

Functional ANOVA Example

November 13, 2018

Simulate Three-Group One-Way Functional ANOVA Data

Three-group one-way functional ANOVA data were simulated using methods described in the paper “Fast Function-on-Scalar Regression with Penalized Basis Expansions” from Reiss et al:

$$\begin{aligned}y_i(t) &= \mu(t) + \beta_{gp(i)}(t) + \epsilon_i(t) \\ \mu(t) &= 0.4 \arctan(10x - 5) + 0.6 \\ \beta_1(t) &= -0.5e^{-10t} - 0.04 \sin(8t) - 0.3t + 0.5 \\ \beta_2(t) &= -(t - 0.5)^2 - 0.15 \sin(13t) \\ \beta_3(t) &= -\beta_1(t) - \beta_2(t)\end{aligned}$$

where $t = m/200$ for $m = 0, \dots, 200$ and the error functions, $\epsilon_i(t)$, were simulated from a mean-zero Gaussian process with covariance $V(s, t) = \sigma_1 0.15^{|s-t|} + \sigma_2 \delta_{st}$ where $\delta_{st} = 1$ if $s = t$ and 0 otherwise. For the simulations, N=10 curves were simulated for each of the 3 groups, $\sigma_1 = 0.15$, and $\sigma_2 = 0.05$. So, we have 6030 observations from 30 curves with 10 curves per group.

```
#####
## Create the "True" Dataset ##
#####

## Model
## y_i(t) = mu(t) + b_gp(i)(t) + e_i(t) for t in [0,1]

## Values
t = 0:200/200      ## Evaluation time points
g = 3                ## Number of groups
N = 10               ## Number of curves per group, N = 10 or 60

## Coefficients from the paper
mu.t = 0.4*atan(10*t - 5) + 0.6
b1.t = -0.5*exp(-10*t) - 0.04*sin(8*t) - 0.3*t + 0.5
b2.t = -(t - 0.5)^2 - 0.15*sin(13*t)
b3.t = -b1.t - b2.t

## Mean functions by group
mean_1 = mu.t + b1.t
mean_2 = mu.t + b2.t
mean_3 = mu.t + b3.t

## Create the "true" dataset
true.data = data.frame(Y_True = c(mean_1, mean_2, mean_3),
                       Time = rep(t, 3),
                       Group = as.factor(c(rep(1, length(t)),
                                           rep(2, length(t)),
                                           rep(3, length(t)))) )
```

Note that the X variable, Time, was centered and scaled.

```

#####
## Generate Simulated Data ##
#####

## Create a stacked dataframe for the simulated data
dat = data.frame(Y_True = c(rep(mean_1, N),
                            rep(mean_2, N),
                            rep(mean_3, N)),
                  Time = rep(t, N*g),
                  Group = as.factor( c(rep(1, N*length(t)),
                                         rep(2, N*length(t)),
                                         rep(3, N*length(t))) ),
                  ID = factor( rep(1:(N*g),
                                    length(t))[ order(rep(1:(N*g), length(t))) ] ) )
rm(mean_1, mean_2, mean_3)

## Define values
sigma_1 = 0.15    ## Simulations used 0.05 and 0.15
sigma_2 = 0.05    ## 0.05 for all simulations

## Calculate the covariance matrix
grid = expand.grid(t, t)
cov.matrix = apply(X = grid, MARGIN = 1,
                   FUN = function(x){ ((sigma_1^2)*0.15^(abs(x[1] - x[2])) ) +
                     (sigma_2^2)*as.numeric(x[1] == x[2]) } )
cov.matrix = matrix(data = cov.matrix, ncol = length(t), nrow = length(t))
rm(grid)

## Generate errors
seed = 87654321
set.seed(seed)
errors = mvrnorm(n = N*g, mu = rep(0, length(t)), Sigma = cov.matrix)

## Add to the dataframe
dat$Errors = c( errors[1:(N*g),] )

## Calculate simulated Y's
dat$Y_Sim = (dat$Y_True + dat$Errors)
rm(cov.matrix, errors, sigma_1, sigma_2)

## Pre-smooth data
dat$Y_Smooth = rep(NA, N*g*length(t))
for(i in 1:(N*g)){
  start = (i-1)*length(t) + 1
  end = i*length(t)
  dat$Y_Smooth[start:end] = with(dat,
                                    smooth.spline(Time[start:end], Y_Sim[start:end],
                                                   nknots = 20))$y
}
rm(i, start, end, t, mu.t)

## Center and scale the time variable
dat$Time_Standardized = scale(dat$Time)

```

```
## Calculate higher-order time terms
dat$Time_Stan_2 = dat$Time_Standardized^2
dat$Time_Stan_3 = dat$Time_Standardized^3
dat$Time_Stan_4 = dat$Time_Standardized^4
dat$Time_Stan_5 = dat$Time_Standardized^5
```

Figure 1: The true effect functions along with the simulated data.

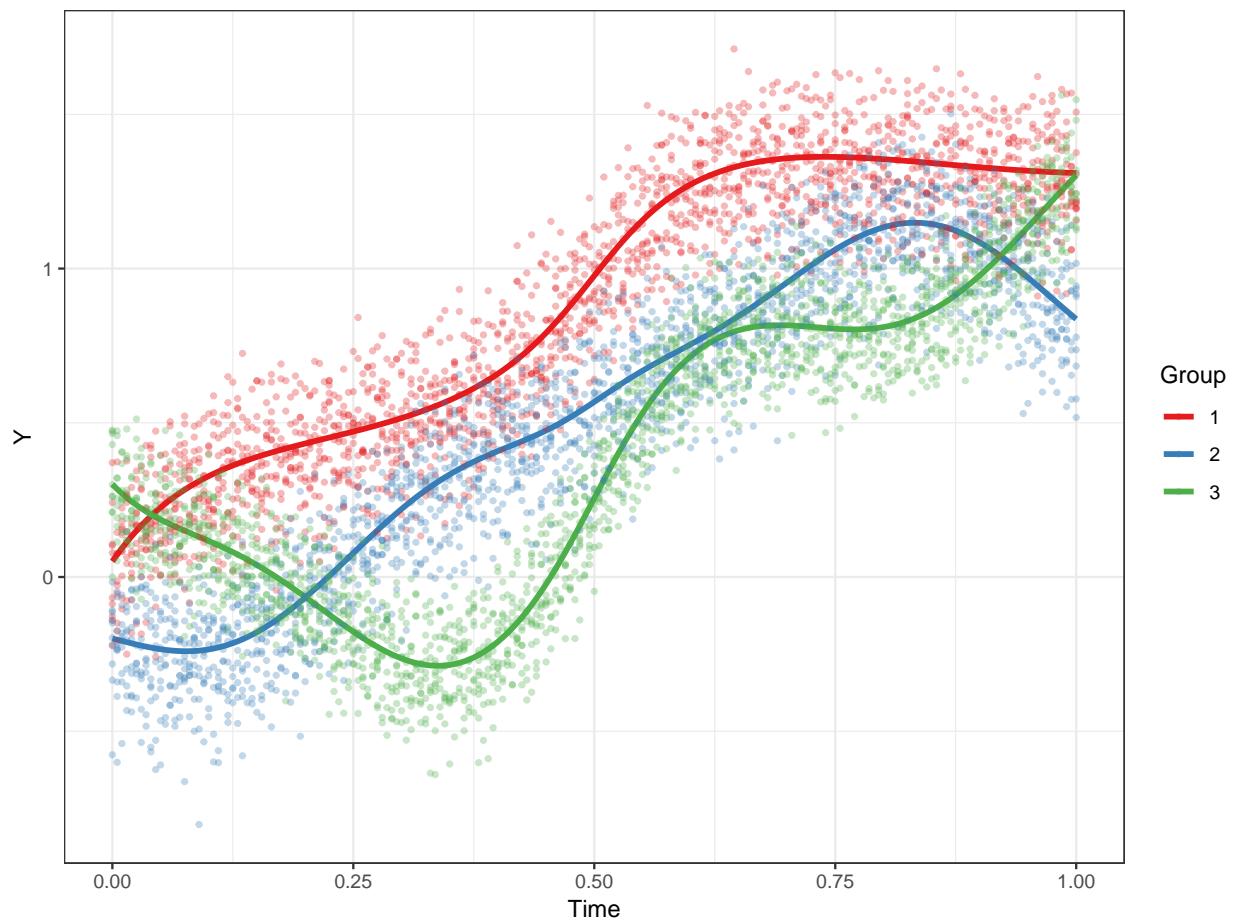


Figure 2: The smoothed subject-specific curves from the simulated data.

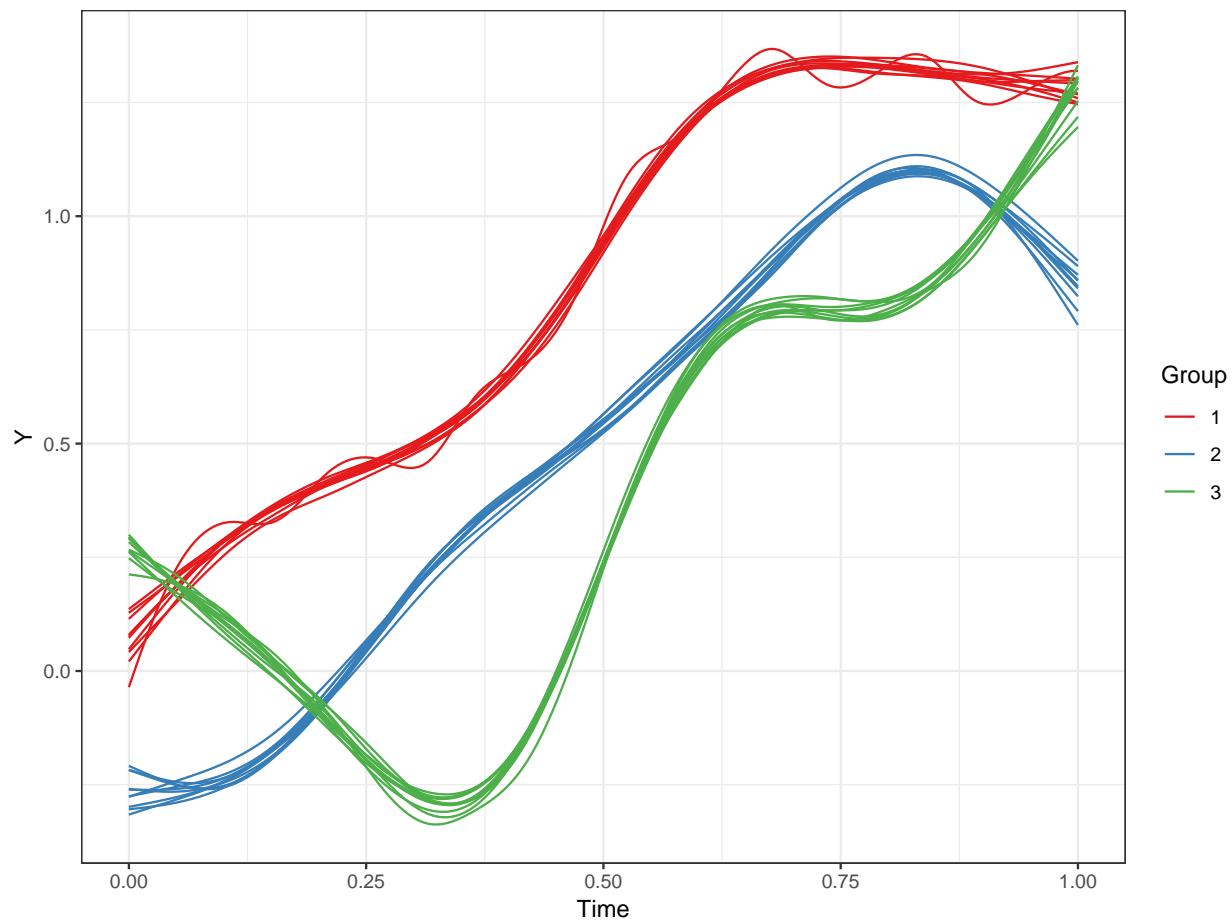
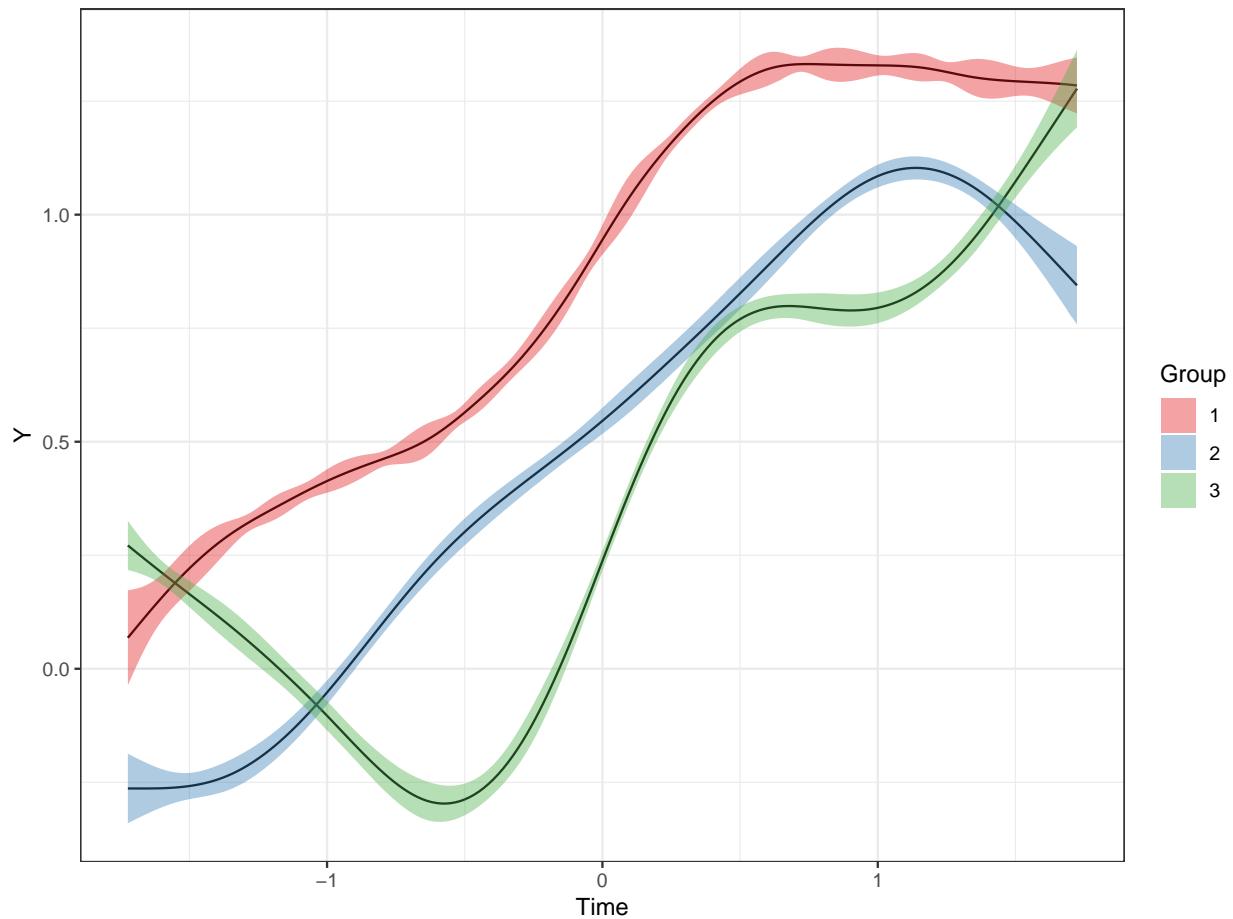


Figure 3: The group-level mean functions for the smoothed simulated data ± 2 point-wise standard deviations.



