


Supplementary Materials: Out-of-sample prediction in multidimensional P-spline models

Alba Carballo ^{1,†}, María Durbán ^{1,†}  and Dae-Jin Lee ^{2,†,*} 

Proof of Theorem 1

Differentiating Eq. (12) in the main text with respect to θ_+ leads to

$$\frac{\partial S}{\partial \theta_+} = -2B'_+ \tilde{R}_+^{-1} (y_+ - B_+ \theta_+) + 2(\lambda_z P_{++}^z + \lambda_x P_{++}^{x+}) = 0$$

i.e., the penalized least squares solution is given by:

$$\hat{\theta}_+ = (B'_+ \tilde{R}_+^{-1} B_+ + \lambda_z P_{++}^z + \lambda_x P_{++}^{x+})^{-1} B'_+ \tilde{R}_+^{-1} y_+. \quad (1)$$

Let us define $C = (B'_+ \tilde{R}_+^{-1} B_+ + \lambda_z P_{++}^z + \lambda_x P_{++}^{x+})$ and $C^{-1} = \begin{bmatrix} C^{11} & C^{12} \\ C^{21} & C^{22} \end{bmatrix}$, with this notation and since $\tilde{R}_+^{-1} = \tilde{R}_{x_+}^{-1} \otimes \tilde{R}_z^{-1} = \text{blockdiag}(I, O)$, with I an identity matrix of dimension $n_x n_z \times n_x n_z$ and O a null matrix of dimension $n_{x_p} n_z \times n_{x_p} n_z$, equation (1) can be rewritten as

$$\theta_+ = C^{-1} B'_+ \tilde{R}_+^{-1} y_+ = \begin{bmatrix} C^{11} B'_+ y \\ C^{21} B'_+ y \end{bmatrix}. \quad (2)$$

If $C = \begin{bmatrix} C_{11} & C_{12} \\ C_{21} & C_{22} \end{bmatrix}$, by Theorem 8.5.11 given in [1] we have that:

$$C^{-1} = \begin{bmatrix} K^{-1} & -K^{-1} C_{12} C_{22}^{-1} \\ -C_{22}^{-1} C_{21} K^{-1} & C_{22}^{-1} + C_{22}^{-1} C_{21} K^{-1} C_{12} C_{22}^{-1} \end{bmatrix},$$

with $K = C_{11} - C_{12} C_{22}^{-1} C_{21}$. Therefore:

$$C^{11} = K^{-1} = \left(B'_+ B + \lambda_x P_{++}^{x+} + \lambda_z P_{++}^z - \lambda_x^2 P_{++}^{x+} (\lambda_x P_{++}^{x+} + \lambda_z P_{++}^z)^{-1} P_{++}^{x+} \right)^{-1}$$

and

$$\begin{aligned} C^{21} &= -C_{22}^{-1} C_{21} K^{-1} \\ &= -(\lambda_x P_{++}^{x+} + \lambda_z P_{++}^z)^{-1} \lambda_x P_{++}^{x+} C^{11} \end{aligned}$$

and by equation (2) the coefficients for the fit and for the prediction are given by equations (18) and (19) in the main text, respectively, as we wanted to show.

Proof Colloraly 1

Notice that if $P_{++}^z = O$, by Eq. (18), the coefficients that give the fit are:

$$\hat{\theta}_{+1,\dots,c} = (B'_+ B + \lambda_x (D'_x D_x \otimes I_{c_z}) + \lambda_z (I_{c_x} \otimes D'_z D_z))^{-1} B'_+ y,$$

i.e., the same as the coefficients we obtain only fitting the data without a prediction. Let us see which are the coefficients that determine the forecast when the penalty orders are two or three.

- Differences of order 2.

Suppose a difference matrix with second order penalty D_{x_+} of dimensions $(c_{x_+} - 2) \times c_{x_+}$:

$$D_{x_+} = \begin{bmatrix} D & O \\ D_{x(1)} & D_{x(2)} \end{bmatrix} = \begin{bmatrix} 1 & -2 & 1 & 0 & 0 & 0 & 0 & \cdots \\ 0 & 1 & -2 & 1 & 0 & 0 & 0 & \cdots \\ 0 & 0 & 1 & -2 & 1 & 0 & 0 & \cdots \\ \vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \vdots \\ 0 & 0 & 0 & 0 & 0 & 1 & -2 & 1 \end{bmatrix},$$

where $D_{x(2)}$:

$$D_{x(2)} = \begin{bmatrix} 1 & 0 & 0 & 0 & 0 & \cdots & 0 \\ -2 & 1 & 0 & 0 & 0 & \cdots & 0 \\ 1 & 2 & 1 & 0 & 0 & \cdots & 0 \\ 0 & 1 & -2 & 1 & 0 & \cdots & 0 \\ 0 & 0 & 1 & -2 & 1 & \cdots & 0 \\ \vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \vdots \\ 0 & 0 & 0 & 0 & 1 & -2 & 1 \end{bmatrix},$$

of dimension $c_{x_p} \times c_{x_p}$, where c_{x_p} is the number of columns of $B_{x(2)}$. Therefore, $(D_{x(2)} \otimes I_{c_z})^{-1}$ has the form

$$\begin{bmatrix} 1 & & & & & & & \\ & \ddots & & & & & & \\ & & 1 & & & & & \\ 2 & & & 1 & & & & \\ & \ddots & & & \ddots & & & \\ & & 2 & & 1 & & & \\ 3 & & & 2 & & 1 & & \\ & \ddots & & & \ddots & & \ddots & \\ & & 3 & & 2 & & 1 & \\ 4 & & & 3 & & 2 & & 1 \\ & \ddots & & & \ddots & & \ddots & \\ & & 4 & & 3 & & 2 & 1 \\ & & & \ddots & & \ddots & & \ddots \end{bmatrix}$$

of dimension $(c_{x_p} \cdot c_z) \times (c_{x_p} \cdot c_z)$, each block has dimension $c_z \times c_z$. Moreover,

$$D_{x(1)} \otimes I_{c_z} = \begin{bmatrix} 0 & 0 & & 1 & -2 & & \\ & \ddots & & \ddots & & \ddots & \\ 0 & 0 & 0 & 0 & & 1 & -2 \\ & \ddots & & \ddots & & \ddots & \\ 0 & 0 & 0 & 0 & & 0 & 1 \\ & \ddots & & \ddots & & \ddots & \\ & & 0 & 0 & & 0 & 0 \end{bmatrix},$$

i.e., is a matrix of dimension $(c_{x_p} \cdot c_z) \times (c_x \cdot c_z)$ with just three blocks of dimension $c_z \times c_z$ that are not blocks of zeros. Therefore,

