

Functional ANOVA Example

November 09, 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.

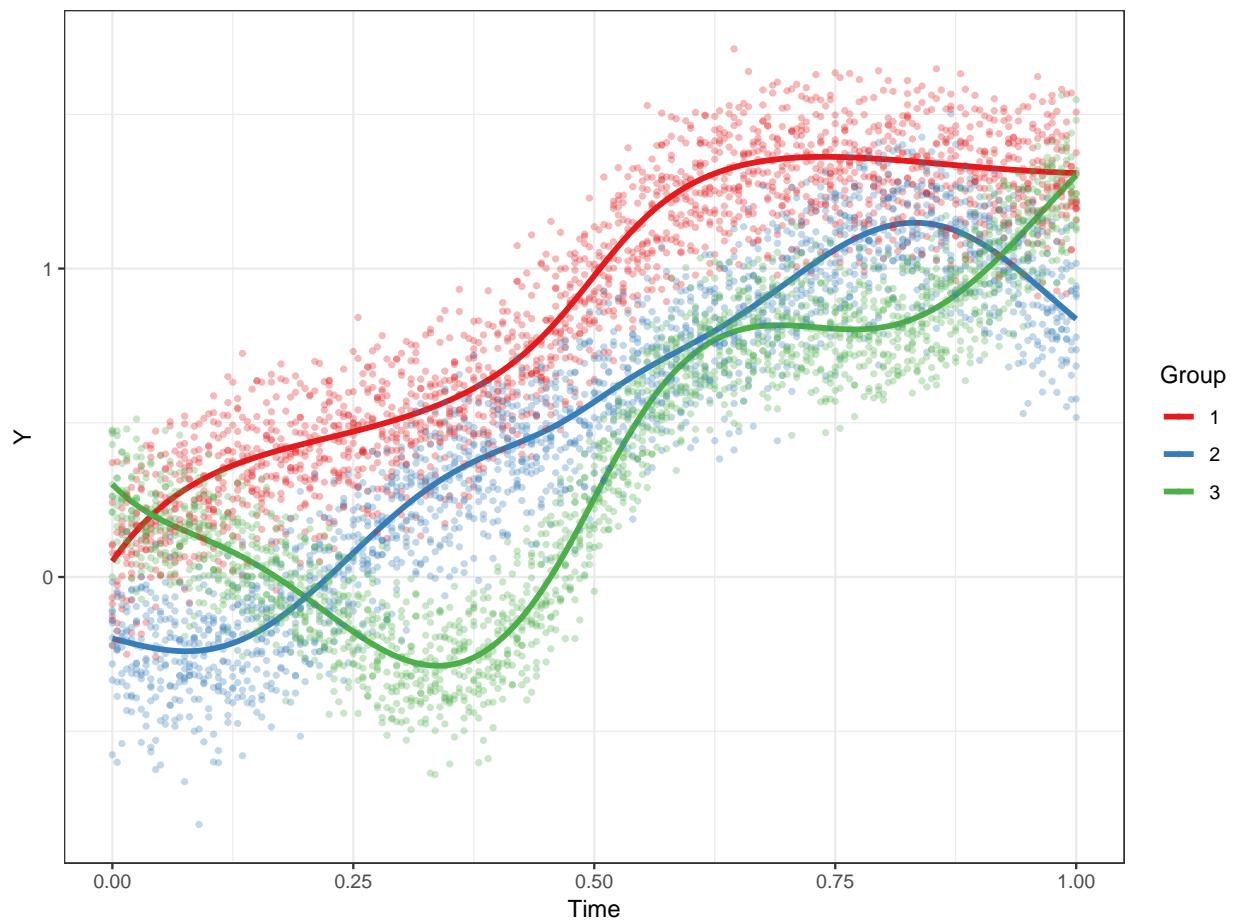


Figure 2: The smoothed subject-specific curves from the simulated data.