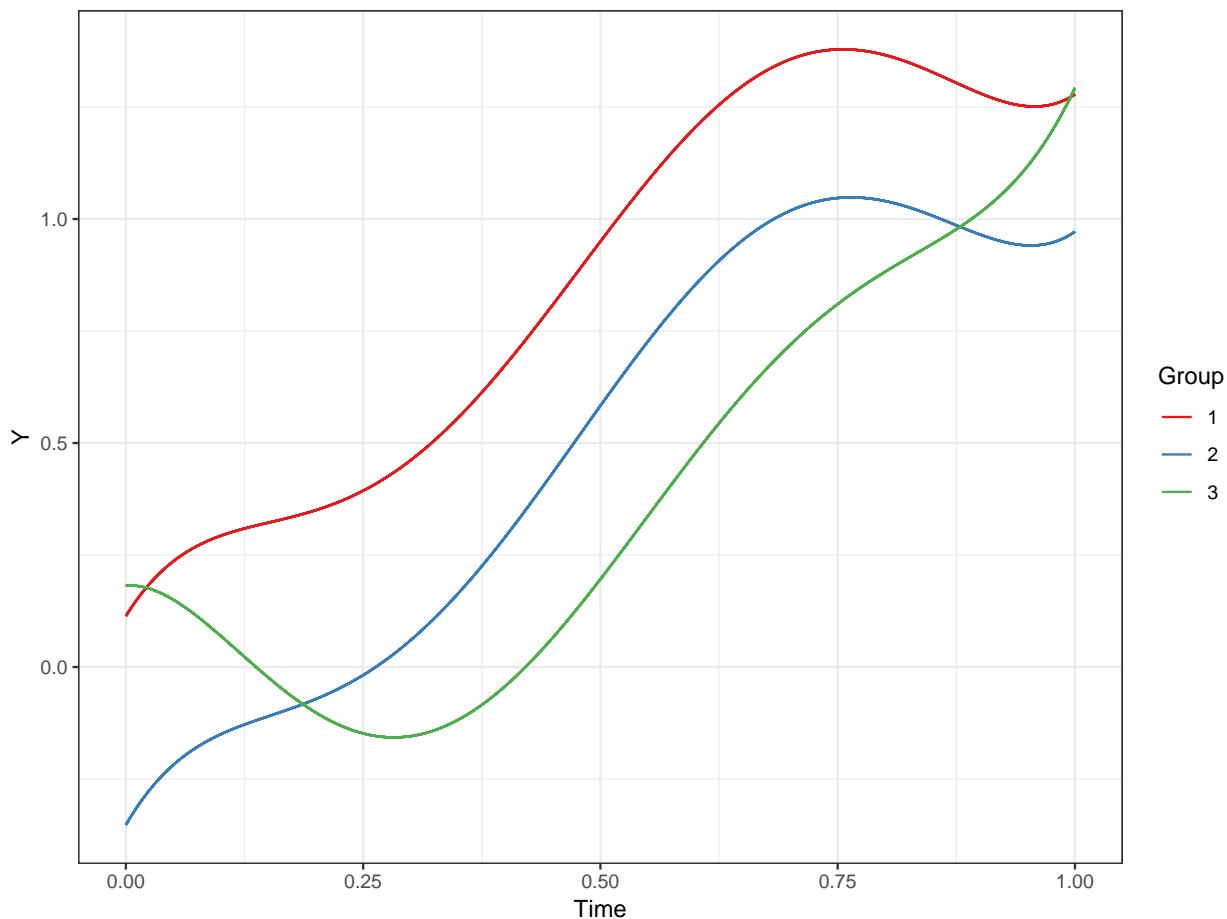
Analyze Using lm()

Fit a 5th-order linear model with time-by-group and Time²-by-group interactions using lm():

```
## Fit the model
mod = lm(Y_Smooth ~ Group + Time_Standardized + Time_Stan_2 + Time_Stan_3 +
          Time_Stan_4 + Time_Stan_5 +
          Group*Time_Standardized + Group*Time_Stan_2, data = dat)

## Calculate the fitted values
dat$Y_Smooth_Fitted_lm = fitted(mod)
```

Figure 4: The group-level mean functions from lm() using a 5th-order linear model with time-by-group and Time²-by-group interactions.



Analyze Using Penalized Splines and lme()

Fit a penalized spline using lme():

```
## Penalized basis functions
K = 24
qtiles = seq(0, 1, length = K + 2)[-c(1, K + 2)]
knots = quantile(dat$Time_Standardized, qtiles)
random.basis = cbind(sapply(knots,
  function(k){
    I((dat$Time_Standardized - k)^2)*(dat$Time_Standardized - k > 0)
  })
)
rm(qtiles)

## Define the fixed basis
fixed.basis = cbind(1,
  as.numeric(dat$Group == "2"),
  as.numeric(dat$Group == "3"),
  dat$Time_Standardized,
  dat$Time_Stan_2)

## Partition the random.basis matrix
random.basis.1 = as.numeric(dat$Group == "1")*random.basis
random.basis.2 = as.numeric(dat$Group == "2")*random.basis
random.basis.3 = as.numeric(dat$Group == "3")*random.basis

## Define Y
Y = dat$Y_Smooth

## Fit the model
group.1 = group.2 = group.3 = rep(1, nrow(dat))
mod = lme(Y ~ fixed.basis - 1, random = list(group.1 = pdIdent(~ random.basis.1 - 1),
                                              group.2 = pdIdent(~ random.basis.2 - 1),
                                              group.3 = pdIdent(~ random.basis.3 - 1)))
rm(group.1, group.2, group.3)

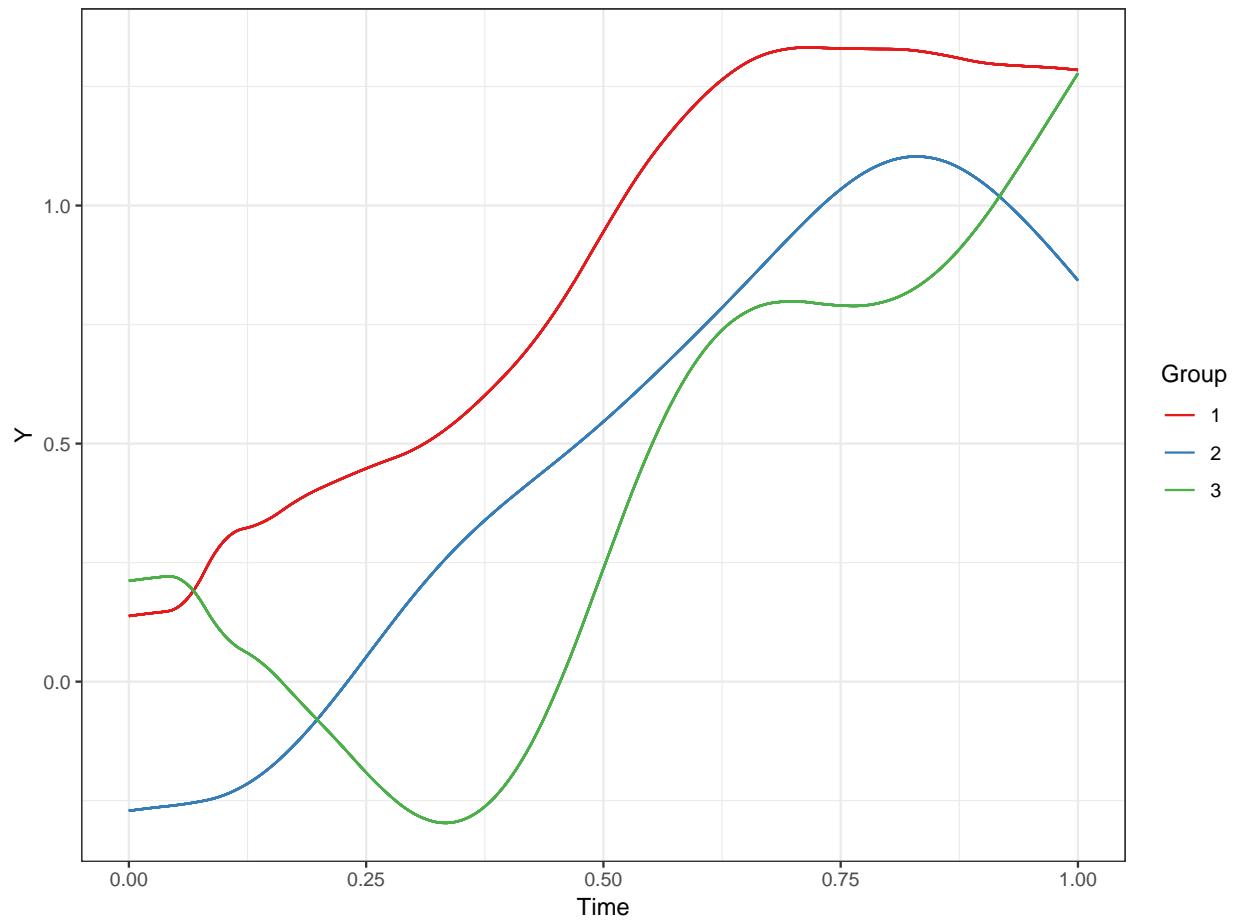
## Extract the model coefficients
coefs = c(unlist(mod$coefficients$fixed), unlist(mod$coefficients$random) )

## Extract the lambda estimates
#var.e2 = mod$sigma^2
#var.u2 = getVarCov(mod)[1,1]

## Calculate the fitted values
dat$Y_Smooth_Fitted_lme = as.vector( cbind(fixed.basis,
                                              random.basis.1,
                                              random.basis.2,
                                              random.basis.3) %*% coefs )

## Remove R objects
rm(fixed.basis, random.basis, coefs, knots, Y)
```

Figure 5: The group-level mean functions using penalized splines and lme().



Analyze Using JAGS

Fit a 5th-order linear model with time-by-group and Time²-by-group interactions using JAGS:

```
## Define values
n = nrow(dat)
Y = dat$Y_Smooth
X = c(dat$Time_Standardized)
X_2 = c(dat$Time_Stan_2)
X_3 = c(dat$Time_Stan_3)
X_4 = c(dat$Time_Stan_4)
X_5 = c(dat$Time_Stan_5)
G_2 = as.numeric(dat$Group == "2")
G_3 = as.numeric(dat$Group == "3")

## Create the model
model_string <- "model{

# Likelihood
for(i in 1:n){
Y[i] ~ dnorm(mu[i], inv.var)
mu[i] <- beta[1] + beta[2]*X[i] + beta[3]*X_2[i] + beta[4]*X_3[i] + beta[5]*X_4[i] + beta[6]*X_5[i] + b
}

# Prior for beta
for(j in 1:12){
beta[j] ~ dnorm(0,0.0001)
}

# Prior for the inverse variance
inv.var ~ dgamma(0.01, 0.01)
sigma <- 1/sqrt(inv.var)

}"

## Compile the model
model = jags.model(textConnection(model_string),
                    data = list(Y = Y,
                                n = n,
                                X = X,
                                X_2 = X_2,
                                X_3 = X_3,
                                X_4 = X_4,
                                X_5 = X_5,
                                G_2 = G_2,
                                G_3 = G_3),
                    n.chains = 3,
                    n.adapt = 1000)

## Compiling model graph
## Resolving undeclared variables
## Allocating nodes
## Graph information:
## Observed stochastic nodes: 6030
## Unobserved stochastic nodes: 13
```

```

##      Total graph size: 50880
##
## Initializing model
## Burn-in samples
update(model,
       1000,
       progress.bar = "none")

## Draw additional samples
samp = coda.samples(model,
                     variable.names = c("beta","sigma"),
                     thin = 3,
                     n.iter = 5000,
                     progress.bar = "none")

```

Investigate the fit of the model and extract the fitted values:

```

## Investigate the model
summary(samp)

##
## Iterations = 1003:5998
## Thinning interval = 3
## Number of chains = 3
## Sample size per chain = 1666
##
## 1. Empirical mean and standard deviation for each variable,
##    plus standard error of the mean:
##
##           Mean        SD  Naive SE Time-series SE
## beta[1]   0.9498982 0.0029020 4.105e-05    1.292e-04
## beta[2]   0.8128099 0.0049792 7.043e-05    5.054e-04
## beta[3]  -0.0864888 0.0043397 6.139e-05    2.794e-04
## beta[4]  -0.3799715 0.0063077 8.922e-05    7.626e-04
## beta[5]   0.0003549 0.0014858 2.102e-05    7.885e-05
## beta[6]   0.0740752 0.0018439 2.608e-05    2.142e-04
## beta[7]  -0.3665793 0.0037292 5.275e-05    1.126e-04
## beta[8]  -0.7536554 0.0037278 5.273e-05    1.114e-04
## beta[9]   0.0464071 0.0024524 3.469e-05    4.309e-05
## beta[10]  -0.0154831 0.0024778 3.505e-05    4.508e-05
## beta[11]  -0.0066518 0.0028241 3.995e-05    8.498e-05
## beta[12]   0.2676462 0.0028334 4.008e-05    8.939e-05
## sigma     0.0785762 0.0007096 1.004e-05    1.025e-05
##
## 2. Quantiles for each variable:
##
##          2.5%       25%       50%       75%     97.5%
## beta[1]  0.944181  0.9479650  0.9499019  0.951916  0.955420
## beta[2]  0.802991  0.8096110  0.8128233  0.816107  0.822659
## beta[3] -0.094905 -0.0894462 -0.0864700 -0.083608 -0.078123
## beta[4] -0.392670 -0.3838866 -0.3799998 -0.376212 -0.367346
## beta[5] -0.002596 -0.0006482  0.0003426  0.001362  0.003295
## beta[6]  0.070404  0.0729362  0.0740730  0.075218  0.077851
## beta[7] -0.373652 -0.3691649 -0.3665483 -0.364094 -0.358944
## beta[8] -0.760821 -0.7562073 -0.7536427 -0.751145 -0.746443

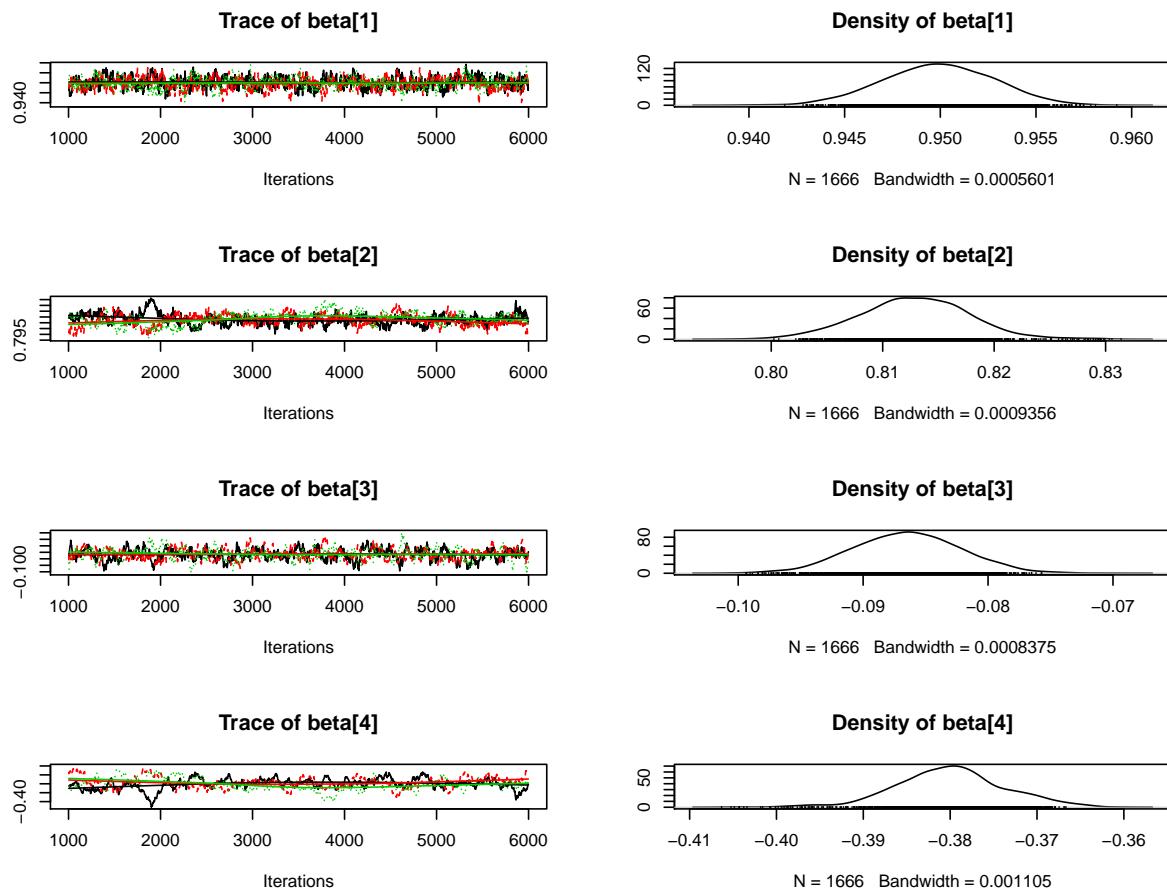
```