$$(D_{x(2)} \otimes I_{c_z})^{-1}(D_{x(1)} \otimes I_{c_z}) = \begin{bmatrix} 0 & 0 & 1 & -2 & & & \\ & \ddots & & & \ddots & & \\ 0 & 0 & 0 & 0 & 2 & 1 & -3 & -2 \\ & \ddots & & & \ddots & & & \\ 0 & 0 & 0 & 0 & 3 & 2 & -4 & -3 \\ & \ddots & & & \ddots & & & \\ 0 & 0 & 0 & 0 & 4 & 3 & -5 & -4 \\ & \ddots & & & \ddots & & & \\ 0 & 0 & 0 & 0 & 4 & 4 & -5 & -5 \\ & \ddots & & & \ddots & & & \\ & & \vdots & & \vdots & & \vdots & \end{bmatrix},$$

with dimension $(c_{x_p} \cdot c_z) \times (c_x \cdot c_z)$. Hence, considering the matrix of coefficients that give the fit, $\hat{\Theta}$, and the matrix of coefficients that give the forecast, $\hat{\Theta}_p$, each row $j = 1, \dots, c_z$, of the additional matrix of coefficients is a linear combination of two old coefficients of that row:

$$\hat{\Theta}_{j \cdot} = \hat{\theta}_{j \cdot c_x} \begin{bmatrix} 1 \\ 1 \\ 1 \\ \vdots \end{bmatrix} + (\hat{\theta}_{j \cdot c_x} - \hat{\theta}_{j \cdot c_x - 1}) \begin{bmatrix} 1 \\ 2 \\ 3 \\ \vdots \end{bmatrix}.$$

- Differences of order 3.

Suppose a difference matrix with third order penalty, D_{x+} of dimensions $(c_{x+} - 3) \times c_{x+}$:

$$D_{x+} = \begin{bmatrix} -1 & 3 & -3 & 1 & 0 & 0 & \cdots & 0 & 0 & 0 & 0 \\ 0 & -1 & 3 & -3 & 1 & 0 & \cdots & 0 & 0 & 0 & 0 \\ 0 & 0 & -1 & 3 & -3 & 1 & \cdots & 0 & 0 & 0 & 0 \\ \vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \cdots & \vdots & \vdots & \vdots & \vdots \\ 0 & 0 & 0 & 0 & 0 & 0 & \cdots & -1 & 3 & -3 & 1 \end{bmatrix}.$$

In this case, $D_{x(2)}$ is:

$$D_{x(2)} = \begin{bmatrix} 1 & 0 & 0 & 0 & \cdots & 0 & 0 & 0 & 0 \\ -3 & 1 & 0 & 0 & \cdots & 0 & 0 & 0 & 0 \\ 3 & -3 & 1 & 0 & \cdots & 0 & 0 & 0 & 0 \\ \vdots & \vdots & \vdots & \vdots & \cdots & \vdots & \vdots & \vdots & \vdots \\ 0 & 0 & 0 & 0 & \cdots & -1 & 3 & -3 & 1 \end{bmatrix}.$$

$(D_{x(2)} \otimes I_{c_z})^{-1}$ and $D_{x(1)} \otimes I_{c_z}$ are:

$$\begin{aligned}
 (D_{x(2)} \otimes I_{c_z})^{-1} &= \begin{bmatrix} 1 & & & & & & & & \\ & \ddots & & & & & & & \\ & & 1 & & & & & & \\ 3 & & & 1 & & & & & \\ & \ddots & & & \ddots & & & & \\ & & 3 & & 1 & & & & \\ 6 & & & 3 & & 1 & & & \\ & \ddots & & & \ddots & & \ddots & & \\ & & 6 & & 3 & & 1 & & \\ 10 & & & 6 & & 3 & & 1 & \\ & \ddots & & & \ddots & & \ddots & & \ddots \\ & & 10 & & 6 & & 3 & & 1 \\ & \vdots & & \vdots & & \vdots & & \vdots & \ddots \end{bmatrix}, \\
 D_{x(1)} \otimes I_{c_z} &= \begin{bmatrix} 0 & & & -1 & & 3 & & -3 & \\ & \ddots & & & \ddots & & \ddots & & \ddots \\ & & 0 & & & -1 & & 3 & -3 \\ 0 & & & 0 & & -1 & & 3 & \\ & \ddots & & & \ddots & & \ddots & & \ddots \\ & & 0 & & & 0 & & -1 & 3 \\ 0 & & & 0 & & 0 & & -1 & \\ & \ddots & & & \ddots & & \ddots & & \ddots \\ & & 0 & & & 0 & & 0 & -1 \\ & \vdots & & \vdots & & \vdots & & \vdots & \ddots \end{bmatrix}.
 \end{aligned}$$

Then,

$$(D_{x(2)} \otimes I_{c_z})^{-1} (D_{x(1)} \otimes I_{c_z}) = \begin{bmatrix} 0 & & & -1 & & 3 & & -3 & \\ & \ddots & & & \ddots & & \ddots & & \ddots \\ & & 0 & & & -1 & & 3 & -3 \\ 0 & & & -3 & & 8 & & -6 & \\ & \ddots & & & \ddots & & \ddots & & \ddots \\ & & 0 & & & -3 & & 8 & -6 \\ 0 & & & -6 & & 15 & & -10 & \\ & \ddots & & & \ddots & & \ddots & & \ddots \\ & & 0 & & & -6 & & 15 & -10 \\ 0 & & & -10 & & 24 & & -15 & \\ & \ddots & & & \ddots & & \ddots & & \ddots \\ & & 0 & & & -10 & & 24 & -15 \\ & \vdots & & \vdots & & \vdots & & \vdots & \ddots \end{bmatrix}.$$

Therefore, each row, $j = 1, \dots, c_z$, of the additional matrix of coefficients is a linear combination of three old coefficients of that row:

$$\hat{\Theta}_{p_j} = \hat{\theta}_{j \ c_x} \begin{bmatrix} 1 \\ 1 \\ 1 \\ 1 \\ 1 \\ 1 \\ \vdots \end{bmatrix} + \frac{3\hat{\theta}_{j \ c_x} - 4\hat{\theta}_{j \ c_x-1} + \hat{\theta}_{j \ c_x-2}}{2} \begin{bmatrix} 1 \\ 2 \\ 3 \\ 4 \\ 5 \\ 6 \\ \vdots \end{bmatrix} + \frac{\hat{\theta}_{j \ c_x} - 2\hat{\theta}_{j \ c_x-1} + \hat{\theta}_{j \ c_x-2}}{2} \begin{bmatrix} 1 \\ 2 \\ 3 \\ 4 \\ 5 \\ 6 \\ \vdots \end{bmatrix}^2.$$

