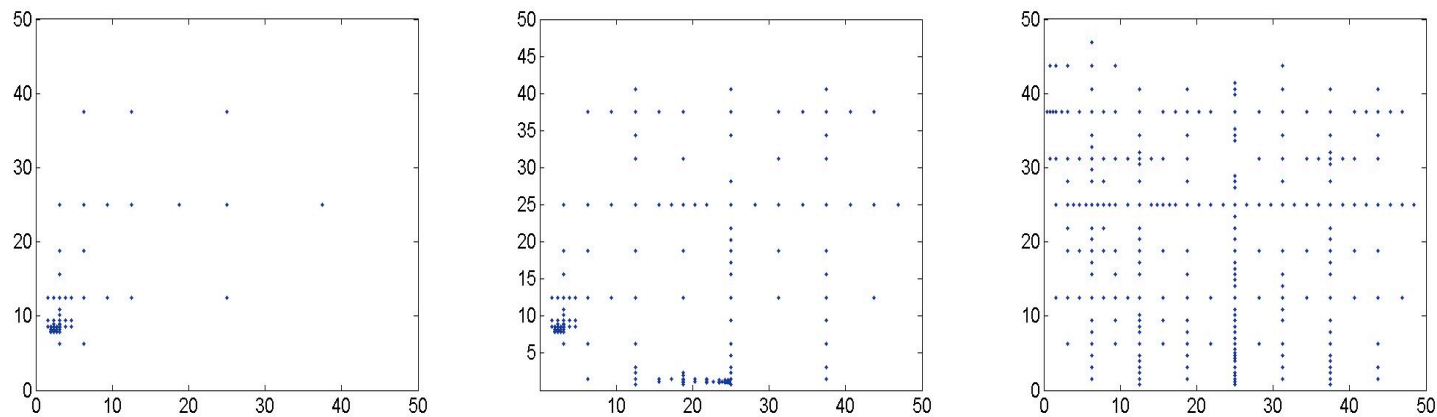
The objective values of the new objective function  $H(\beta)$  are:



# Calibration of the Svensson model

## Reformulation of the problem:splitting

The global optimization of the 2 dimensional problem yields

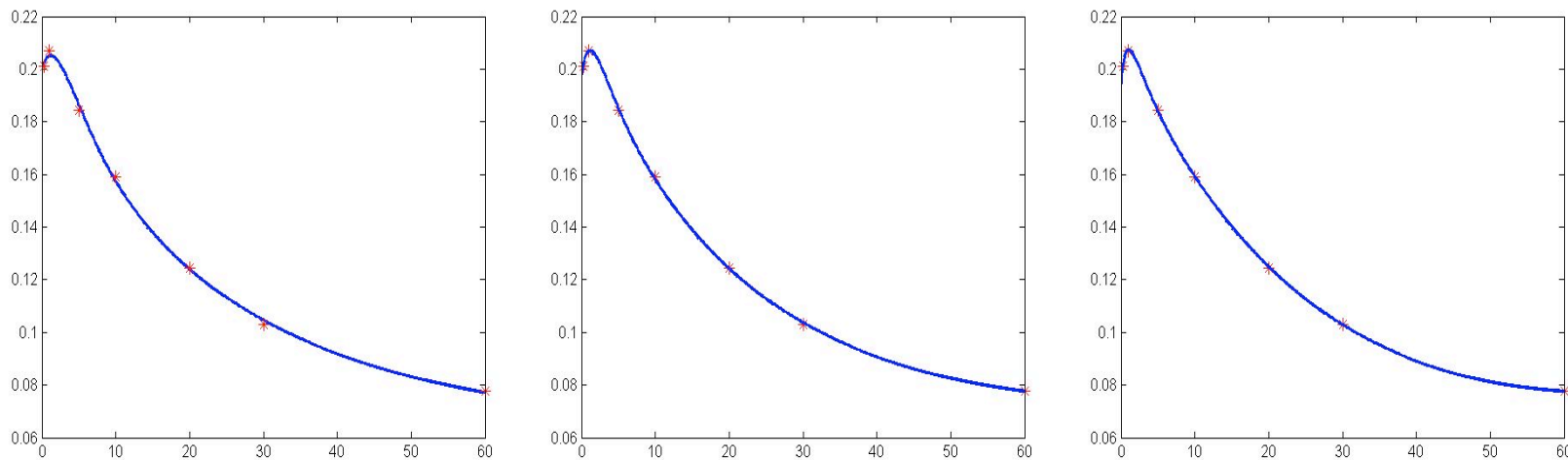


adaptiveness	#points	time (sec.)	objective value	minimizer
0.5	100	5	-2.3824	[2.3533, 7.8210]
0.3	150	8	-2.7723	[24.8097, 1.1816]
0.1	250	14	-3.1283	[0.7911, 37.5025]

# Calibration of the Svensson model

## Reformulation of the problem:splitting

The corresponding yield curves for this problem are:



The objective values are -2.3824, -2.7723 and -3.1283.

# Calibration of the Svensson model

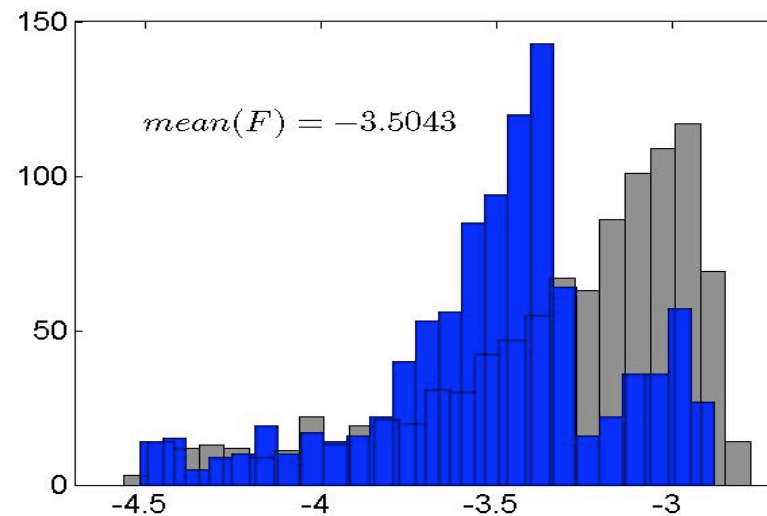
Variable-transformation: polar coordinates

Idea: introduce polar coordinates for the  $\beta$ 's:

$$\begin{aligned} \min_{\gamma \in \mathbb{R}^2} \quad & H(\gamma) \\ \text{s.t.} \quad & lb \leq \gamma \leq ub. \end{aligned}$$

Where  $\gamma_1 = \sqrt{\beta_1^2 + \beta_2^2}$  and  $\gamma_2 = \arccos\left(\frac{\beta_1}{\rho}\right)$  and  $lb = [\epsilon, -3], ub = [\frac{\pi}{2}, 8]$ .