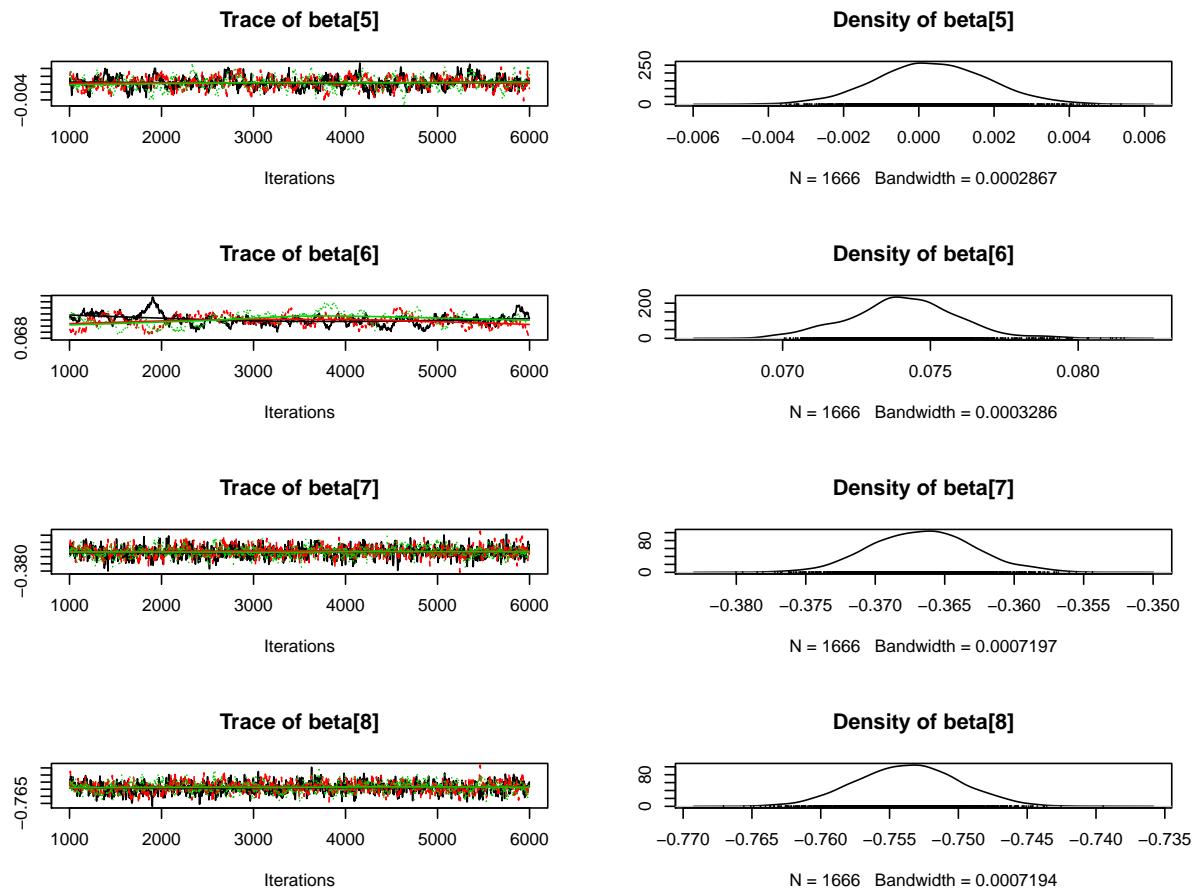
```

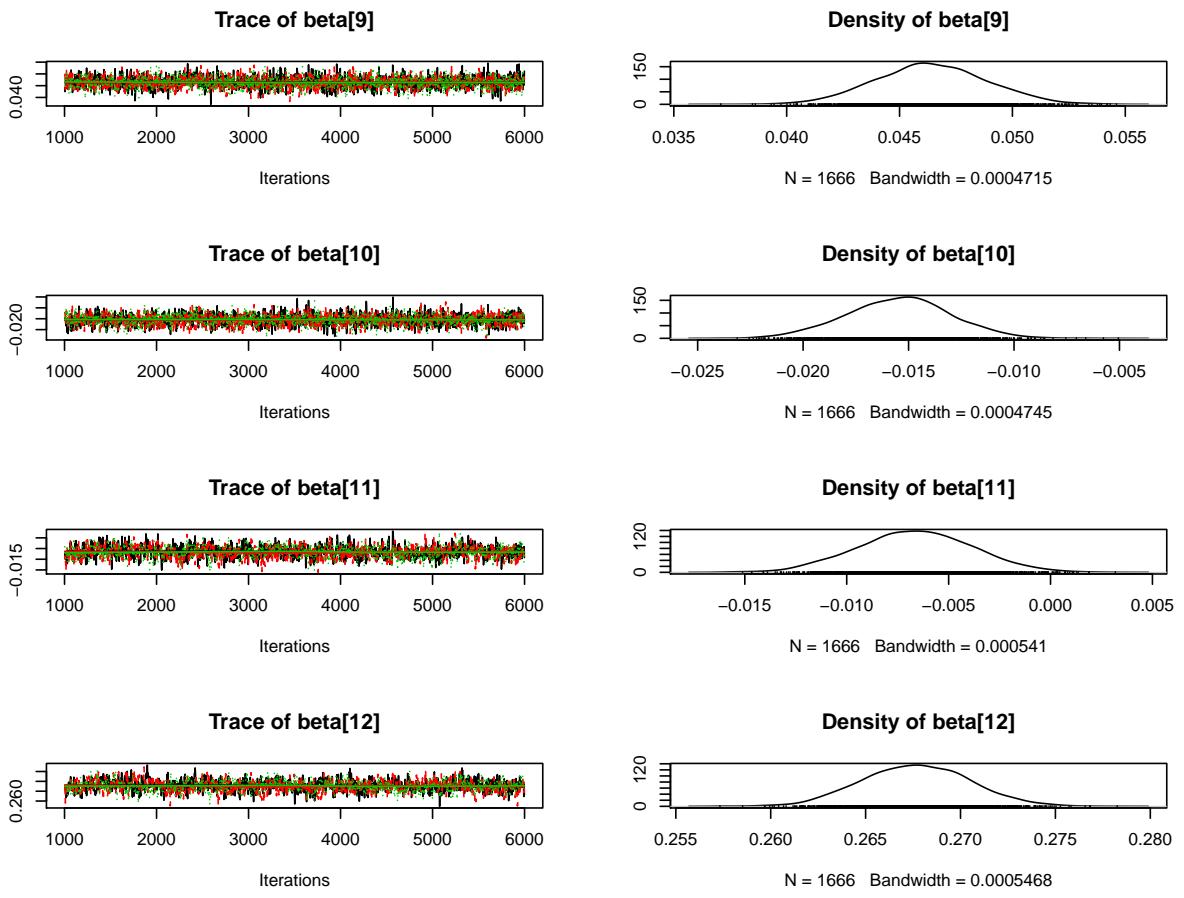
## beta[9]    0.041685  0.0447501  0.0463635  0.048024  0.051257
## beta[10]   -0.020404 -0.0171321 -0.0154066 -0.013837 -0.010696
## beta[11]   -0.012160 -0.0085226 -0.0066474 -0.004767 -0.001147
## beta[12]    0.262254  0.2656973  0.2676661  0.269595  0.273115
## sigma      0.077229  0.0780838  0.0785661  0.079050  0.079953

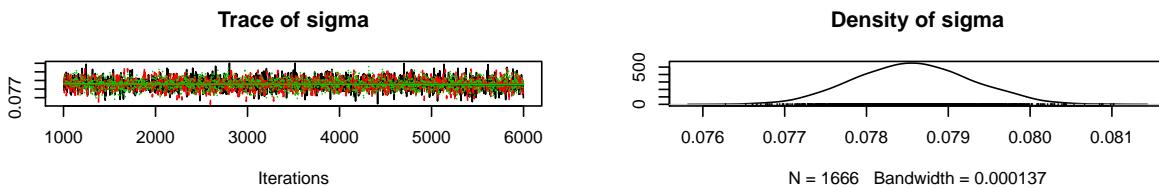
plot(samp)

```









```
## Gelman-Rubin convergence diagnostic
gelman.diag(x = samp,
             confidence = 0.95,
             transform = FALSE,
             autoburnin = FALSE)
```

```
## Potential scale reduction factors:
##
##          Point est. Upper C.I.
## beta[1]      1.01     1.02
## beta[2]      1.01     1.04
## beta[3]      1.00     1.01
## beta[4]      1.02     1.06
## beta[5]      1.00     1.00
## beta[6]      1.02     1.06
## beta[7]      1.01     1.02
## beta[8]      1.00     1.01
## beta[9]      1.00     1.00
## beta[10]     1.00     1.00
## beta[11]     1.00     1.01
## beta[12]     1.00     1.01
## sigma        1.00     1.00
##
## Multivariate psrf
```

```

##  

## 1.02  

## Save the coefficients from the model  

coefs = data.frame( summary(samp)$statistics )  

## Extract the beta estimates  

betas = coefs$Mean[ row.names(coefs) %in% paste0( paste0("beta[",1:12), "]") ]  

## Calculate the fitted values  

dat$Y_Smooth_Fitted_JAGS_5 = c(t(betas) %*% t(cbind(1, X, X_2, X_3, X_4, X_5,  

G.2, G.3, X*G.2, X*G.3,  

X_2*G.2, X_2*G.3)) )  

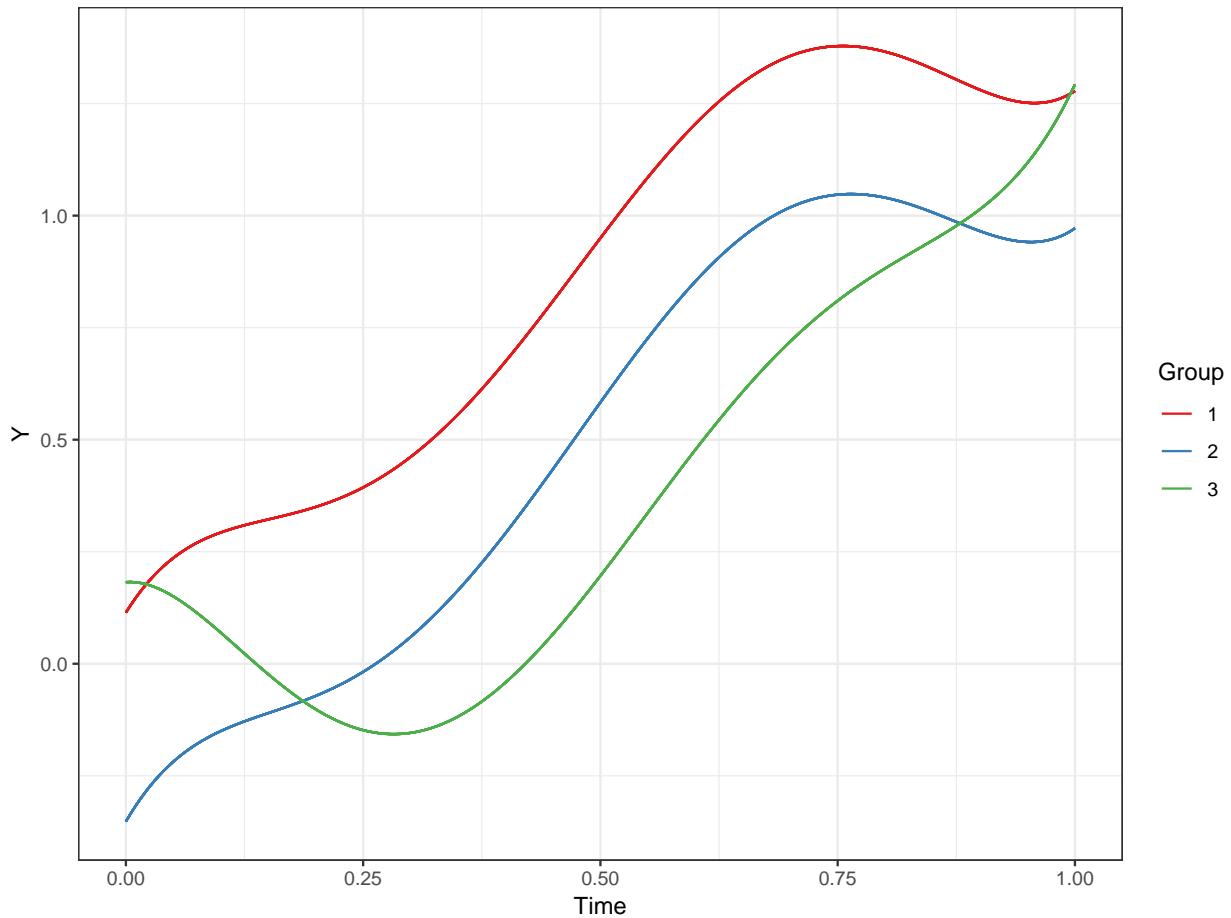
  

## Remove R objects  

rm(model, samp, coefs, model_string, n, X_3, X_4, X_5, betas)

```

Figure 6: The group-level mean functions from JAGS using a 5th-order linear model with time-by-group and Time²-by-group interactions.



Analyze Using Penalized Splines and JAGS

Fit a penalized spline using JAGS:

```
# Define values
n = nrow(dat)

## Create the model
model_string <- "model{

# Likelihood
for(i in 1:n){
Y[i] ~ dnorm(mu[i], inv.var)
mu[i] <- beta[1] + beta[2]*G.2[i] + beta[3]*G.3[i] + beta[4]*X[i] + beta[5]*X_2[i] + alpha[1]*random.basis.1[i] + alpha[2]*random.basis.2[i] + alpha[3]*random.basis.3[i]

# Prior for beta
for(j in 1:5){
beta[j] ~ dnorm(0,0.0001)
}

# Prior for alpha
for(k in 1:(3*K)){
alpha[k] ~ dnorm(0,0.0001)
}

# Prior for the inverse variance
inv.var ~ dgamma(0.01, 0.01)
sigma <- 1/sqrt(inv.var)

}""

## Compile the model
model = jags.model(textConnection(model_string),
                    data = list(Y = Y,
                                n = n,
                                X = X,
                                X_2 = X_2,
                                G.2 = G.2,
                                G.3 = G.3,
                                K = K,
                                random.basis.1 = random.basis.1,
                                random.basis.2 = random.basis.2,
                                random.basis.3 = random.basis.3),
                    n.chains = 3,
                    n.adapt = 1000)

## Compiling model graph
## Resolving undeclared variables
## Allocating nodes
## Graph information:
## Observed stochastic nodes: 6030
## Unobserved stochastic nodes: 78
## Total graph size: 472577
##
```

```

## Initializing model
## Burn-in samples
update(model,
       1000,
       progress.bar = "none")

## Draw additional samples
samp = coda.samples(model,
                     variable.names = c("beta", "alpha", "sigma"),
                     thin = 3,
                     n.iter = 5000,
                     progress.bar = "none")

```

Investigate the fit of the model and extract the fitted values:

```

## Investigate the model
summary(samp)

##
## Iterations = 1003:5998
## Thinning interval = 3
## Number of chains = 3
## Sample size per chain = 1666
##
## 1. Empirical mean and standard deviation for each variable,
##    plus standard error of the mean:
##
##           Mean        SD  Naive SE Time-series SE
## alpha[1]  0.113424  0.035434 5.012e-04   1.126e-02
## alpha[2]  0.086439  0.044434 6.285e-04   6.730e-03
## alpha[3]  0.045598  0.040094 5.671e-04   7.453e-03
## alpha[4] -0.046597  0.022348 3.161e-04   7.201e-03
## alpha[5] -0.037036  0.047944 6.782e-04   2.263e-02
## alpha[6] -0.043044  0.072531 1.026e-03   1.157e-02
## alpha[7] -0.170157  0.106705 1.509e-03   2.543e-02
## alpha[8]  0.006867  0.042062 5.950e-04   2.098e-02
## alpha[9]  0.042399  0.101395 1.434e-03   1.946e-02
## alpha[10] 0.009517  0.085220 1.205e-03   4.108e-02
## alpha[11] 0.133479  0.128535 1.818e-03   5.122e-02
## alpha[12] -0.025174  0.092888 1.314e-03   1.676e-02
## alpha[13] -0.245378  0.111154 1.572e-03   2.437e-02
## alpha[14] -0.417179  0.130136 1.841e-03   4.159e-02
## alpha[15] -0.431264  0.361252 5.110e-03   1.919e-01
## alpha[16] -0.484419  0.602309 8.520e-03   4.351e-02
## alpha[17]  0.483253  0.608466 8.607e-03   1.813e-01
## alpha[18]  0.498610  0.509885 7.212e-03   9.834e-02
## alpha[19]  1.752580  0.408013 5.771e-03   1.422e-01
## alpha[20] -2.689976  0.599519 8.480e-03   1.834e-01
## alpha[21]  1.009785  1.341639 1.898e-02   3.689e-01
## alpha[22]  1.145701  2.144042 3.033e-02   6.092e-01
## alpha[23] -1.358492  2.307997 3.265e-02   3.692e-01
## alpha[24]  0.742816  2.916018 4.125e-02   2.179e-01
## alpha[25]  0.139015  0.030461 4.309e-04   9.534e-03
## alpha[26]  0.124552  0.036239 5.126e-04   1.101e-02
## alpha[27]  0.117285  0.054277 7.677e-04   5.613e-03

```

```

## alpha[28]  0.104309  0.024670 3.490e-04      1.107e-02
## alpha[29]  0.005285  0.050472 7.139e-04      1.379e-02
## alpha[30] -0.171124  0.071947 1.018e-03      2.490e-02
## alpha[31] -0.218120  0.097013 1.372e-03      3.984e-02
## alpha[32] -0.345771  0.105052 1.486e-03      2.428e-02
## alpha[33] -0.360937  0.057911 8.191e-04      1.290e-02
## alpha[34] -0.205943  0.090493 1.280e-03      3.689e-02
## alpha[35] -0.091932  0.158339 2.240e-03      8.075e-02
## alpha[36]  0.321133  0.259190 3.666e-03      1.105e-01
## alpha[37]  0.659110  0.239679 3.390e-03      1.016e-01
## alpha[38]  0.500718  0.145748 2.062e-03      4.605e-02
## alpha[39]  0.127663  0.504433 7.135e-03      2.707e-01
## alpha[40] -0.301366  0.598886 8.471e-03      3.107e-01
## alpha[41] -0.992310  0.599616 8.482e-03      2.005e-01
## alpha[42] -1.339860  0.855023 1.209e-02      4.868e-01
## alpha[43]  0.619995  1.870425 2.646e-02      1.012e+00
## alpha[44]  1.176992  1.510347 2.136e-02      4.897e-01
## alpha[45] -0.364607  4.423588 6.257e-02      4.225e+00
## alpha[46] -1.728248  6.194526 8.762e-02      3.524e+00
## alpha[47]  2.597209  6.531755 9.239e-02      2.475e+00
## alpha[48] -1.185088  6.292262 8.900e-02      1.569e+00
## alpha[49] -0.242968  0.066207 9.365e-04      2.970e-02
## alpha[50] -0.216271  0.049242 6.965e-04      1.848e-02
## alpha[51] -0.184753  0.039224 5.548e-04      7.005e-03
## alpha[52] -0.072943  0.036702 5.191e-04      9.655e-03
## alpha[53]  0.066279  0.067245 9.512e-04      2.628e-02
## alpha[54]  0.352281  0.114936 1.626e-03      4.885e-02
## alpha[55]  0.509539  0.157179 2.223e-03      6.963e-02
## alpha[56]  0.761584  0.133999 1.895e-03      5.424e-02
## alpha[57]  0.734537  0.086546 1.224e-03      3.085e-02
## alpha[58]  0.543340  0.114379 1.618e-03      5.611e-02
## alpha[59] -0.067810  0.323429 4.575e-03      1.577e-01
## alpha[60] -0.896793  0.483446 6.838e-03      2.152e-01
## alpha[61] -1.762448  0.487830 6.900e-03      1.912e-01
## alpha[62] -2.165925  0.295818 4.184e-03      9.300e-02
## alpha[63] -1.423591  0.760997 1.076e-02      4.345e-01
## alpha[64]  0.636310  1.559526 2.206e-02      7.578e-01
## alpha[65]  3.698968  1.419613 2.008e-02      5.404e-01
## alpha[66]  2.802275  2.052769 2.904e-02      1.260e+00
## alpha[67] -0.623541  3.723119 5.266e-02      1.995e+00
## alpha[68] -5.781914  3.403613 4.814e-02      1.158e+00
## alpha[69]  3.583632  11.428839 1.617e-01      8.176e+00
## alpha[70]  3.496247  14.317736 2.025e-01      1.046e+01
## alpha[71] -6.323298  12.885284 1.823e-01      5.287e+00
## alpha[72]  4.436901  11.647301 1.648e-01      3.378e+00
## beta[1]   0.603385  0.028255 3.997e-04      6.127e-03
## beta[2]  -0.469953  0.005911 8.361e-05      9.755e-04
## beta[3]  -0.153077  0.028790 4.072e-04      1.005e-02
## beta[4]   0.471725  0.036784 5.203e-04      9.786e-03
## beta[5]   0.155674  0.013893 1.965e-04      3.714e-03
## sigma    0.059433  0.010310 1.458e-04      4.154e-03
##
## 2. Quantiles for each variable:
##