Proof of Theorem 2

Given the extended transformation matrix for the random part Ω_{+r} and the extended penalty matrix P_+ defined in the main text in Eq. (45) and (43), respectively, F_+^* is:

$$F_+^* = \Omega_{+r}^{*'} P_+ \Omega_{+r}^* = \begin{bmatrix} 0 & \mathbf{u}_{z+r}^{*'} & \dots \\ \vdots & \mathbf{u}_{x+r}^{*'} & \\ & \mathbf{u}_{x+f}^{*(2)'} \otimes \mathbf{u}_{z+r}^{*'} & \\ & \mathbf{u}_{x+r}^{*'} \otimes \mathbf{u}_{z+f}^{*(2)'} & \\ & \mathbf{u}_{x+r}^{*'} \otimes \mathbf{u}_{z+r}^{*'} & \end{bmatrix} \begin{bmatrix} 0 & \dots \\ \vdots & \lambda_z D'_{z+} D_{z+} \\ & \lambda_x D'_{x+} D_{x+} \\ & \lambda_3 D'_{x+} D_{x+} \otimes I_{c_{z+}} + \lambda_4 I_{c_{x+}} \otimes D'_{z+} D_{z+} \end{bmatrix}$$

$$= \begin{bmatrix} 0 & \dots \\ \mathbf{u}_{zr}^* & \\ \vdots & \mathbf{u}_{x+r}^* \\ & \mathbf{u}_{x+f}^{*(2)} \otimes \mathbf{u}_{z+r}^* \mid \mathbf{u}_{x+r}^* \otimes \mathbf{u}_{z+f}^{*(2)} \mid \mathbf{u}_{x+r}^* \otimes \mathbf{u}_{z+r}^* \\ & \lambda_z \mathbf{u}_{z+r}^{*'} D'_{z+} D_{z+} \mathbf{u}_{z+r}^* \\ & \lambda_x \mathbf{u}_{x+r}^{*'} D'_{x+} D_{x+} \mathbf{u}_{x+r}^* \\ & \mathbf{F}_+^{(1,2)} \end{bmatrix},$$

where $\mathbf{F}_+^{(1,2)} = \begin{bmatrix} \mathbf{F}_{+11}^{(1,2)} & \mathbf{O} & \mathbf{F}_{+13}^{(1,2)} \\ \mathbf{O} & \mathbf{F}_{+22}^{(1,2)} & \mathbf{O} \\ \mathbf{F}_{+13}^{(1,2)'} & \mathbf{O} & \mathbf{F}_{+33}^{(1,2)} \end{bmatrix}$, with

$$\begin{aligned} \mathbf{F}_{+11}^{(1,2)} &= \tau_x \mathbf{u}_{x+f}^{*(2)'} D'_{x+} D_{x+} \mathbf{u}_{x+f}^{*(2)} \otimes \mathbf{u}_{zr}^{*'} \mathbf{u}_{z+r}^* + \tau_z \mathbf{u}_{x+f}^{*(2)'} \mathbf{u}_{x+f}^{*(2)} \otimes \mathbf{u}_{z+r}^{*'} D'_{z+} D_{z+} \mathbf{u}_{z+r}^* \\ \mathbf{F}_{+13}^{(1,2)} &= \tau_z \mathbf{u}_{x+f}^{*(2)'} \mathbf{u}_{x+r}^* \otimes \mathbf{u}_{z+r}^{*'} D'_{z+} D_{z+} \mathbf{u}_{z+r}^* + \tau_x \mathbf{u}_{x+f}^{*(2)'} D'_{x+} D_{x+} \mathbf{u}_{x+r}^* \otimes \mathbf{u}_{z+r}^{*'} \mathbf{u}_{z+r}^* \\ \mathbf{F}_{+22}^{(1,2)} &= \tau_x \mathbf{u}_{x+r}^{*'} D'_{x+} D_{x+} \mathbf{u}_{x+r}^* \otimes \mathbf{u}_{z+f}^{*(2)'} \mathbf{u}_{z+f}^{*(2)} + \tau_z \mathbf{u}_{x+r}^{*'} \mathbf{u}_{x+r}^* \otimes \mathbf{u}_{z+f}^{*(2)'} D'_{z+} D_{z+} \mathbf{u}_{z+f}^* \\ \mathbf{F}_{+23}^{(1,2)} &= \tau_x \mathbf{u}_{x+r}^{*'} D'_{x+} D_{x+} \mathbf{u}_{x+r}^* \otimes \mathbf{u}_{z+f}^{*(2)'} \mathbf{u}_{z+r}^* + \tau_z \mathbf{u}_{x+r}^{*'} \mathbf{u}_{x+r}^* \otimes \mathbf{u}_{z+f}^{*(2)'} D'_{z+} D_{z+} \mathbf{u}_{z+r}^* \\ \mathbf{F}_{+33}^{(1,2)} &= \tau_z \mathbf{u}_{x+r}^{*'} \mathbf{u}_{x+r}^* \otimes \mathbf{u}_{z+r}^{*'} D'_{z+} D_{z+} \mathbf{u}_{z+r}^* + \tau_x \mathbf{u}_{x+r}^{*'} D'_{x+} D_{x+} \mathbf{u}_{x+r}^* \otimes \mathbf{u}_{z+r}^{*'} \mathbf{u}_{z+r}^* \end{aligned}$$

using $\mathbf{u}_{if}^{*(2)'} D'_i = \mathbf{O}$ for $i = z_+, x_+$, we obtain the extended mixed model penalty F_+^* in Eq. (49) in the main text.

Simulation results for Scenario 1

- $n_{z_p} = 0, n_{x_p} = 10$

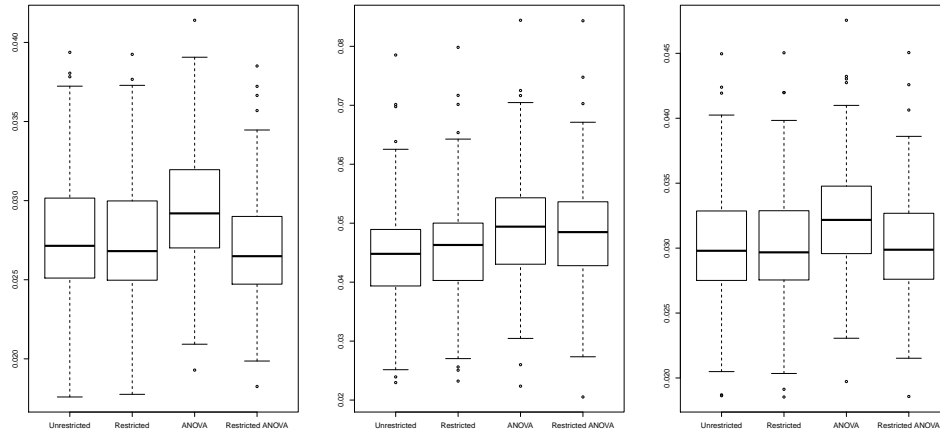


Figure S1. MAE in the fit (left panel), in the forecast (middle panel) and in total (right panel) of smooth models in scenario 1 and $n_{z_p} = 0$ and $n_{x_p} = 10$.