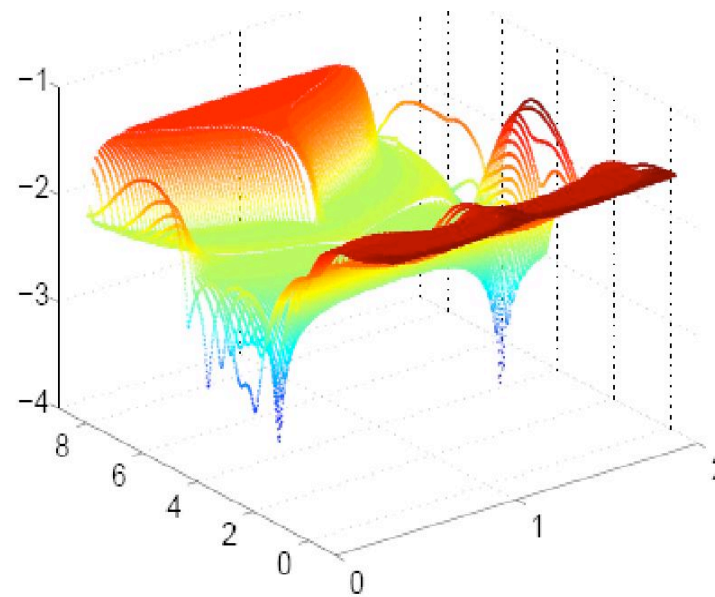
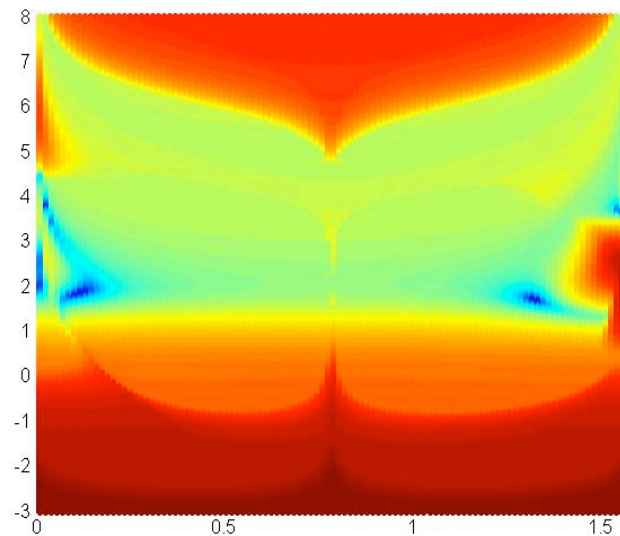
The minimization over all parameters yields an improvement of 0.1729:



# Calibration of the Svensson model

Variable-transformation: polar coordinates

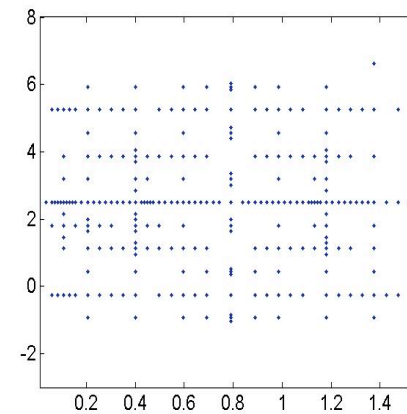
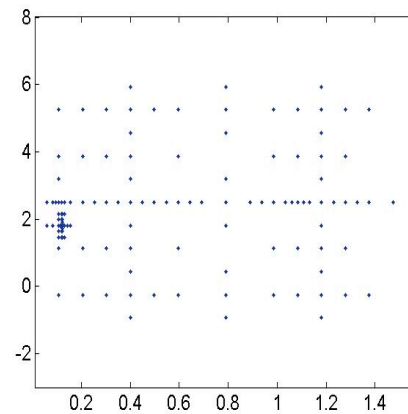
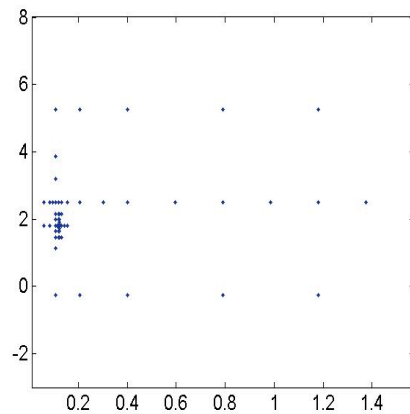
The objective values of  $H(\gamma)$  are:



# Calibration of the Svensson model

## Results of the global optimization

As expected, the global algorithm performs better:



adaptiveness	#points	time (sec.)	objective value	minimizer
0.5	100	5	-2.3824	[2.3533, 7.8210]
0.3	150	8	-2.7723	[24.8097, 1.1816]
0.1	250	14	-3.1283	[0.7911, 37.5025]
0.5	100	4	-3.3526	[0.1213, 1.8125]
0.3	150	7	-3.3526	[0.1213, 1.8125]
0.1	250	14	-3.1122	[0.1075, 1.8125]

# Calibration of the Svensson model

## New objective function

We take another look at the original objective function:

$$F(\alpha, \beta) = \sum_{j=1}^J \left( R(\tau_j) - \hat{R}(\tau_j) \right)^2$$

where  $\alpha \in \mathbb{R}^4$  and  $\beta \in \mathbb{R}^2$ .

this is equivalent to

$$F^*(\alpha, \beta) = \sqrt{\sum_{j=1}^J \left( R(\tau_j) - \hat{R}(\tau_j) \right)^2}.$$

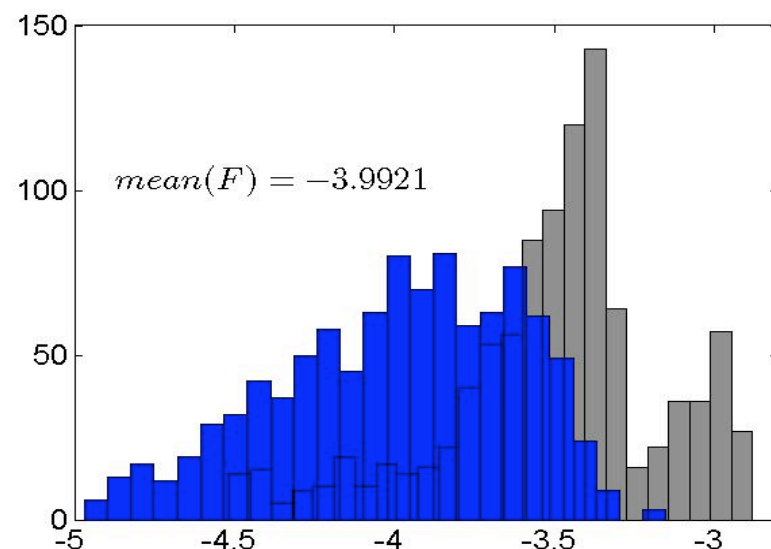
This objective function has the effect that `fmincon` makes more iterations, whereas the behavior of the global method is not influenced.



# Calibration of the Svensson model

## New objective function

The minimization of  $F^*$  over all parameters with `fmincon` yields an improvement of 0.4878:



The figures show the results of `fmincon` for polar coordinates.

# Calibration of the Svensson model

## Algorithm

The previous considerations lead to the following algorithm:

for each time step and each scenario do

1. minimize  $F^*(\alpha, \gamma)$  over all parameters with fmincon;
2. if the solution is below a certain threshold:
  - 2.1 minimize  $H(\gamma)$  ( $\gamma \in \mathbb{R}^2$ ) with the global algorithm;  
 $x^*$  is the minimizer of  $H$ ;
  - 2.2 minimize  $F^*(\alpha, \gamma)$  with fmincon;  
use  $x^*$  as the starting point;

# Calibration of the Svensson model

## Summary of the results

We calibrated the svensson model for 1000 scenarios and one time step. The global algorithm was adaptive and used at most 100 points.

For cartesian coordinates:

	min	mean	max	time (sec.)
after step 1	-4.9443	-3.9417	-3.3351	90
after step 2.1.	-4.9443	-3.8862	-2.3824	721
after step 2.2.	-4.9443	-3.9696	-3.3584	8
total change	-	0.0279	0.0233	819

For polar coordinates:

	min	mean	max	time (sec.)
after step 1	-4.9691	-3.9921	-3.1508	92
after step 2.1.	-4.9691	-3.9451	-2.7187	715
after step 2.2.	-4.9691	-3.9939	-3.3351	10
total change	-	0.0018	0.1843	817