```

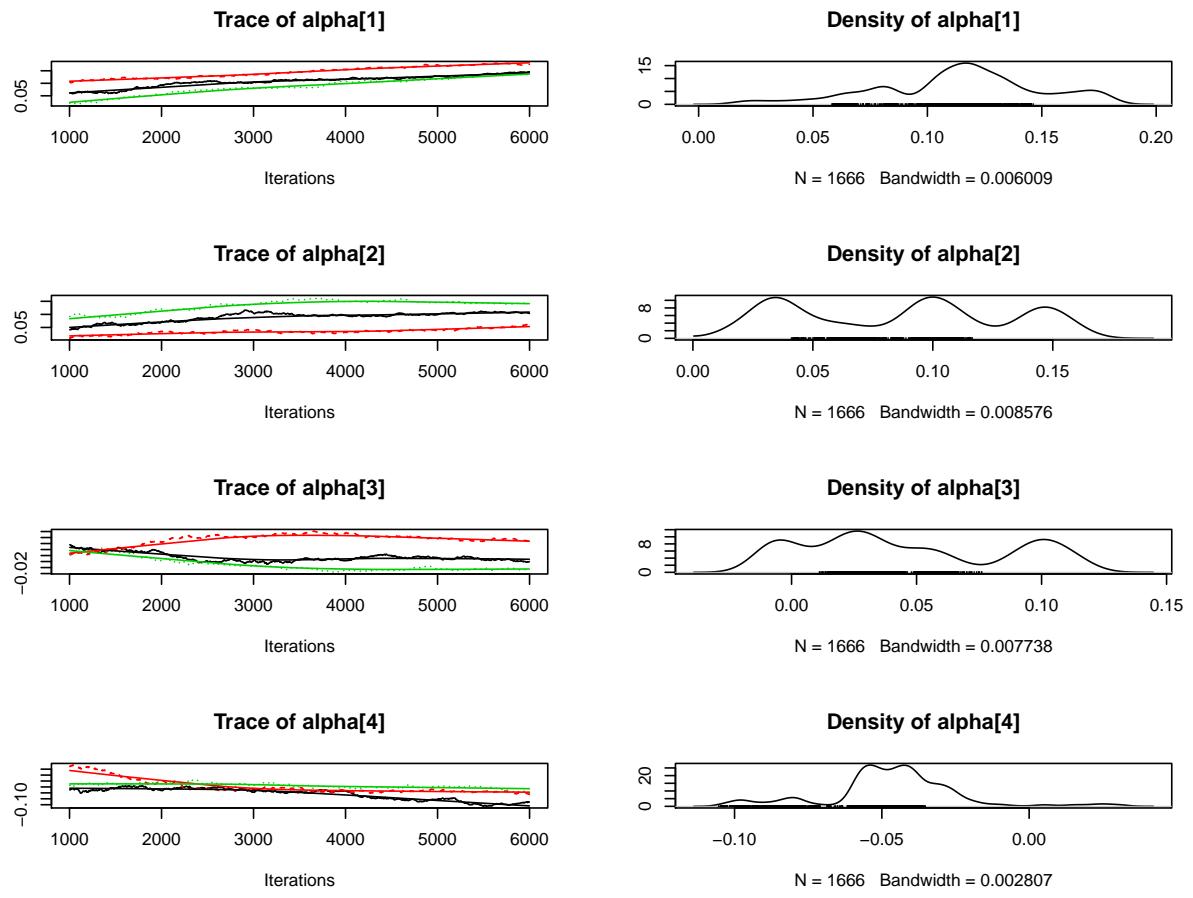
	2.5%	25%	50%	75%	97.5%
## alpha[1]	0.03296	0.09203	0.116514	0.133745	0.175829
## alpha[2]	0.01875	0.03972	0.094123	0.118600	0.157035
## alpha[3]	-0.01109	0.01616	0.035290	0.089085	0.113670
## alpha[4]	-0.09800	-0.05591	-0.045901	-0.036424	0.014462
## alpha[5]	-0.11094	-0.07926	-0.041667	0.002377	0.050466
## alpha[6]	-0.20662	-0.11684	-0.015894	0.004321	0.057485
## alpha[7]	-0.33313	-0.25716	-0.175642	-0.078534	0.001868
## alpha[8]	-0.04872	-0.02036	-0.002022	0.014779	0.121385
## alpha[9]	-0.08902	-0.05391	0.029827	0.124282	0.235354
## alpha[10]	-0.12583	-0.05394	0.008170	0.059659	0.197173
## alpha[11]	-0.11790	0.04267	0.148772	0.231780	0.341037
## alpha[12]	-0.17062	-0.10314	-0.044390	0.063493	0.132635
## alpha[13]	-0.43549	-0.33129	-0.264841	-0.144158	-0.064040
## alpha[14]	-0.64200	-0.51268	-0.433671	-0.299378	-0.199632
## alpha[15]	-1.16992	-0.58171	-0.474064	-0.193054	0.218972
## alpha[16]	-1.19504	-1.03640	-0.692149	0.237375	0.542187
## alpha[17]	-0.34404	-0.06860	0.398650	0.842924	1.840094
## alpha[18]	-0.15652	0.11327	0.370219	0.844568	1.438710
## alpha[19]	0.68381	1.52281	1.850179	2.057172	2.312576
## alpha[20]	-3.56099	-3.12791	-2.859463	-2.284896	-1.340238
## alpha[21]	-2.46915	0.38772	1.158856	1.955266	2.926980
## alpha[22]	-1.75500	-0.25242	1.093440	2.069315	9.077034
## alpha[23]	-7.15805	-2.47439	-1.108872	0.117855	2.393170
## alpha[24]	-4.63105	-1.11388	0.607518	2.367671	7.122755
## alpha[25]	0.07398	0.12150	0.139165	0.158106	0.202323
## alpha[26]	0.06207	0.10222	0.119310	0.138415	0.190217
## alpha[27]	0.05388	0.06435	0.094151	0.181762	0.199548
## alpha[28]	0.05677	0.08449	0.111172	0.123682	0.136419
## alpha[29]	-0.09195	-0.03613	0.020415	0.049752	0.065395
## alpha[30]	-0.32301	-0.20107	-0.175524	-0.130878	-0.009875
## alpha[31]	-0.42118	-0.28135	-0.220389	-0.150796	-0.048176
## alpha[32]	-0.53433	-0.39434	-0.342319	-0.284706	-0.136022
## alpha[33]	-0.45914	-0.39995	-0.360325	-0.326337	-0.238094
## alpha[34]	-0.30791	-0.27431	-0.238653	-0.153408	-0.004276
## alpha[35]	-0.34397	-0.22259	-0.087218	0.036686	0.261077
## alpha[36]	-0.19424	0.13502	0.397738	0.523784	0.745076
## alpha[37]	0.08474	0.53640	0.743265	0.831003	0.972990
## alpha[38]	0.21191	0.39758	0.515744	0.615183	0.750959
## alpha[39]	-0.81418	-0.31269	0.193037	0.576472	0.846047
## alpha[40]	-1.00303	-0.82927	-0.483214	0.210809	0.890992
## alpha[41]	-2.00083	-1.31997	-1.033304	-0.762403	0.441059
## alpha[42]	-2.54375	-2.10889	-1.477469	-0.693330	0.272003
## alpha[43]	-2.95997	-0.85282	1.220280	1.900666	3.419896
## alpha[44]	-2.30139	0.19823	1.457086	2.289585	3.611935
## alpha[45]	-5.83746	-4.80369	-1.166498	4.198056	6.578248
## alpha[46]	-12.01707	-7.28570	-1.373310	4.442959	6.998735
## alpha[47]	-11.39655	-2.36834	2.823148	8.452786	12.750035
## alpha[48]	-11.39272	-5.89636	-1.765827	2.477937	13.381794
## alpha[49]	-0.34687	-0.29396	-0.249633	-0.190874	-0.119969
## alpha[50]	-0.30787	-0.26079	-0.205339	-0.180527	-0.139564
## alpha[51]	-0.26446	-0.21910	-0.172567	-0.161340	-0.123445
## alpha[52]	-0.13998	-0.09962	-0.077183	-0.047537	-0.002488
## alpha[53]	-0.04542	0.01667	0.061326	0.122758	0.183748