- $n_{z_p} = 0, n_{x_p} = 15$

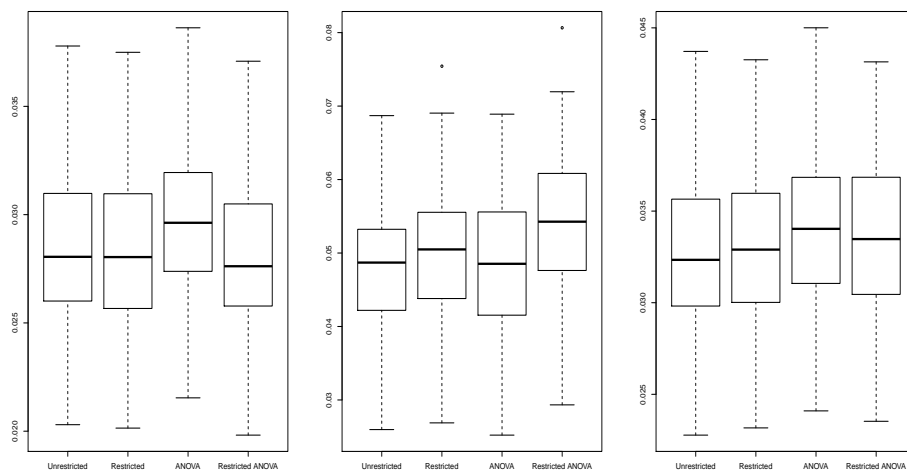


Figure S2. MAE in the fit (left panel), in the forecast (middle panel) and in total (right panel) of smooth models in scenario 1 and $n_{z_p} = 0$ and $n_{x_p} = 15$.

- $n_{z_p} = 0, n_{x_p} = 20$

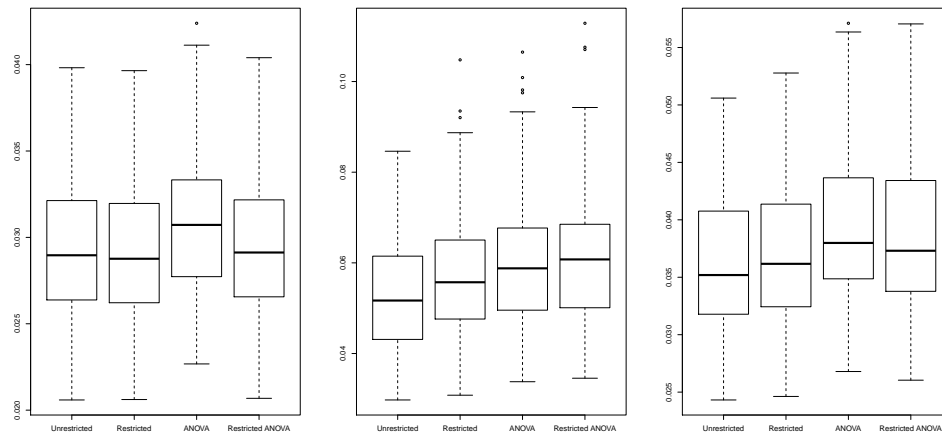


Figure S3. MAE in the fit (left panel), in the forecast (middle panel) and in total (right panel) of smooth models in scenario 1 and $n_{z_p} = 0$ and $n_{x_p} = 20$.

- $n_{z_p} = 10, n_{x_p} = 5$

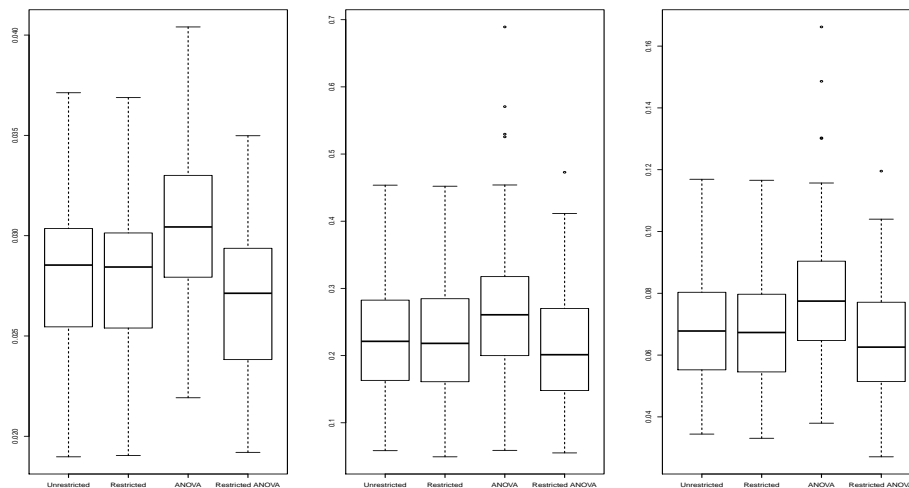


Figure S4. MAE in the fit (left panel), in the forecast (middle panel) and in total (right panel) of smooth models in [scenario 1](#) and $n_{z_p} = 10, n_{x_p} = 5$.

- $n_{z_p} = n_{x_p} = 10$

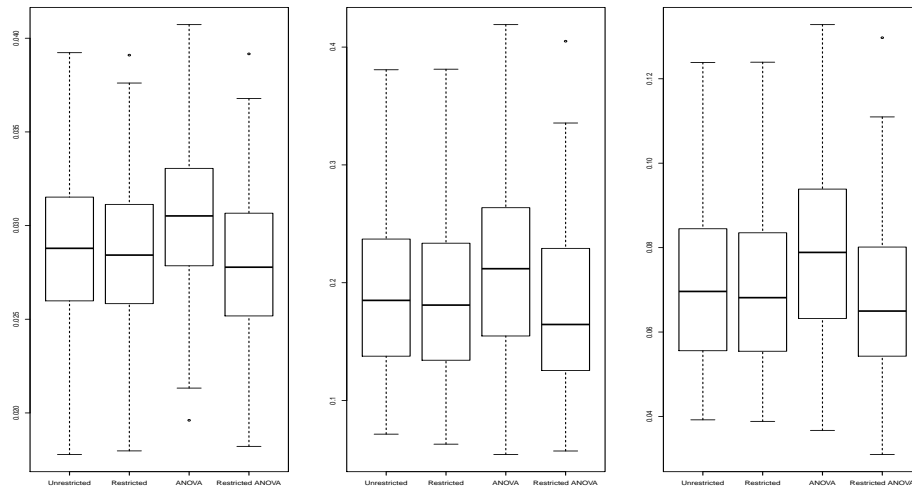


Figure S5. MAE in the fit (left panel), in the forecast (middle panel), and in total (right panel) of smooth models in scenario 1 and $n_{z_p} = 10, n_{x_p} = 10$.