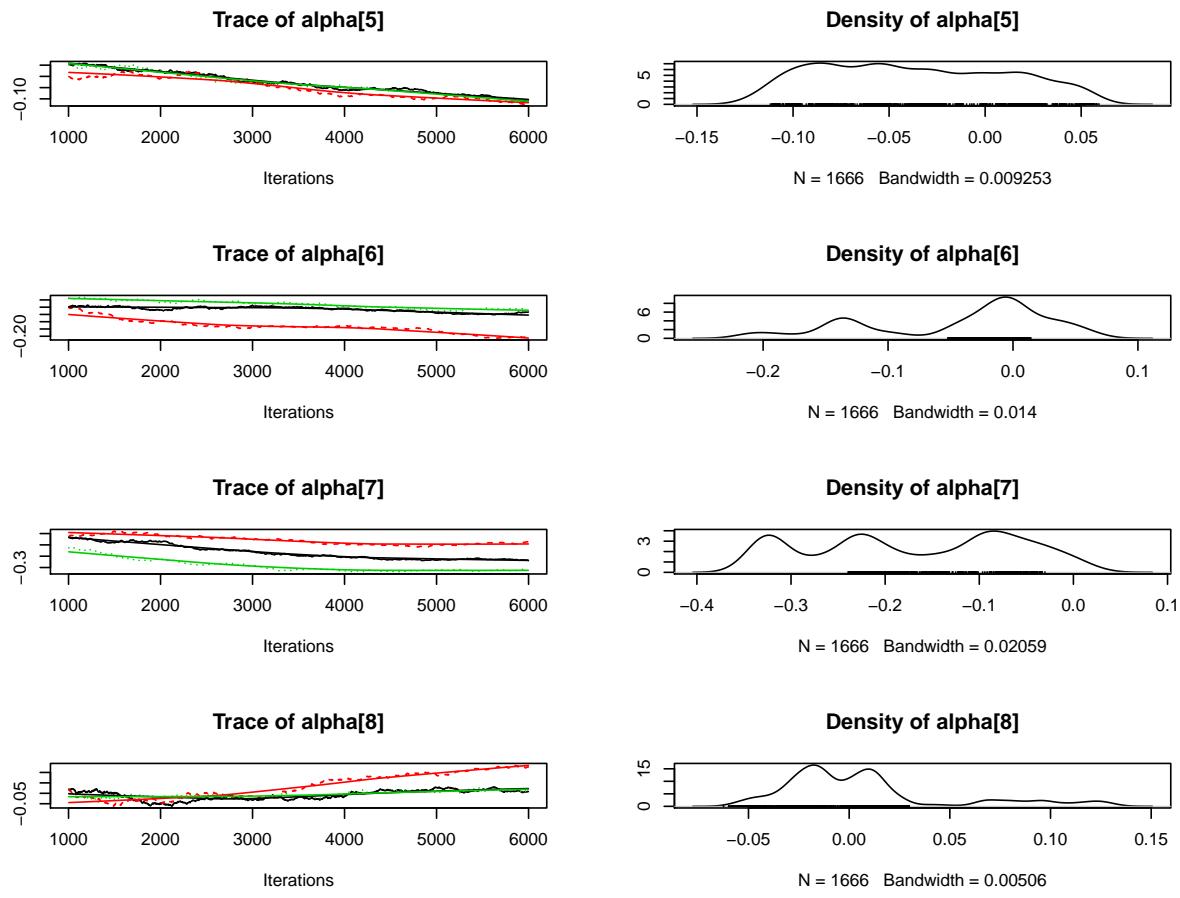
```

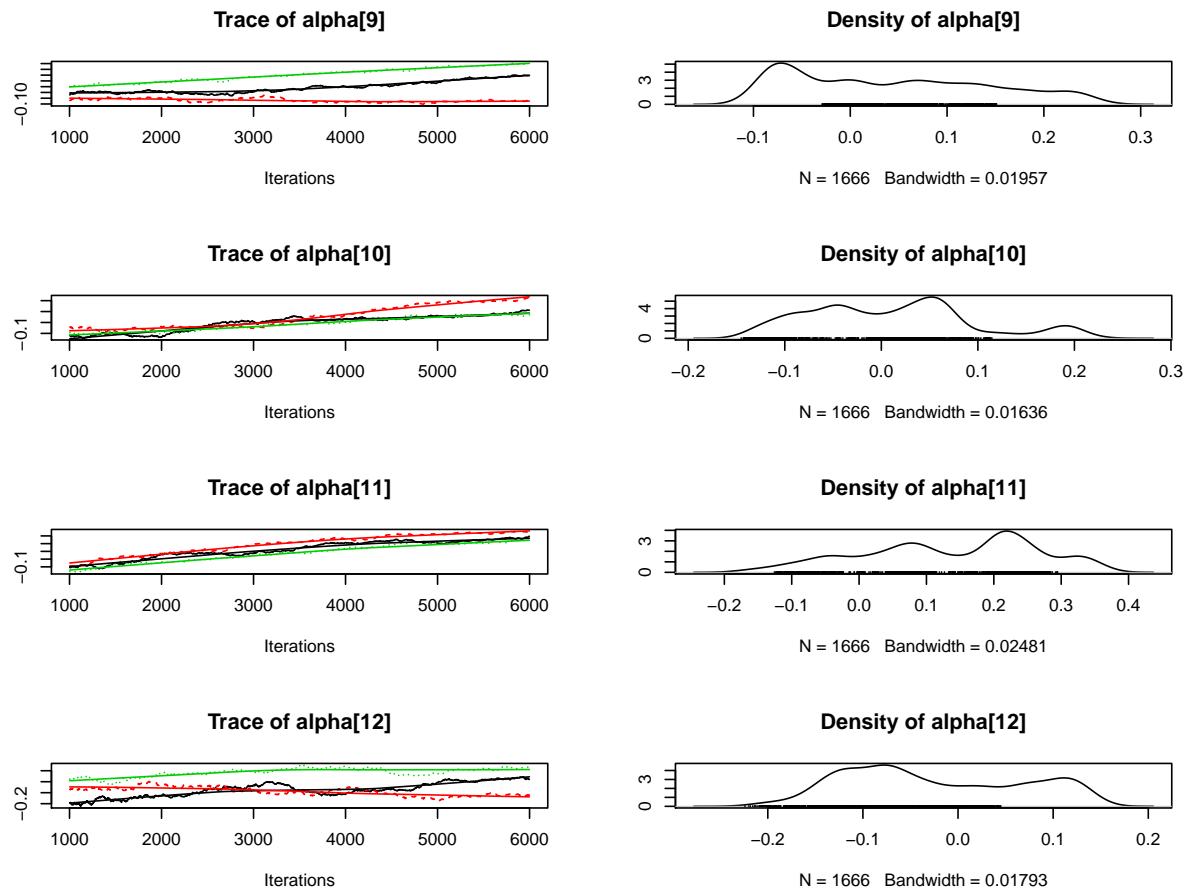
## alpha[54]  0.13146  0.25806  0.372822  0.440960  0.538458
## alpha[55]  0.21094  0.38407  0.530257  0.639004  0.777050
## alpha[56]  0.47896  0.67059  0.782757  0.861058  0.961860
## alpha[57]  0.49753  0.70336  0.760785  0.791526  0.838358
## alpha[58]  0.31430  0.44834  0.565505  0.640122  0.696817
## alpha[59] -0.57566 -0.35207 -0.090923  0.199986  0.525152
## alpha[60] -1.62899 -1.31152 -0.938242 -0.532516  0.031016
## alpha[61] -2.45524 -2.10368 -1.879679 -1.433762 -0.686237
## alpha[62] -2.66244 -2.32298 -2.224146 -1.980207 -1.465394
## alpha[63] -2.45447 -2.17037 -1.520534 -0.750105 -0.108886
## alpha[64] -2.21705 -0.66373  0.932931  1.980325  2.916107
## alpha[65]  0.21948  3.16954  3.969631  4.849347  5.330663
## alpha[66] -0.79267  0.96037  3.119730  4.717257  5.687437
## alpha[67] -4.97157 -3.98449 -1.754310  2.559047  6.644411
## alpha[68] -10.76595 -8.22130 -6.512795 -3.375054  2.409147
## alpha[69] -17.08578 -7.83883  7.826858 14.325017 15.502120
## alpha[70] -16.33715 -10.31884  2.660701 17.196455 26.285080
## alpha[71] -26.75810 -18.16886 -6.265612  5.234938 16.829549
## alpha[72] -23.90260 -3.53299  5.579312 13.933373 21.310008
## beta[1]   0.55155  0.58180  0.602415  0.626457  0.650265
## beta[2]  -0.47967 -0.47441 -0.470270 -0.466249 -0.457019
## beta[3]  -0.21592 -0.17185 -0.145272 -0.129417 -0.116620
## beta[4]   0.40501  0.44384  0.468786  0.499640  0.535427
## beta[5]   0.13065  0.14333  0.157266  0.166975  0.177490
## sigma    0.04705  0.05056  0.056685  0.066634  0.082238

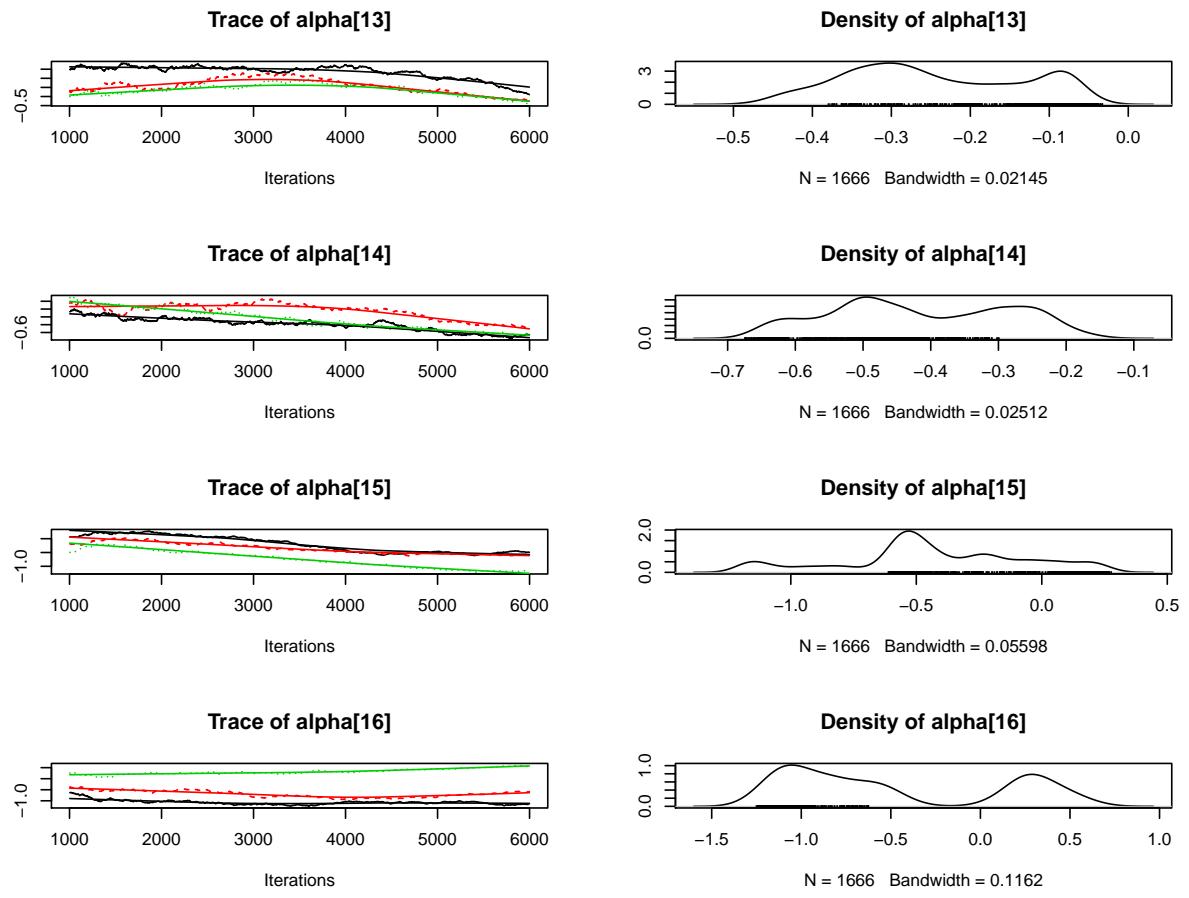
plot(samp)

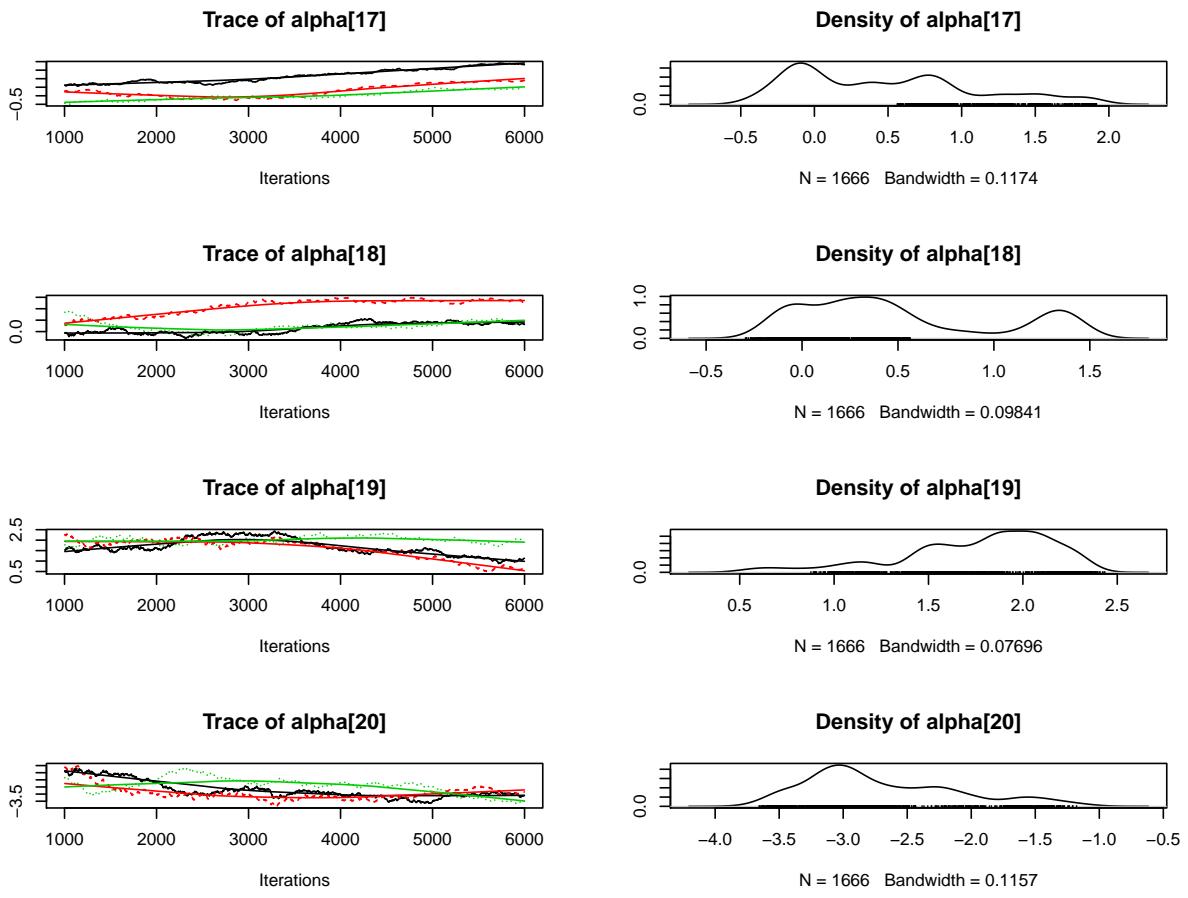
```

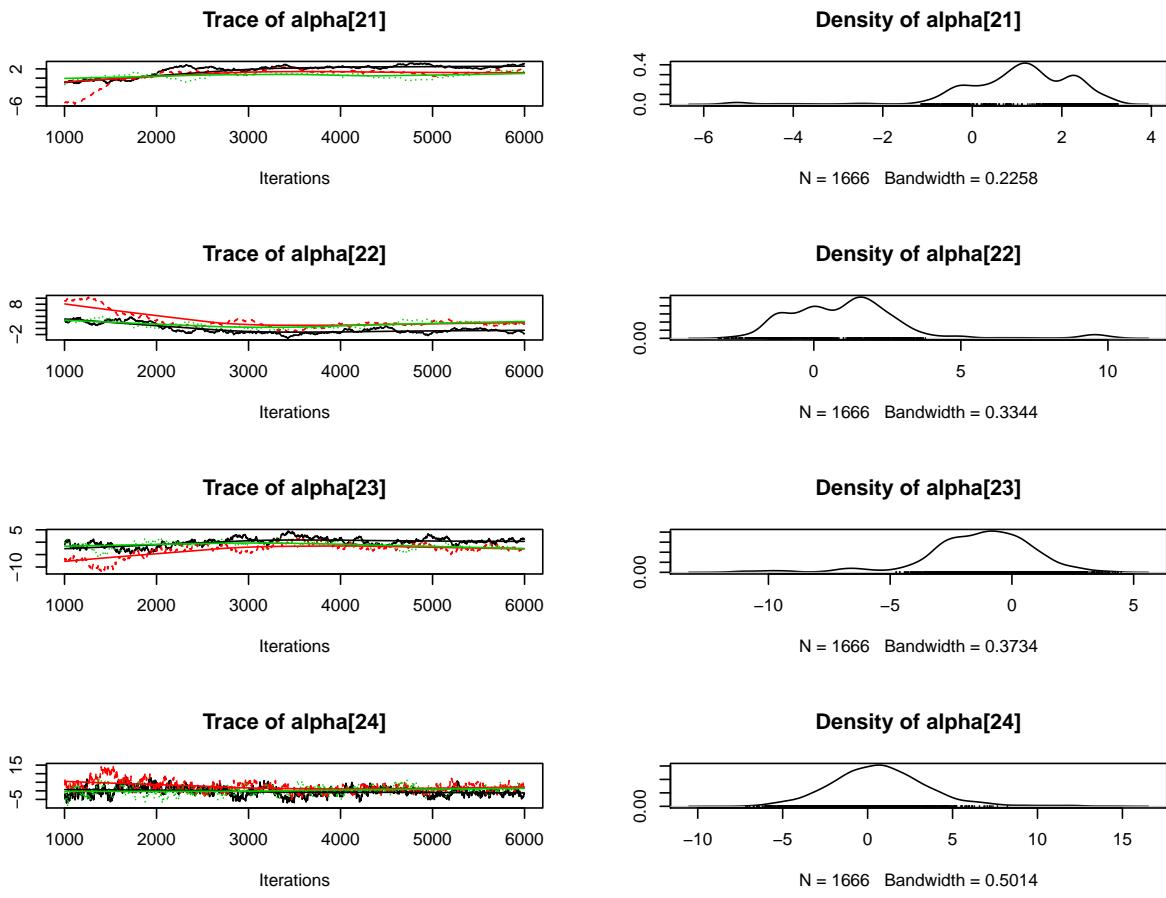


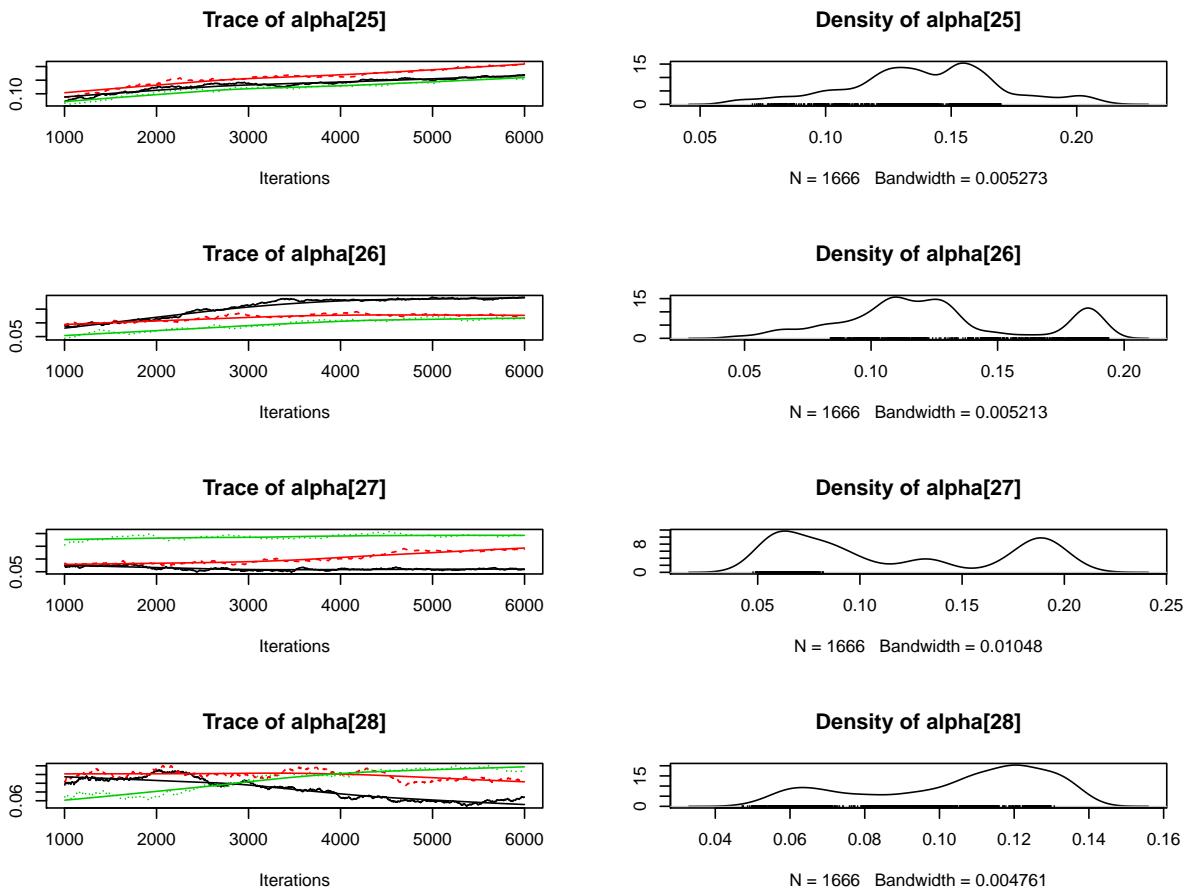


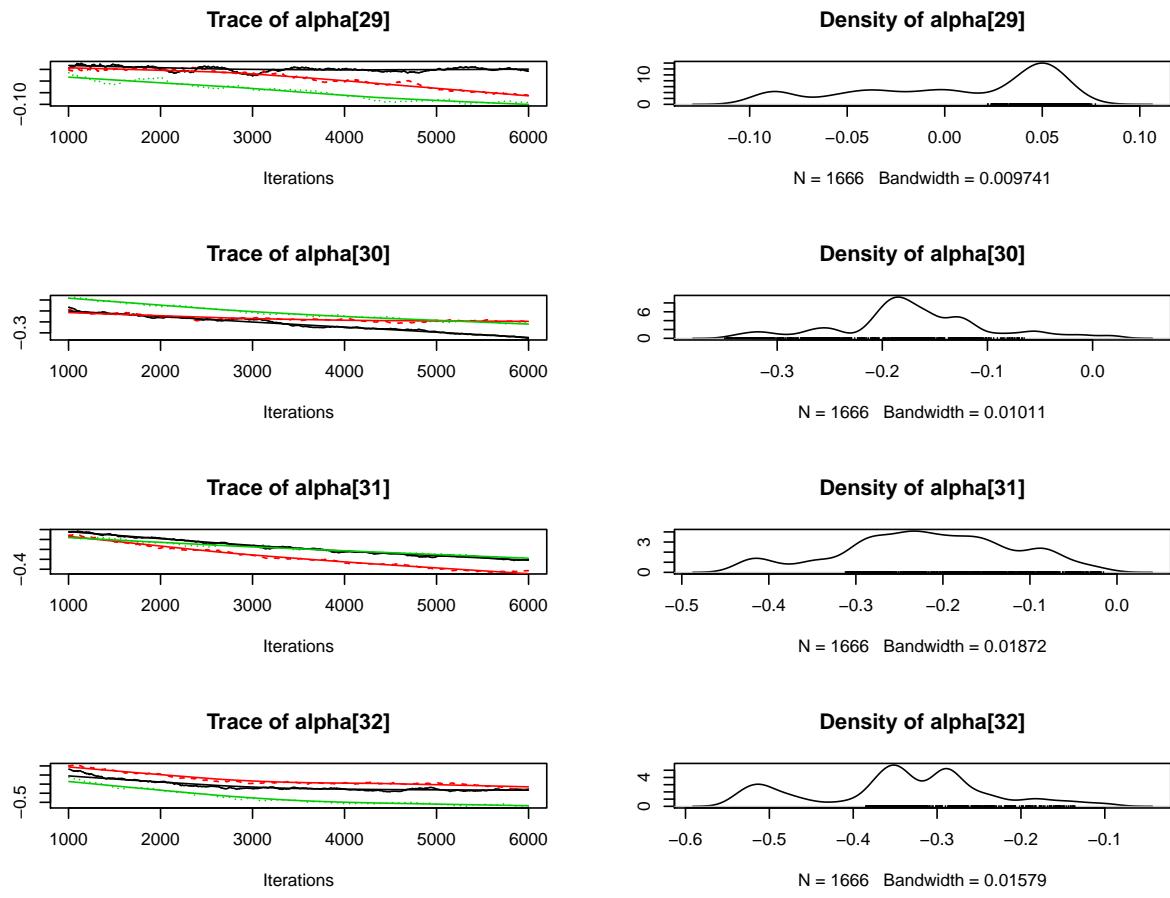


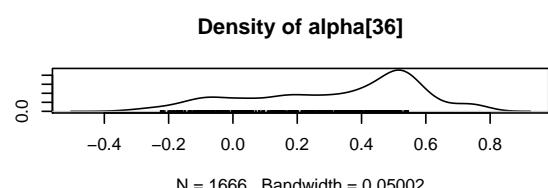
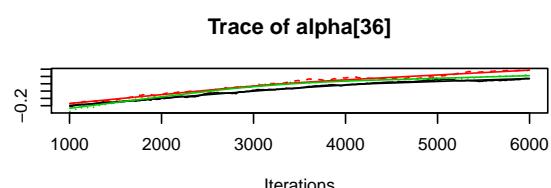
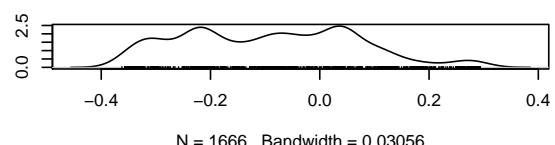
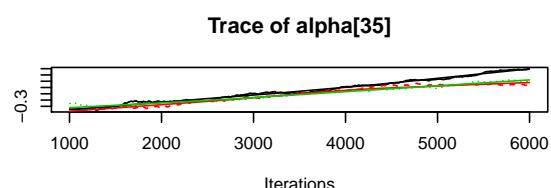
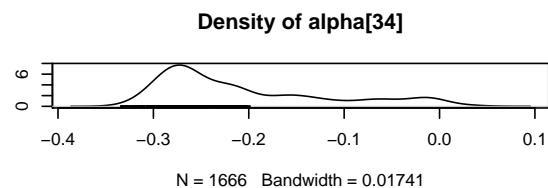
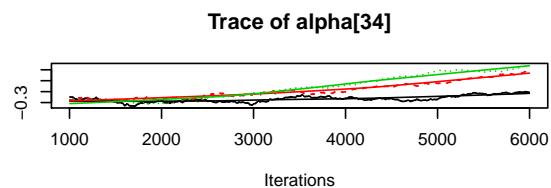
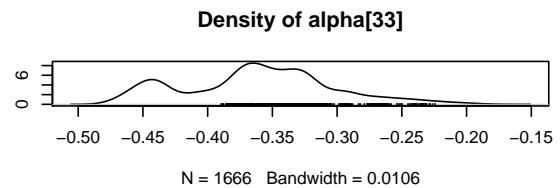
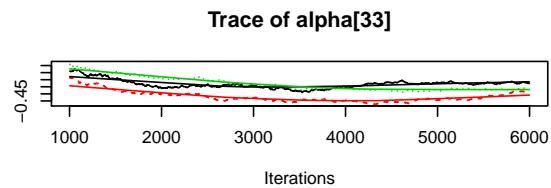