- $n_{z_p} = 10, n_{x_p} = 15$

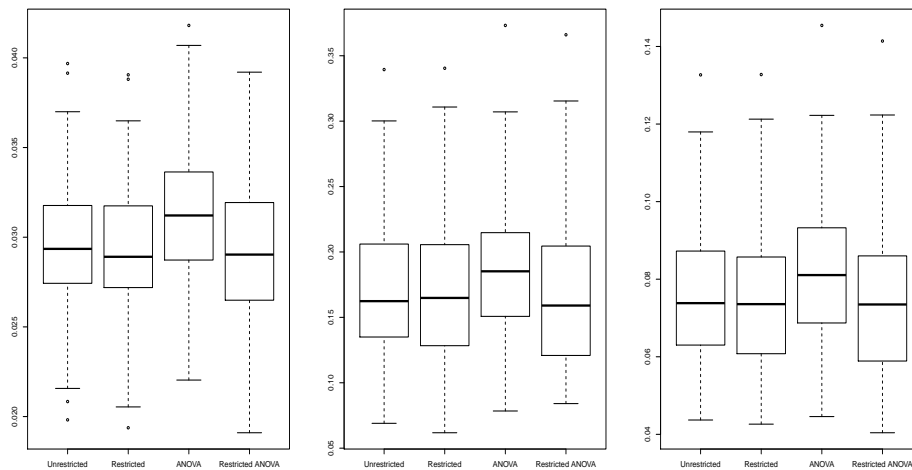


Figure S6. MAE in the fit (left panel), in the forecast (middle panel) and in total (right panel) of smooth models in scenario 1 and $n_{z_p} = 10, n_{x_p} = 15$.

- $n_{z_p} = 10, n_{x_p} = 20$

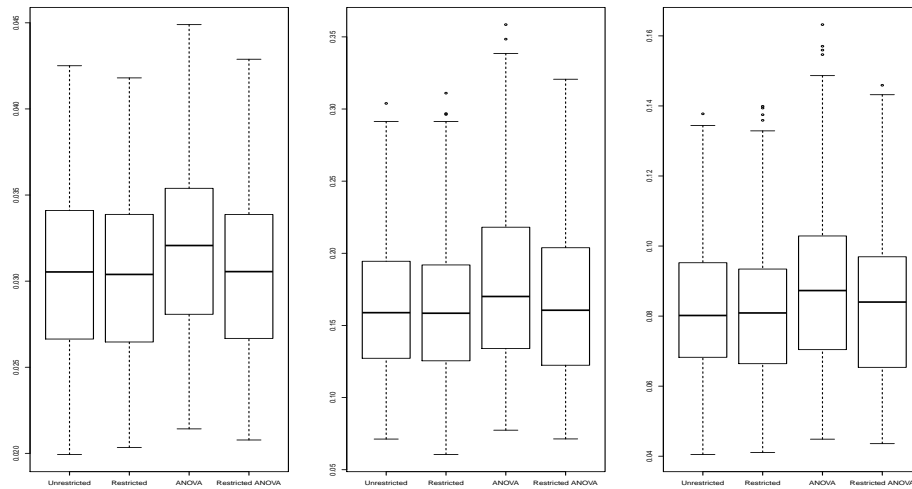


Figure S7. MAE in the fit (left panel), in the forecast (middle panel) and in total (right panel) of smooth models in [scenario 1](#) and $n_{z_p} = 10, n_{x_p} = 30$.

- $n_{z_p} = 20, n_{x_p} = 5$

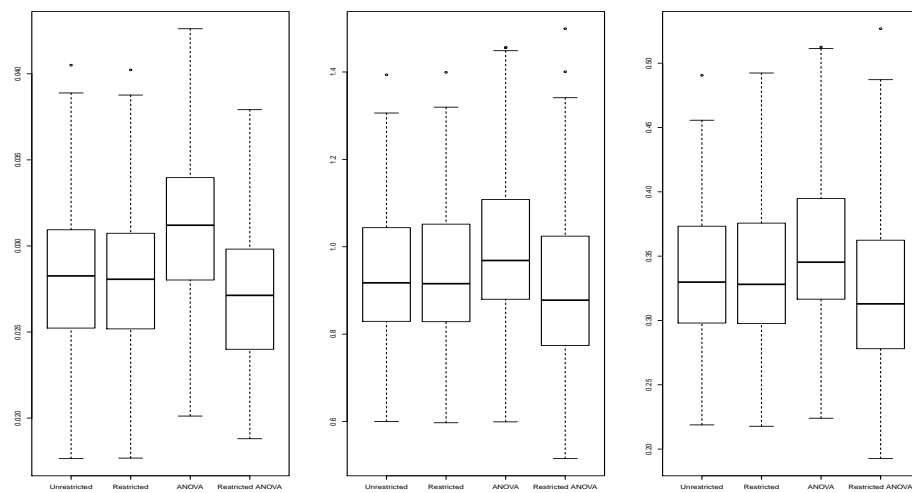


Figure S8. MAE in the fit (left panel), in the forecast (middle panel) and in total (right panel) of smooth models in [scenario 1](#) and $n_{z_p} = 20, n_{x_p} = 5$.

- $n_{z_p} = 20, n_{x_p} = 10$

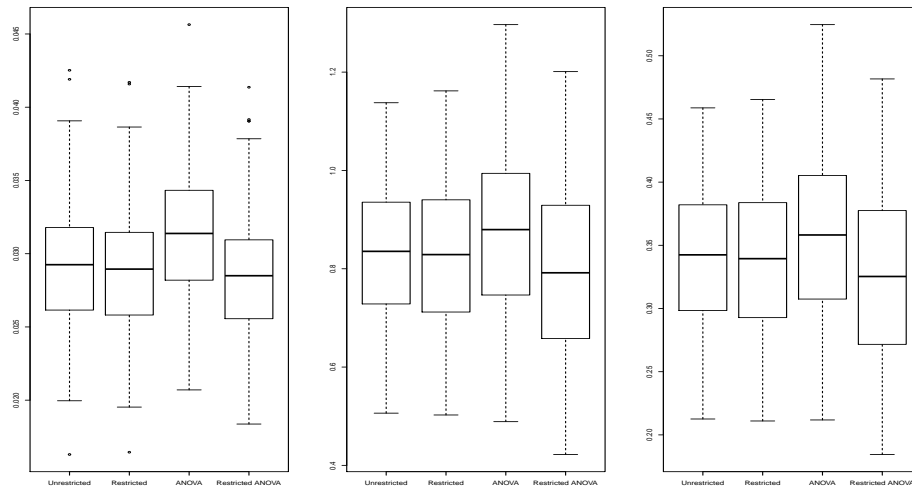


Figure S9. MAE in the fit (left panel), in the forecast (middle panel) and in total (right panel) of smooth models in [scenario 1](#) and $n_{z_p} = 20, n_{x_p} = 10$.

- $n_{z_p} = 20, n_{x_p} = 15$

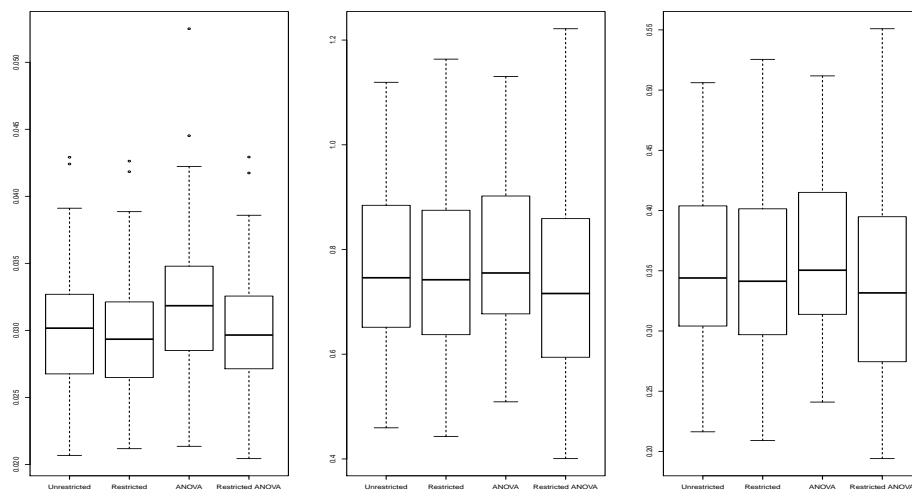


Figure S10. MAE in the fit (left panel), in the forecast (middle panel) and in total (right panel) of smooth models in [scenario 1](#) and $n_{z_p} = 20, n_{x_p} = 15$.