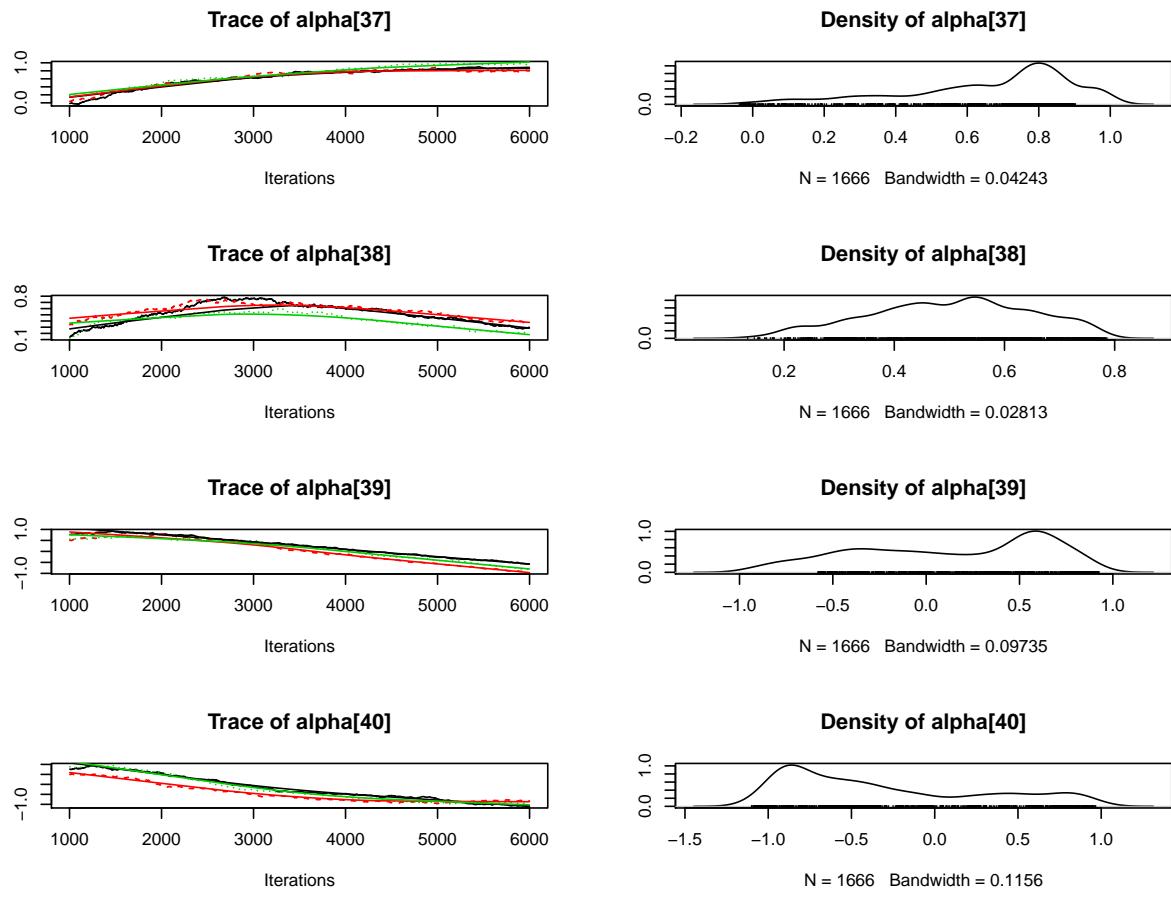


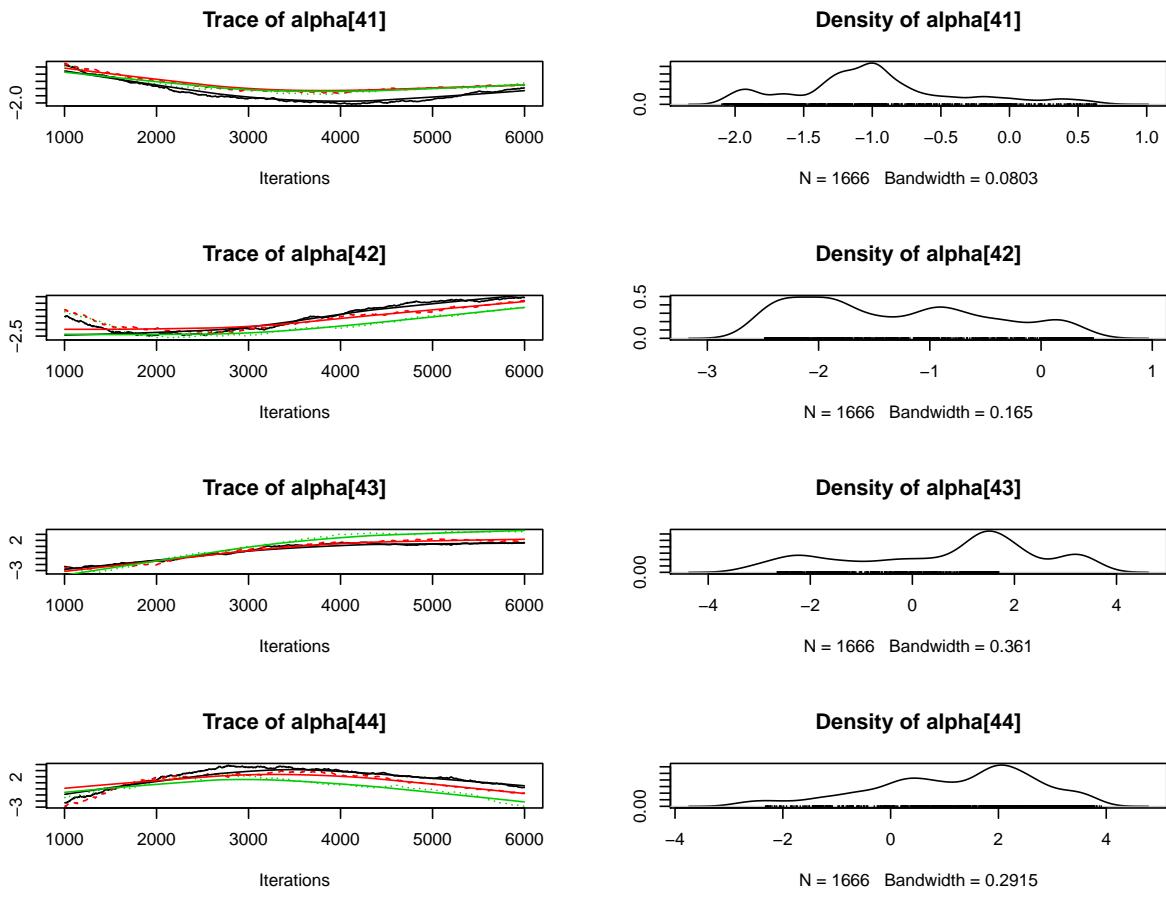


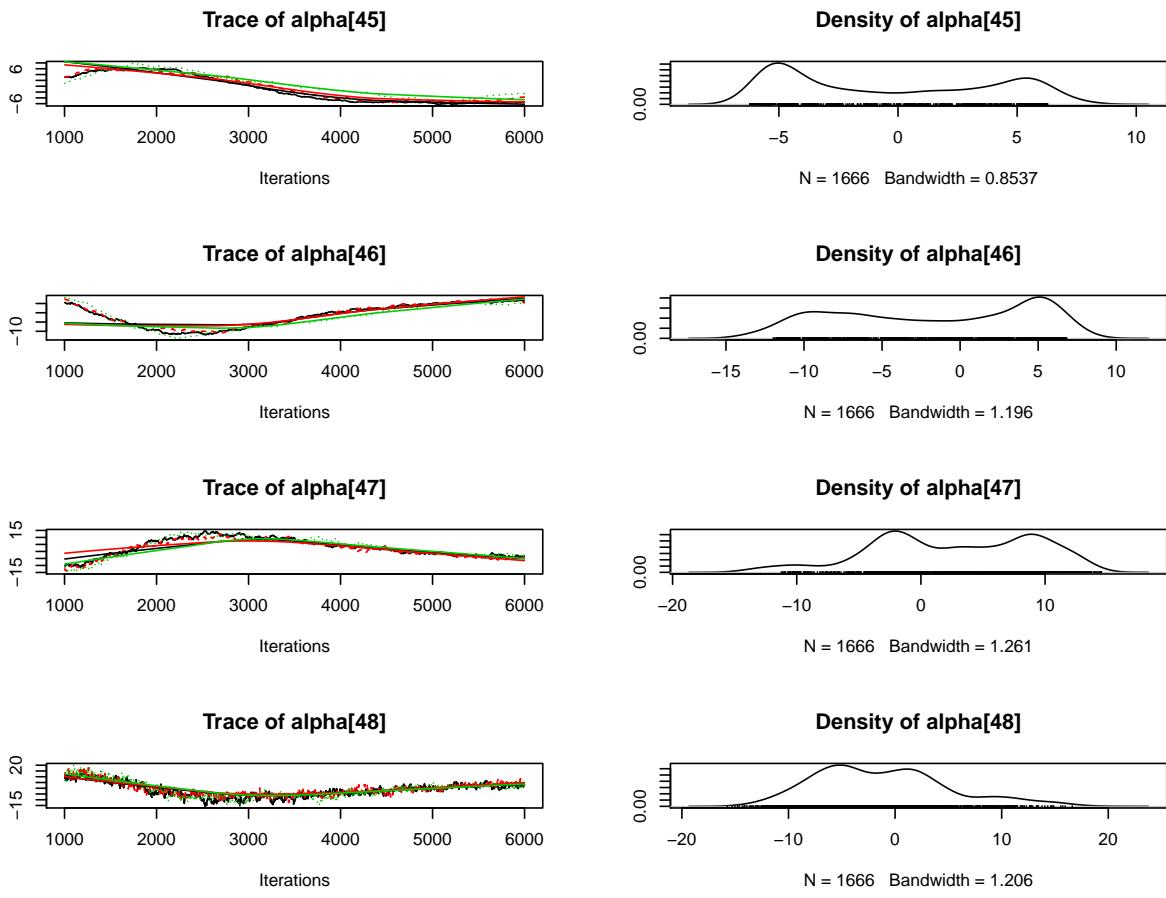


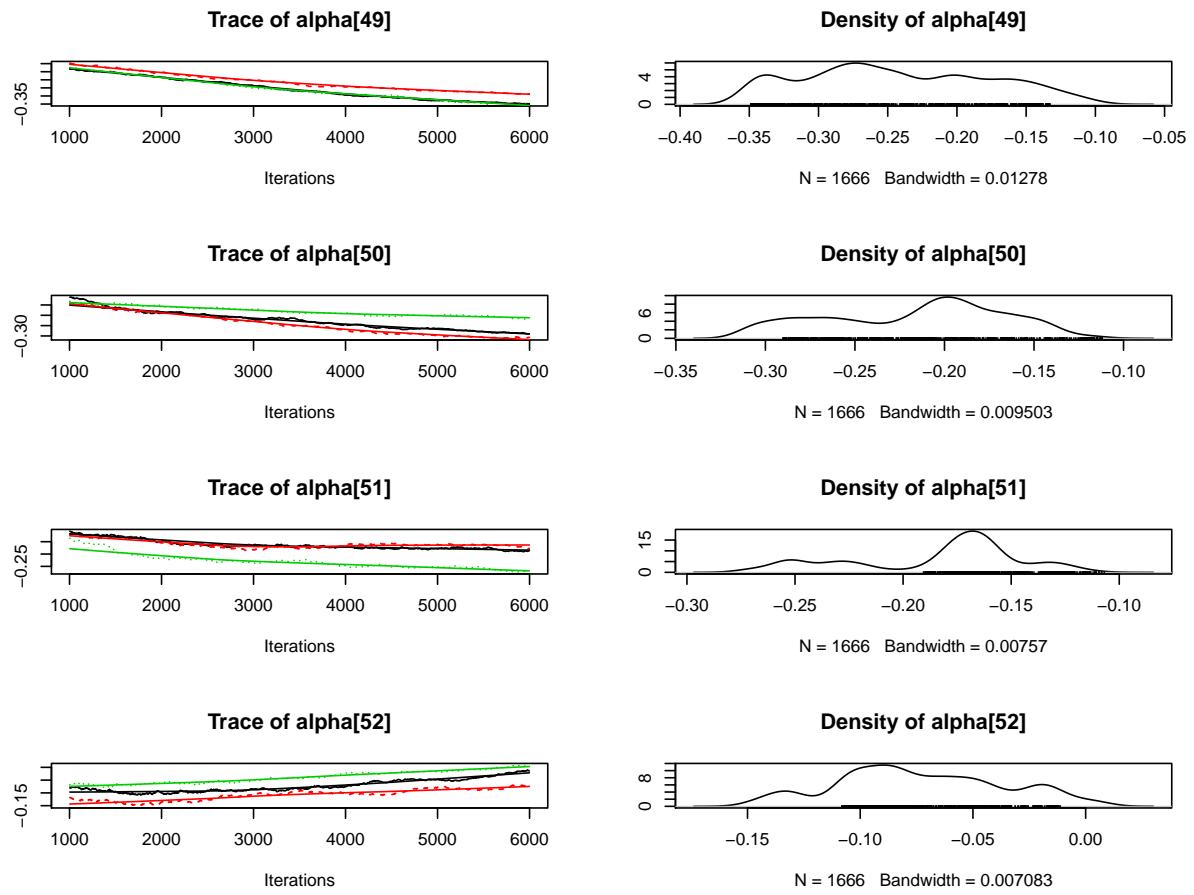


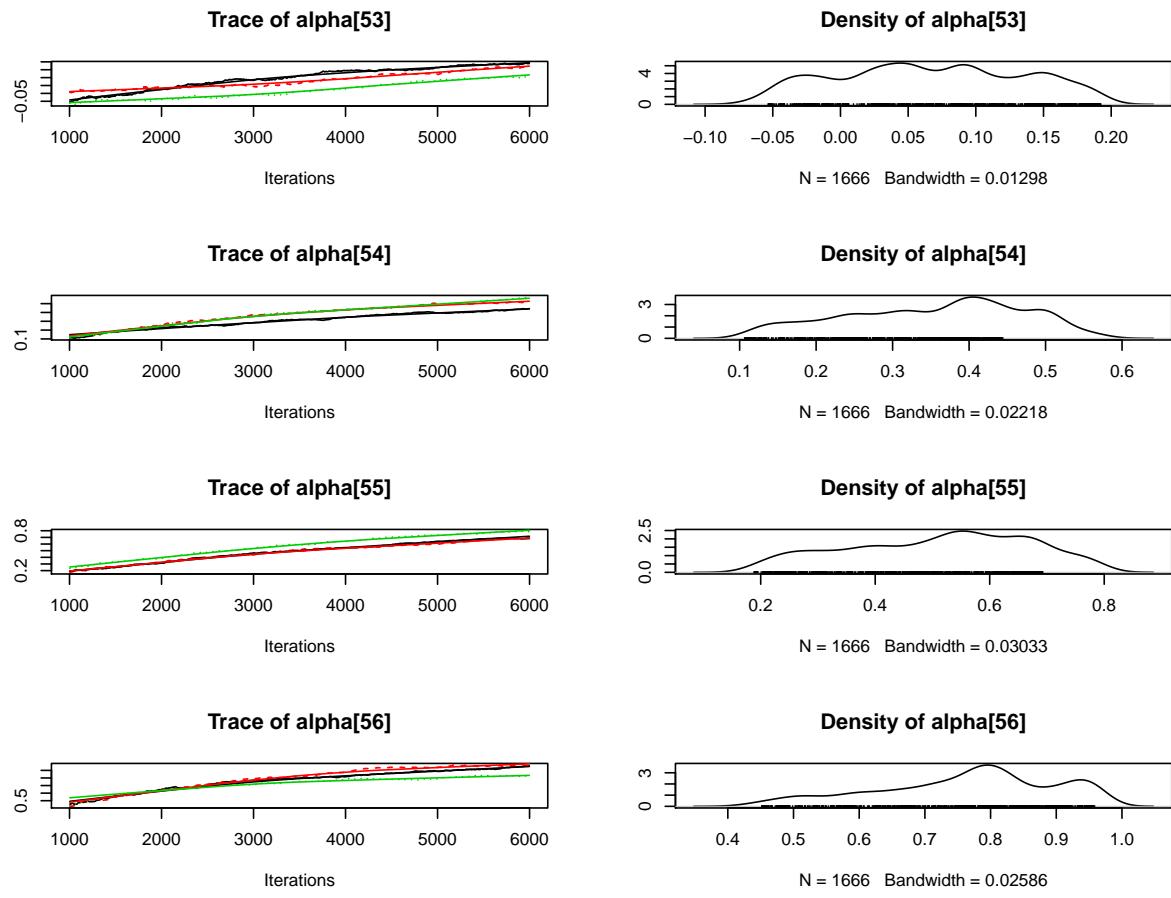


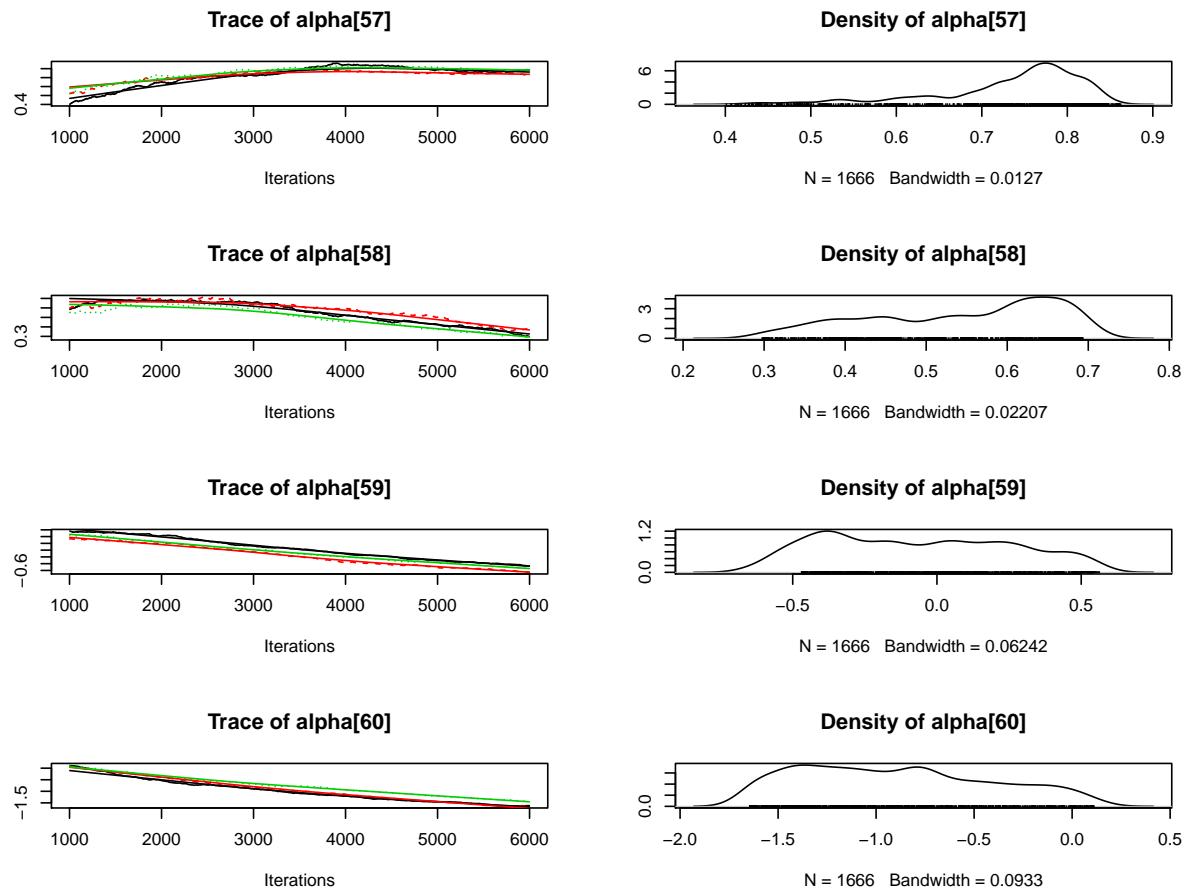


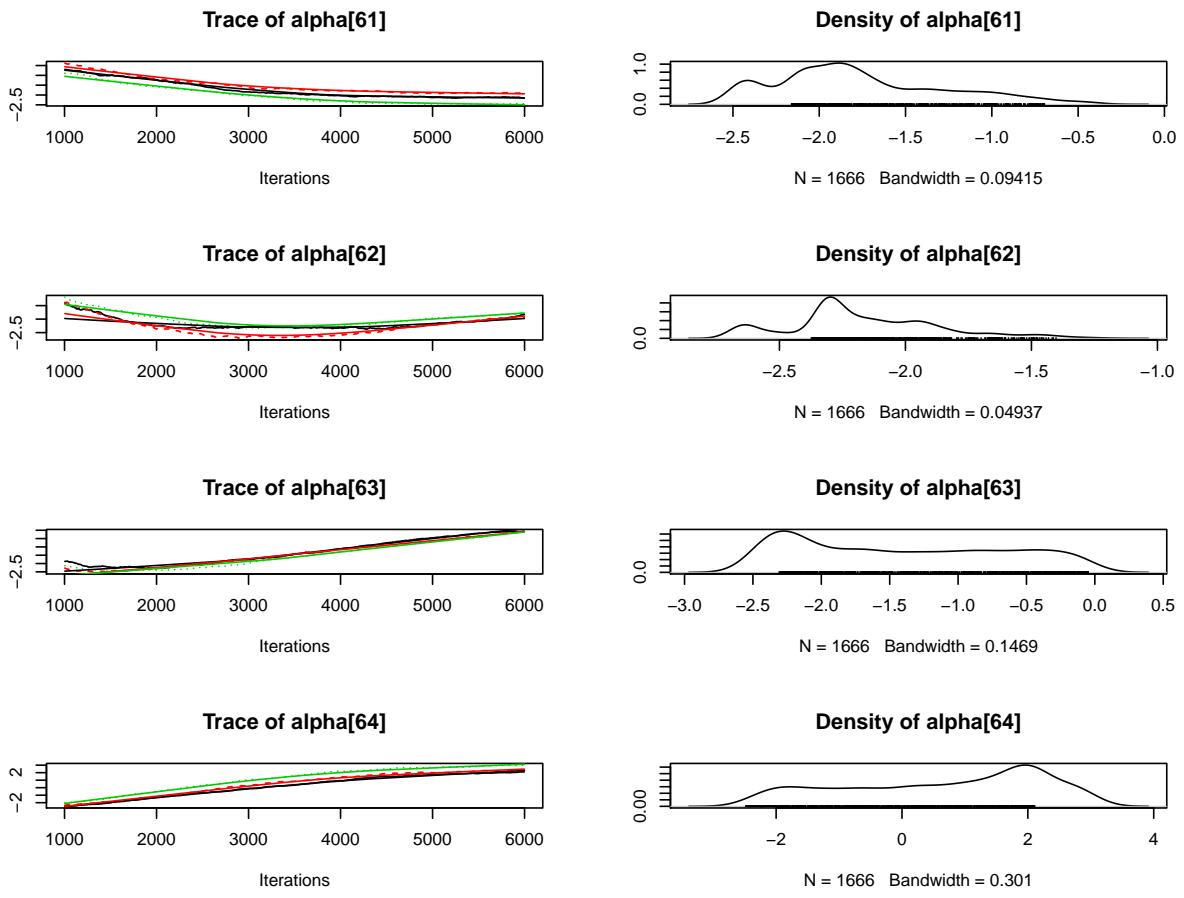


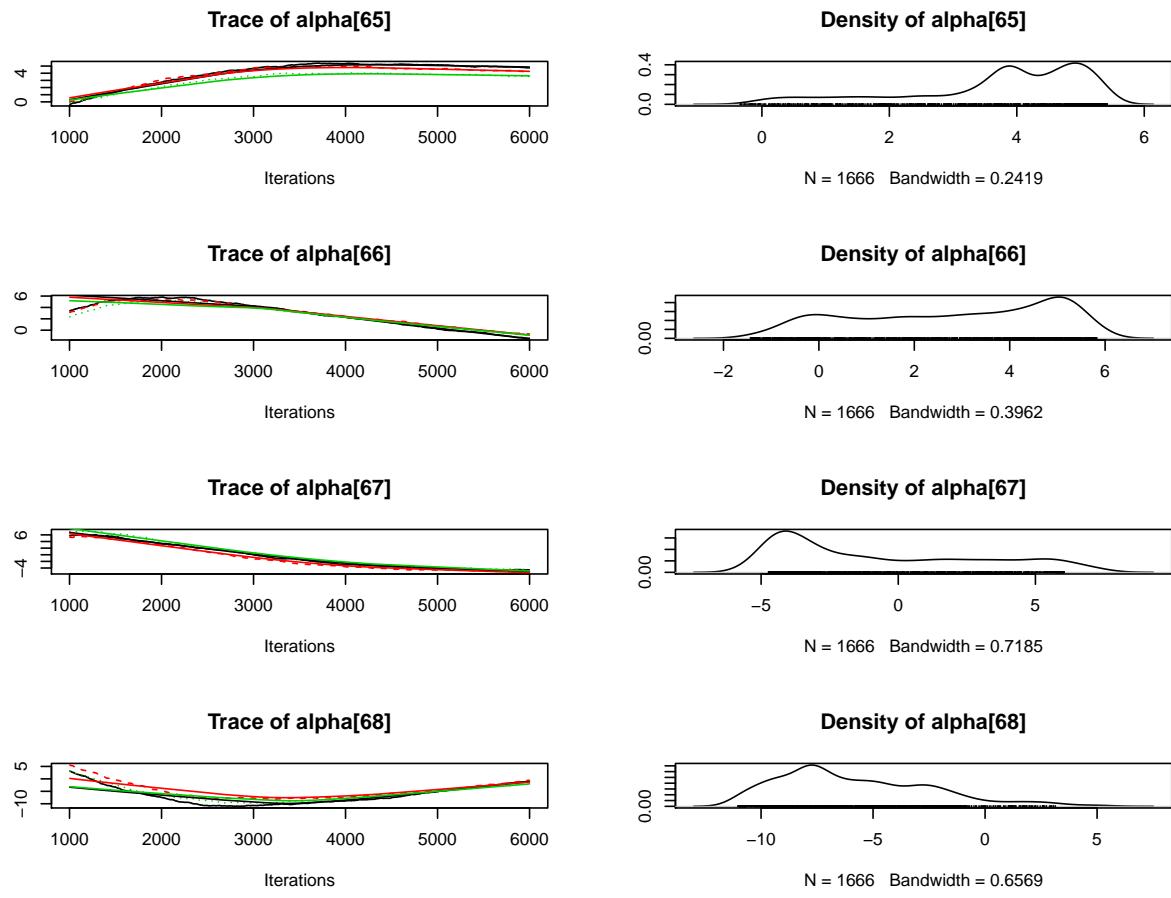


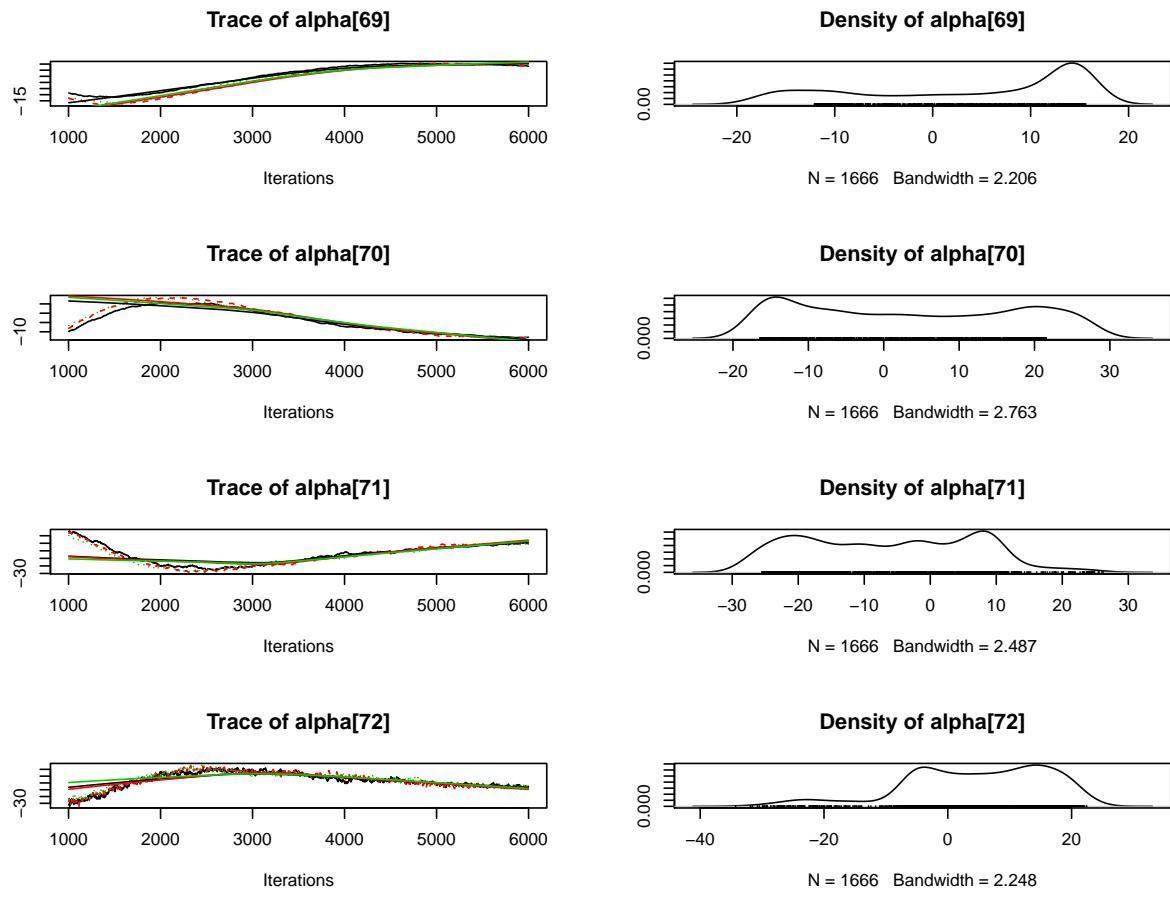


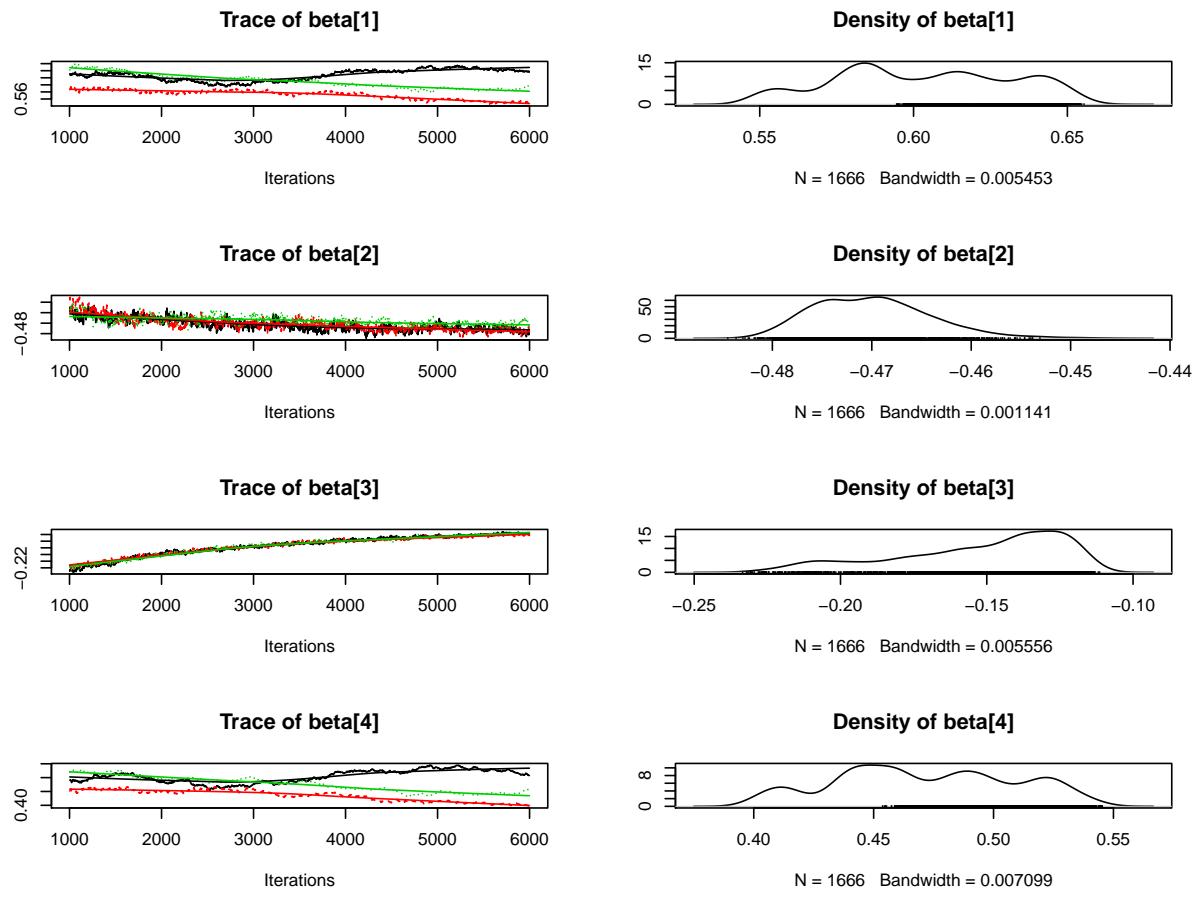


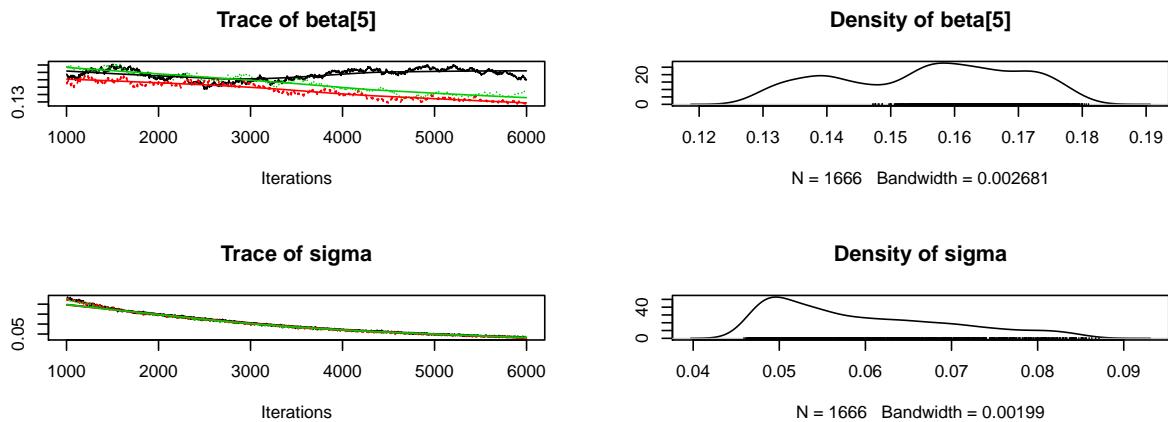












```

## Save the coefficients from the model
coefs = data.frame( summary(samp)$statistics )

## Gelman-Rubin convergence diagnostic
gelman.diag(x = samp,
             confidence = 0.95,
             transform = FALSE,
             autoburnin = FALSE)

## Potential scale reduction factors:
##
##          Point est. Upper C.I.
## alpha[1]      1.90     3.28
## alpha[2]      4.49     9.42
## alpha[3]      3.65     7.01
## alpha[4]      1.51     2.63
## alpha[5]      1.04     1.14
## alpha[6]      3.78     9.03
## alpha[7]      3.20     6.19
## alpha[8]      1.46     3.19
## alpha[9]      3.67     8.25
## alpha[10]     1.18     1.51
## alpha[11]     1.19     1.55
## alpha[12]     3.05     6.21

```

```

## alpha[13]      2.26      3.97
## alpha[14]      1.48      2.34
## alpha[15]      1.79      3.01
## alpha[16]      8.37     16.61
## alpha[17]      2.69      5.00
## alpha[18]      3.11      6.02
## alpha[19]      1.30      2.01
## alpha[20]      1.18      1.52
## alpha[21]      1.29      1.98
## alpha[22]      1.47      2.57
## alpha[23]      1.51      2.53
## alpha[24]      1.24      1.67
## alpha[25]      1.46      2.21
## alpha[26]      2.20      4.84
## alpha[27]      6.81     21.09
## alpha[28]      1.51      2.54
## alpha[29]      2.48      5.20
## alpha[30]      1.61      2.78
## alpha[31]      1.35      1.99
## alpha[32]      2.33      4.21
## alpha[33]      2.10      3.78
## alpha[34]      1.40      2.50
## alpha[35]      1.07      1.18
## alpha[36]      1.06      1.18
## alpha[37]      1.02      1.07
## alpha[38]      1.30      1.89
## alpha[39]      1.04      1.13
## alpha[40]      1.05      1.16
## alpha[41]      1.27      1.75
## alpha[42]      1.11      1.34
## alpha[43]      1.08      1.21
## alpha[44]      1.23      1.63
## alpha[45]      1.03      1.09
## alpha[46]      1.01      1.03
## alpha[47]      1.01      1.02
## alpha[48]      1.01      1.02
## alpha[49]      1.11      1.36
## alpha[50]      1.46      2.39
## alpha[51]      2.81      5.88
## alpha[52]      2.37      4.14
## alpha[53]      1.42      2.13
## alpha[54]      1.10      1.31
## alpha[55]      1.09      1.29
## alpha[56]      1.08      1.24
## alpha[57]      1.08      1.20
## alpha[58]      1.11      1.34
## alpha[59]      1.09      1.27
## alpha[60]      1.04      1.14
## alpha[61]      1.24      1.67
## alpha[62]      1.25      1.71
## alpha[63]      1.01      1.04
## alpha[64]      1.08      1.25
## alpha[65]      1.11      1.35
## alpha[66]      1.01      1.02

```

```