- $n_{z_p} = 20, n_{x_p} = 20$

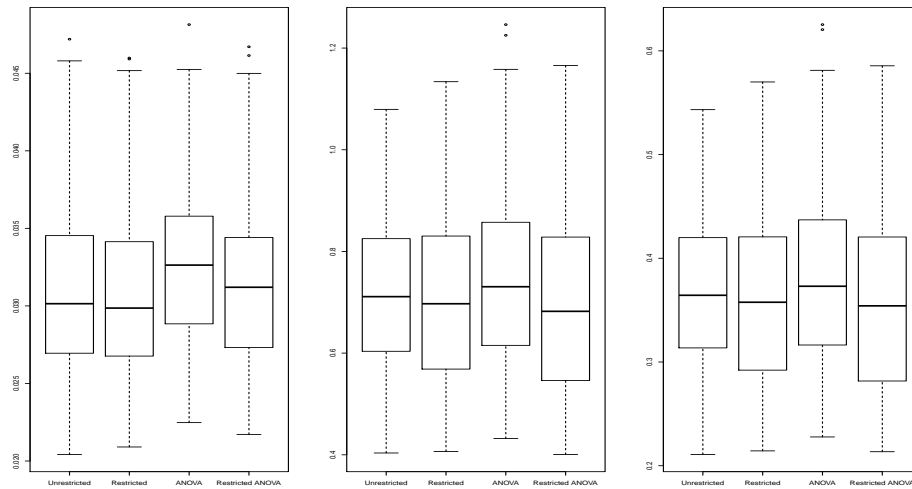


Figure S11. MAE in the fit (left panel), in the forecast (middle panel) and in total (right panel) of smooth models in [scenario 1](#) and $n_{z_p} = 20, n_{x_p} = 20$.

Simulation results for Scenario 2

- $n_{z_p} = 0, n_{x_p} = 10$

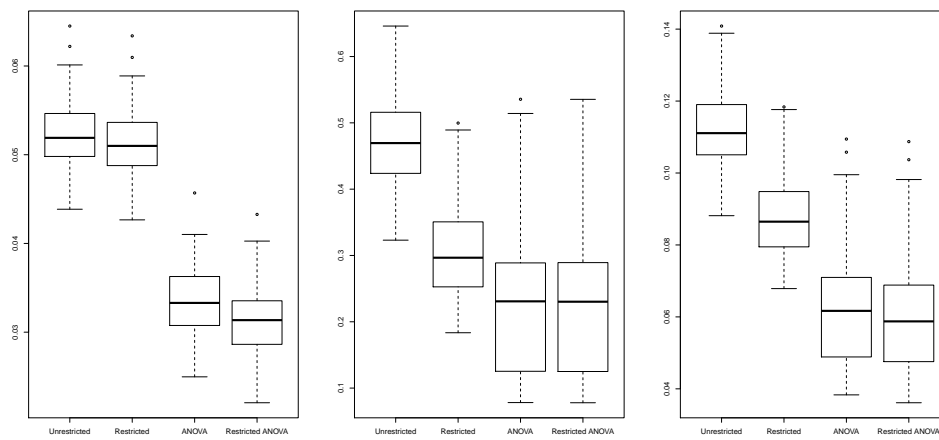


Figure S12. MAE in the fit (left panel), in the forecast (middle panel) and in total (right panel) of smooth models in [scenario 2](#) and $n_{z_p} = 0$ and $n_{x_p} = 10$.

- $n_{z_p} = 0, n_{x_p} = 15$

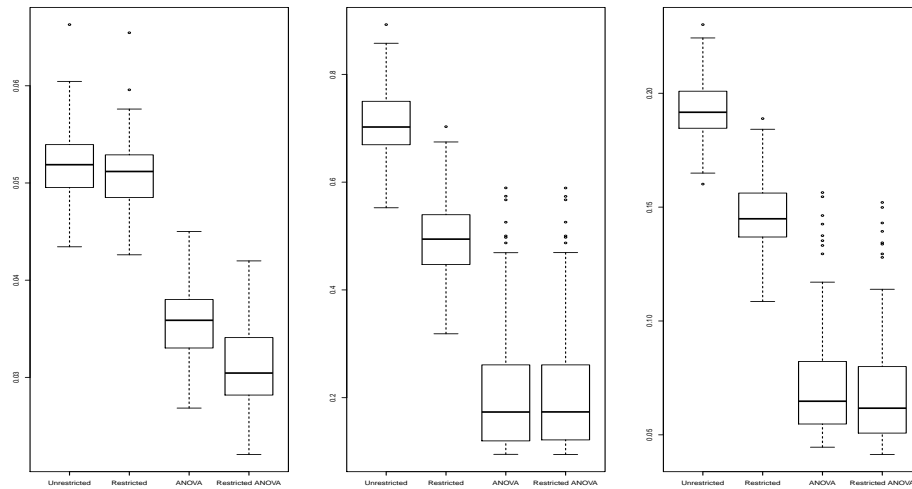


Figure S13. MAE in the fit (left panel), in the forecast (middle panel) and in total (right panel) of smooth models in scenario 2 and $n_{z_p} = 0$ and $n_{x_p} = 15$.

- $n_{z_p} = 0, n_{x_p} = 20$

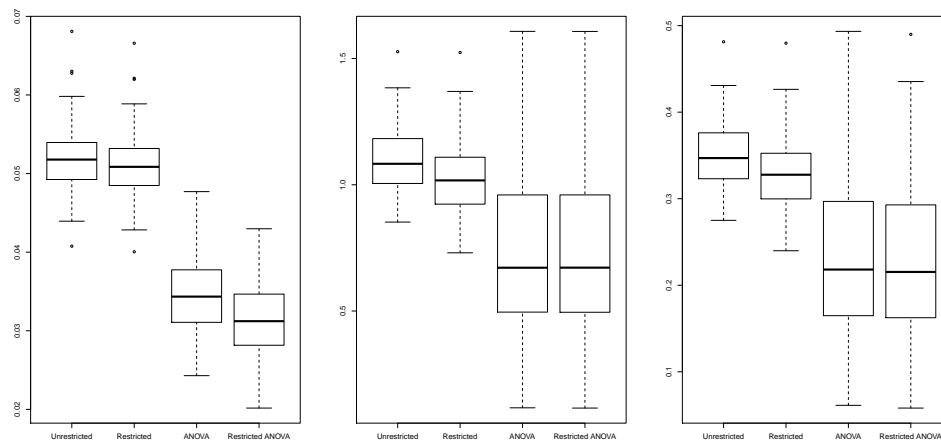


Figure S14. MAE in the fit (left panel), in the forecast (middle panel) and in total (right panel) of smooth models in scenario 2 and $n_{z_p} = 0$ and $n_{x_p} = 20$.

- $n_{z_p} = 10, n_{x_p} = 5$

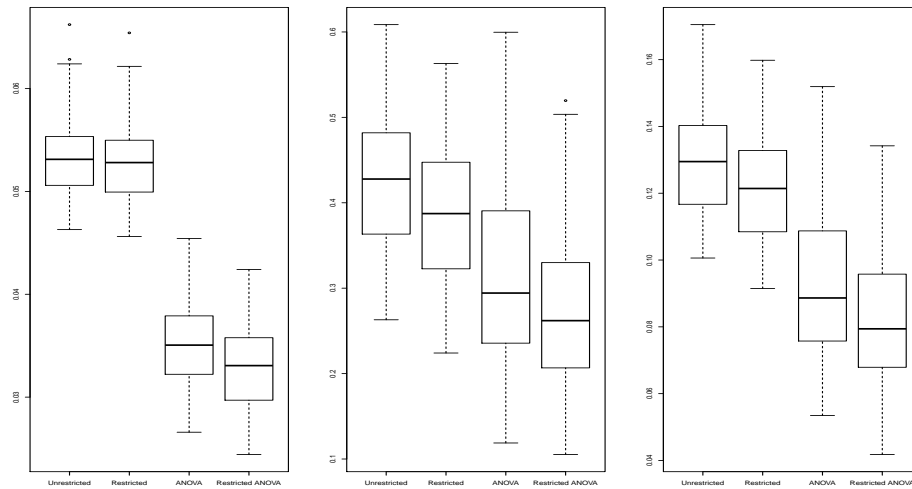


Figure S15. MAE in the fit (left panel), in the forecast (middle panel) and in total (right panel) of smooth models in scenario 2 and $n_{z_p} = 10$ and $n_{x_p} = 5$.

- $n_{z_p} = n_{x_p} = 10$

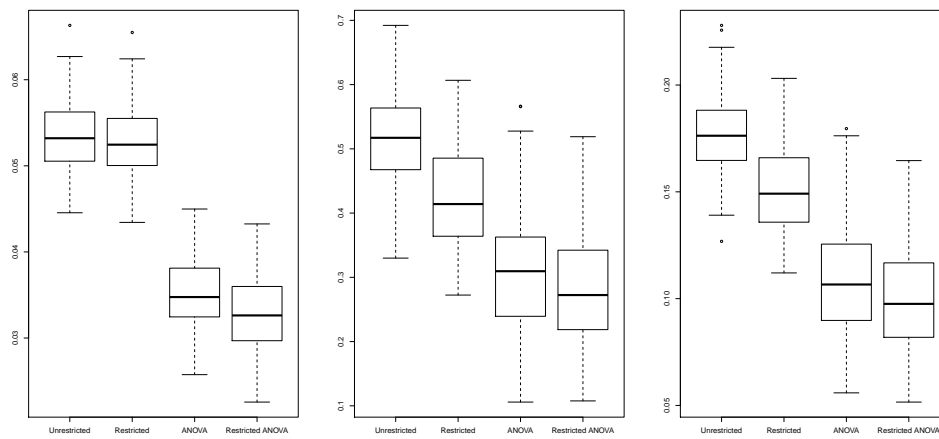


Figure S16. MAE in the fit (left panel), in the forecast (middle panel) and in total (right panel) of smooth models in scenario 2 and $n_{z_p} = n_{x_p} = 10$.

- $n_{z_p} = 10, n_{x_p} = 15$

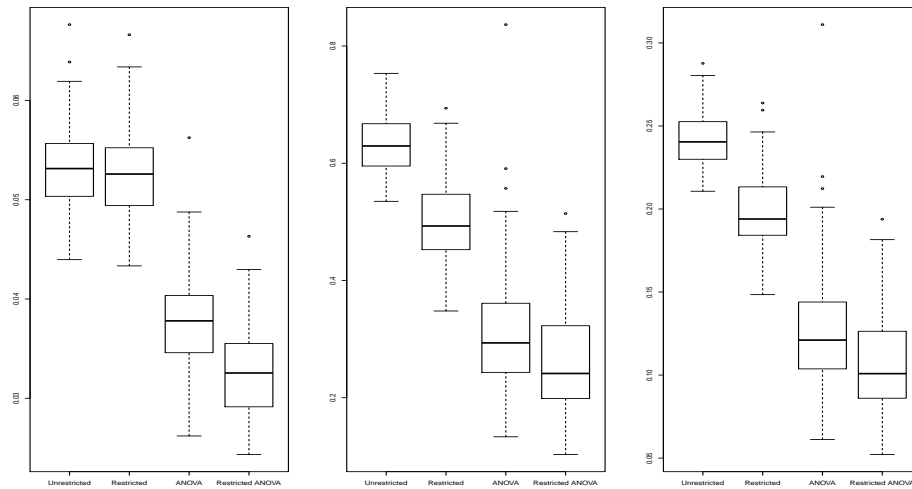


Figure S17. MAE in the fit (left panel), in the forecast (middle panel) and in total (right panel) of smooth models in scenario 2 and $n_{z_p} = 10$ and $n_{x_p} = 15$.

- $n_{z_p} = 10, n_{x_p} = 20$

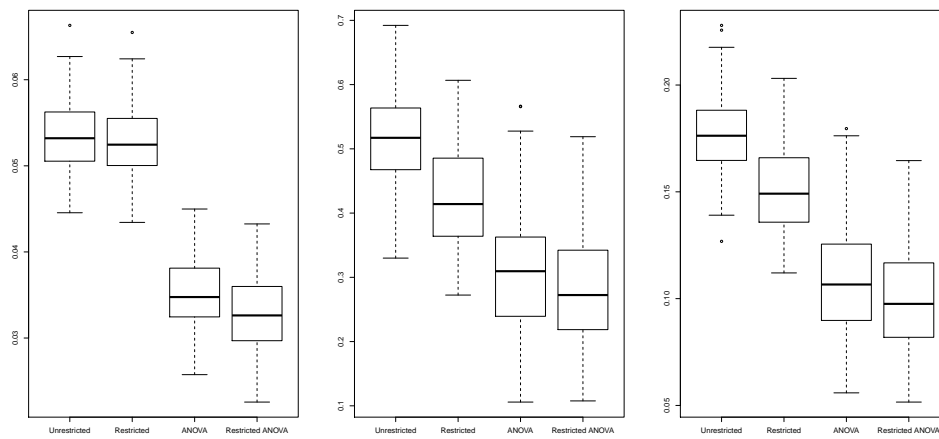


Figure S18. MAE in the fit (left panel), in the forecast (middle panel) and in total (right panel) of smooth models in scenario 2 and $n_{z_p} = 20$ and $n_{x_p} = 5$.