## alpha[67]      1.02      1.06
## alpha[68]      1.06      1.20
## alpha[69]      1.01      1.04
## alpha[70]      1.01      1.03
## alpha[71]      1.01      1.02
## alpha[72]      1.01      1.01
## beta[1]        2.69      5.03
## beta[2]        1.10      1.33
## beta[3]        1.00      1.00
## beta[4]        2.35      4.17
## beta[5]        1.74      2.99
## sigma          1.00      1.00
##
## Multivariate psrf
##
## 47.8

## Save the lambda estimates
#var.e4
#var.u4

## Extract the parameter estimates and order them c(fixed, random)
params = c( coefs$Mean[ row.names(coefs) %in% paste0( paste0("beta[",1:5),""] ) ],
           coefs$Mean[ row.names(coefs) %in% paste0( paste0("alpha[",1:72),""] ) ] )

## Calculate the fitted values
dat$Y_Smooth_Fitted_JAGS_Spline = c(t(params) %*% t(cbind(1,
                                                               G.2,
                                                               G.3,
                                                               X,
                                                               X_2,
                                                               random.basis.1,
                                                               random.basis.2,
                                                               random.basis.3)) )
rm(coefs, model, samp, model_string, random.basis.1, random.basis.2,
   random.basis.3, n, G.2, G.3, K, params)

```

Figure 7: The group-level mean functions using penalized splines and JAGS.

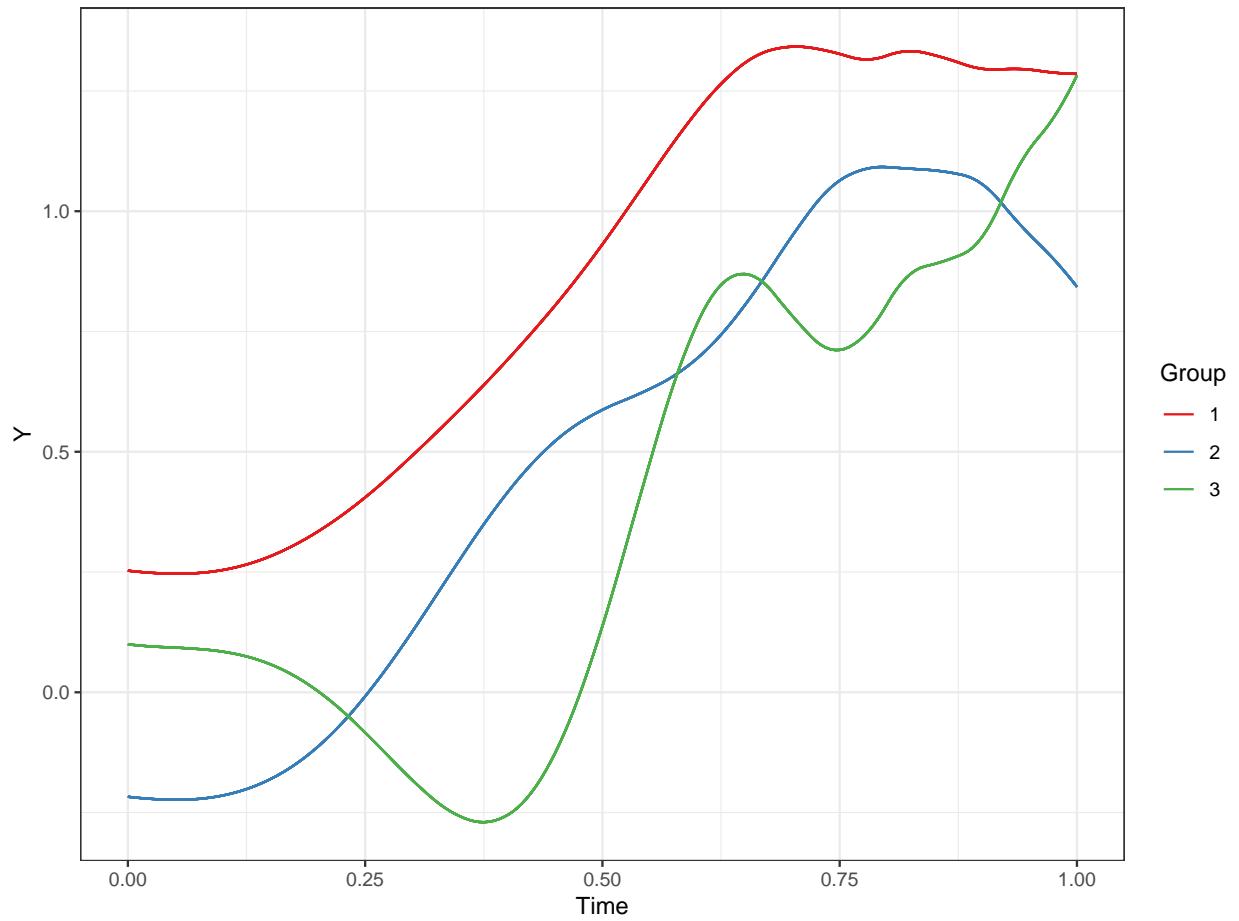
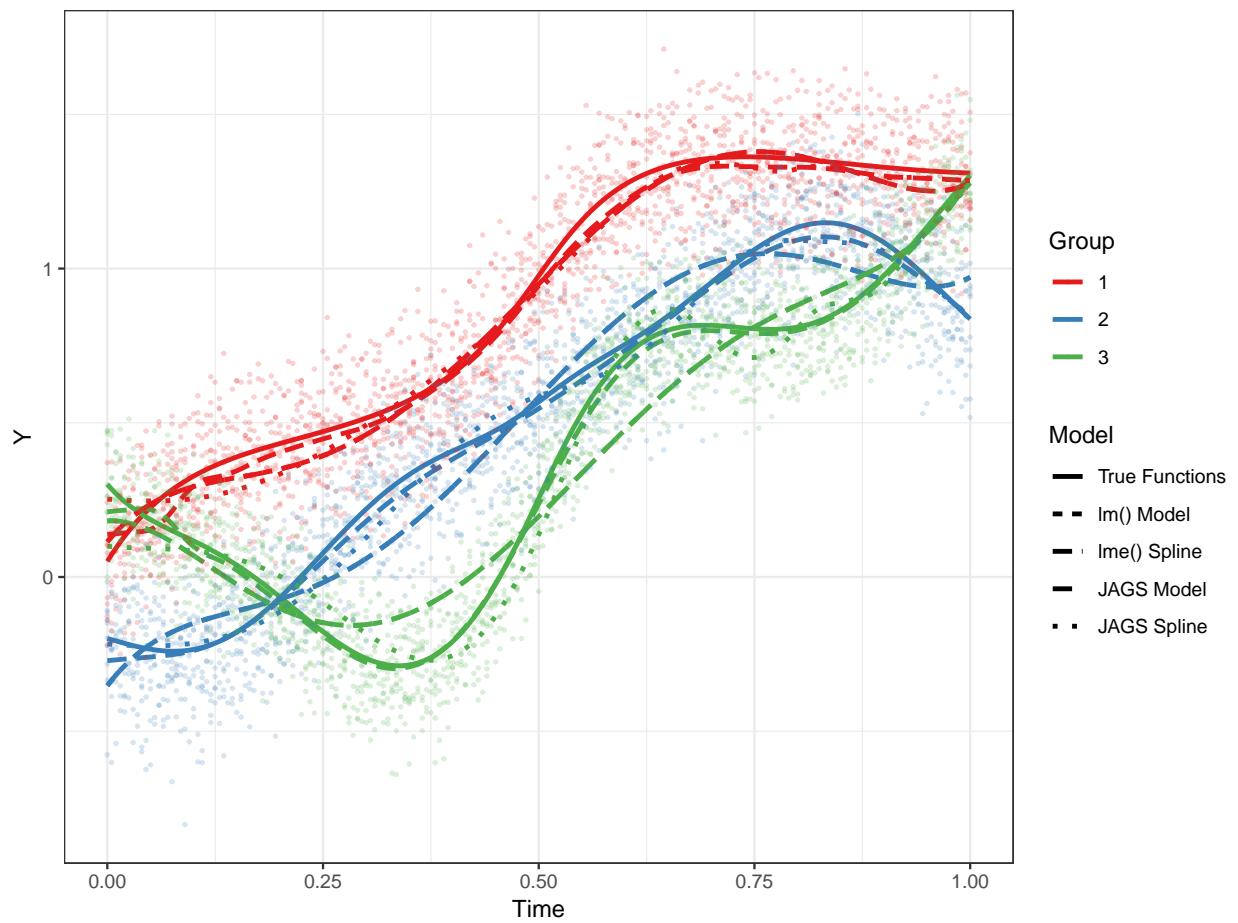


Figure 8: A comparison of the fitted effect functions from each model.



Session Info

A summary of the R session used for the analysis.

```
## R version 3.5.1 (2018-07-02)
## Platform: x86_64-w64-mingw32/x64 (64-bit)
## Running under: Windows 7 x64 (build 7601) Service Pack 1
##
## Matrix products: default
##
## attached base packages:
## [1] stats      graphics   grDevices utils      datasets   methods    base
##
## other attached packages:
## [1] rjags_4-8        coda_0.19-2       lme4_1.1-18-1
## [4] Matrix_1.2-15    nlme_3.1-137      RColorBrewer_1.1-2
## [7] ggpplot2_3.1.0    knitr_1.20       MASS_7.3-51.1
##
## loaded via a namespace (and not attached):
## [1] Rcpp_1.0.0        pillar_1.3.0      compiler_3.5.1    nloptr_1.2.1
## [5] plyr_1.8.4        bindr_0.1.1       tools_3.5.1      digest_0.6.18
## [9] evaluate_0.12     tibble_1.4.2      gtable_0.2.0     lattice_0.20-38
## [13] pkgconfig_2.0.2   rlang_0.3.0.1    rstudioapi_0.8   yaml_2.2.0
## [17] bindrcpp_0.2.2   stringr_1.3.1    withr_2.1.2      dplyr_0.7.7
## [21] rprojroot_1.3-2  grid_3.5.1       tidyselect_0.2.5  glue_1.3.0
## [25] R6_2.3.0         rmarkdown_1.10   minqa_1.2.4     purrr_0.2.5
## [29] magrittr_1.5      backports_1.1.2   htmltools_0.3.6  scales_1.0.0
## [33] splines_3.5.1    assertthat_0.2.0  colorspace_1.3-2 labeling_0.3
## [37] stringi_1.2.4    lazyeval_0.2.1    munsell_0.5.0    crayon_1.3.4
```