- $n_{z_p} = 20, n_{x_p} = 5$

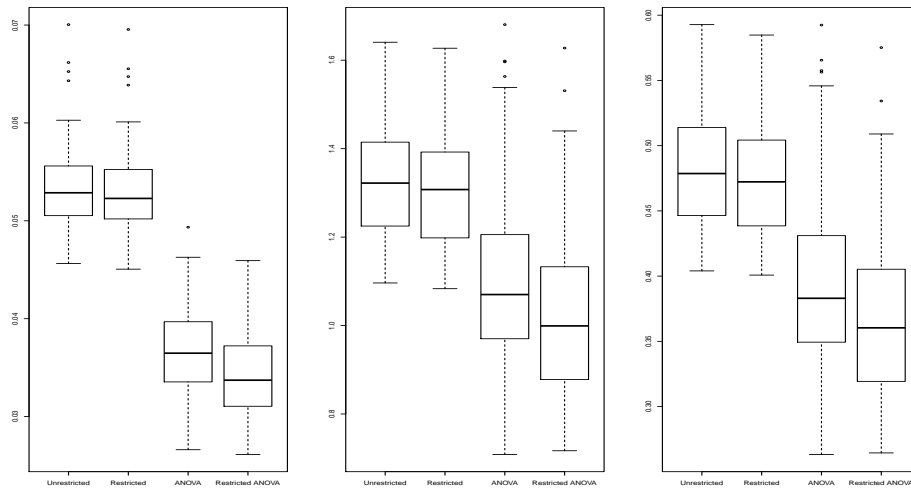


Figure S19. MAE in the fit (left panel), in the forecast (middle panel) and in total (right panel) of smooth models in scenario 2 and $n_{z_p} = 20$ and $n_{x_p} = 5$.

- $n_{z_p} = 20, n_{x_p} = 10$

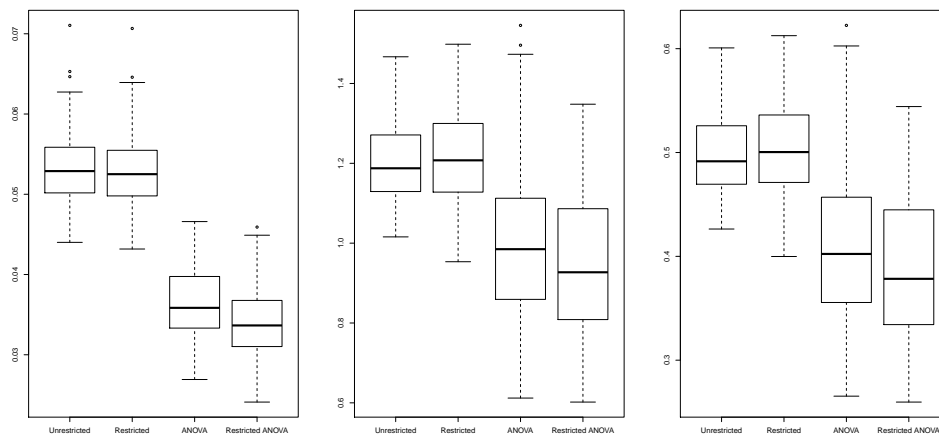


Figure S20. MAE in the fit (left panel), in the forecast (middle panel) and in total (right panel) of smooth models in scenario 2 and $n_{z_p} = 20$ and $n_{x_p} = 10$.

- $n_{z_p} = 20, n_{x_p} = 15$

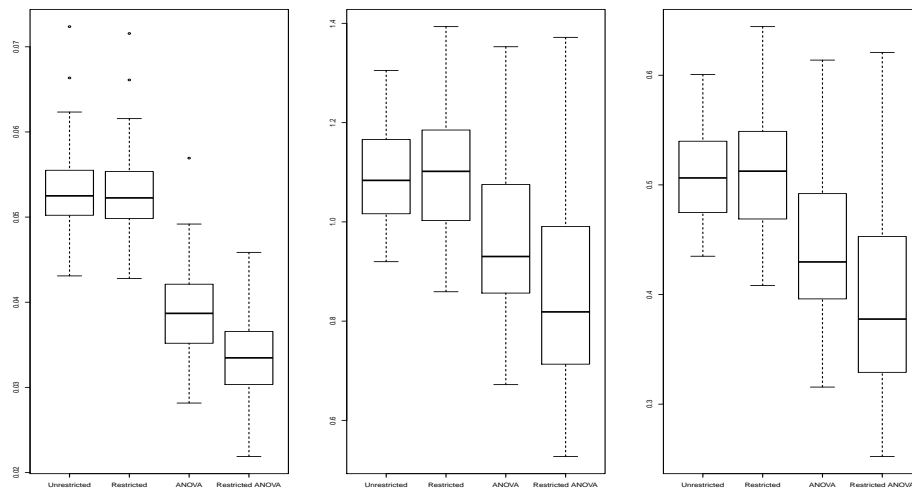


Figure S21. MAE in the fit (left panel), in the forecast (middle panel) and in total (right panel) of smooth models in scenario 2 and $n_{z_p} = 20$ and $n_{x_p} = 15$.

- $n_{z_p} = n_{x_p} = 20$

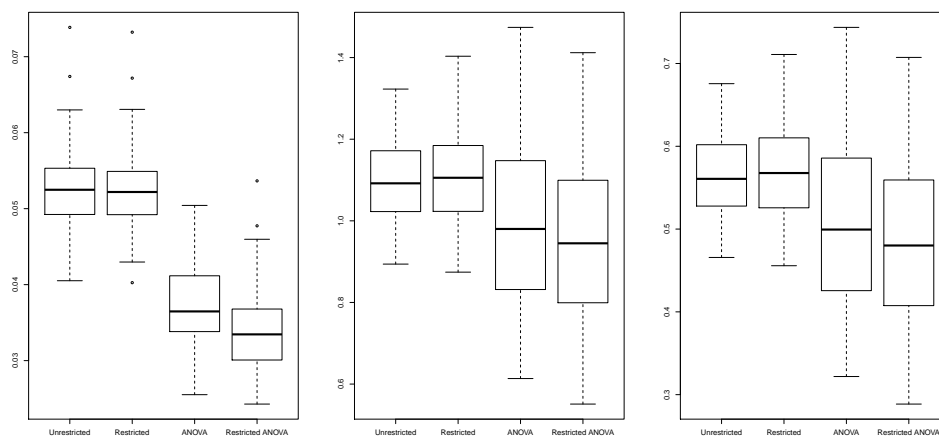


Figure S22. MAE in the fit (left panel), in the forecast (middle panel) and in total (right panel) of smooth models in scenario 2 and $n_{z_p} = n_{x_p} = 20$.

References

1. Harville, D. *Matrix Algebra from a Statistician's Perspective*; Springer, 2000.