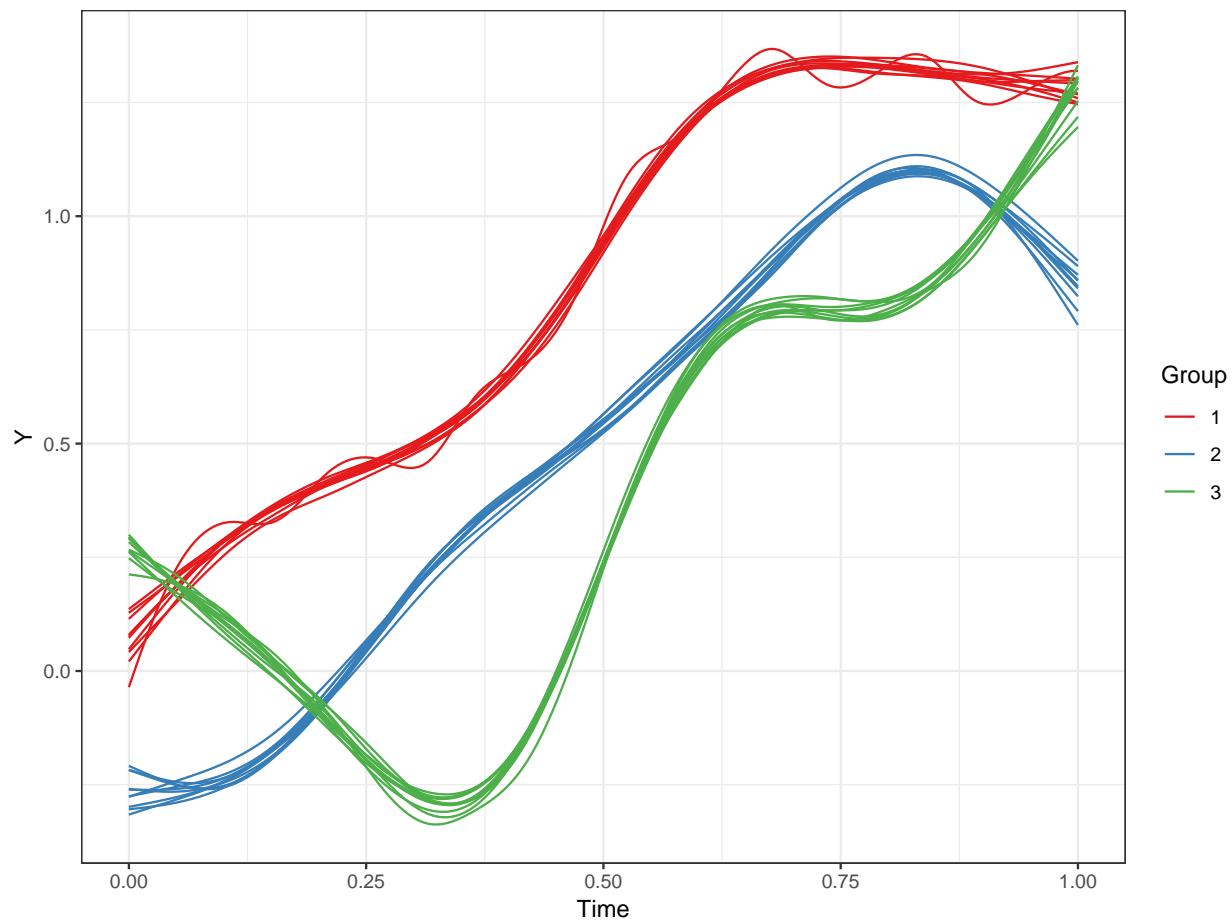
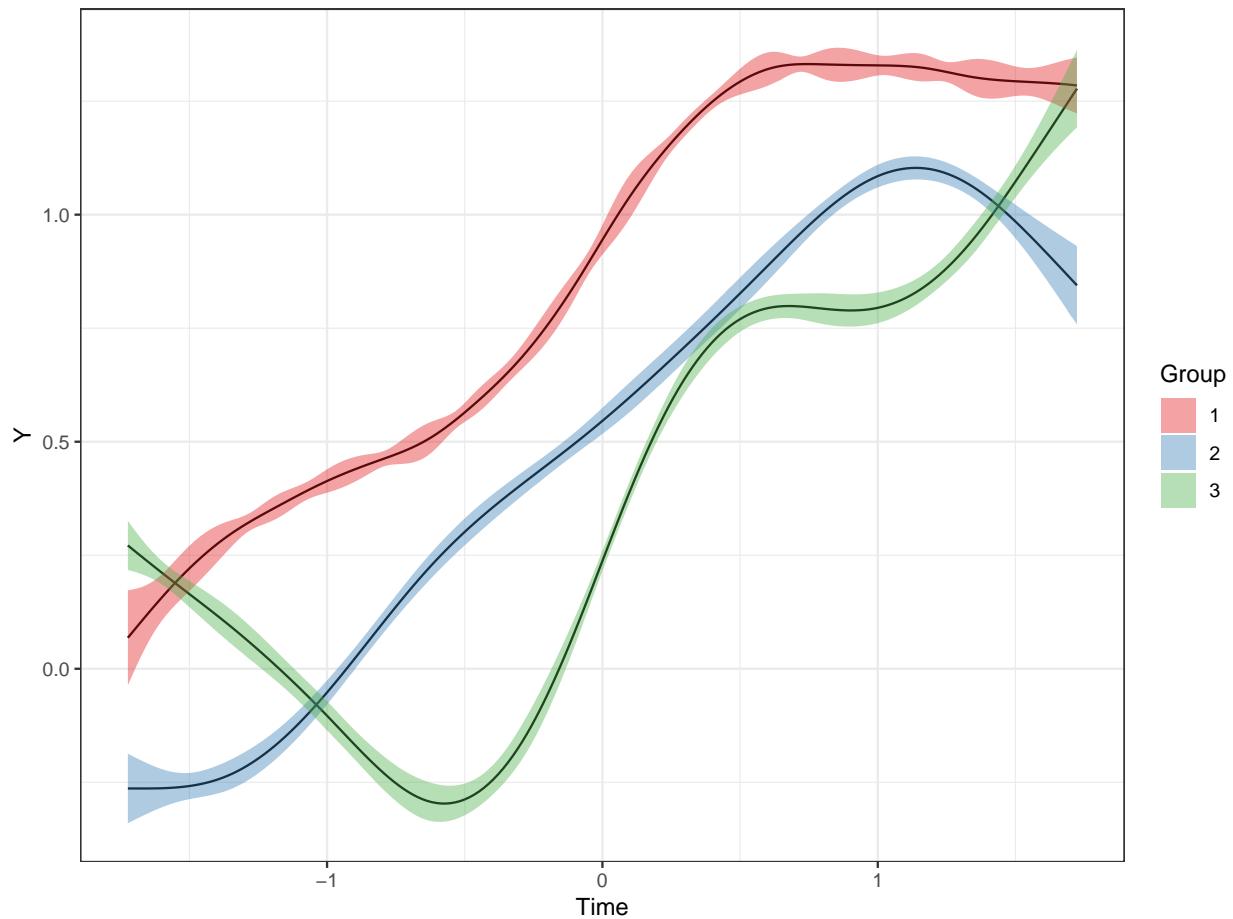


Figure 3: The group-level mean functions for the smoothed simulated data ± 2 point-wise standard deviations.



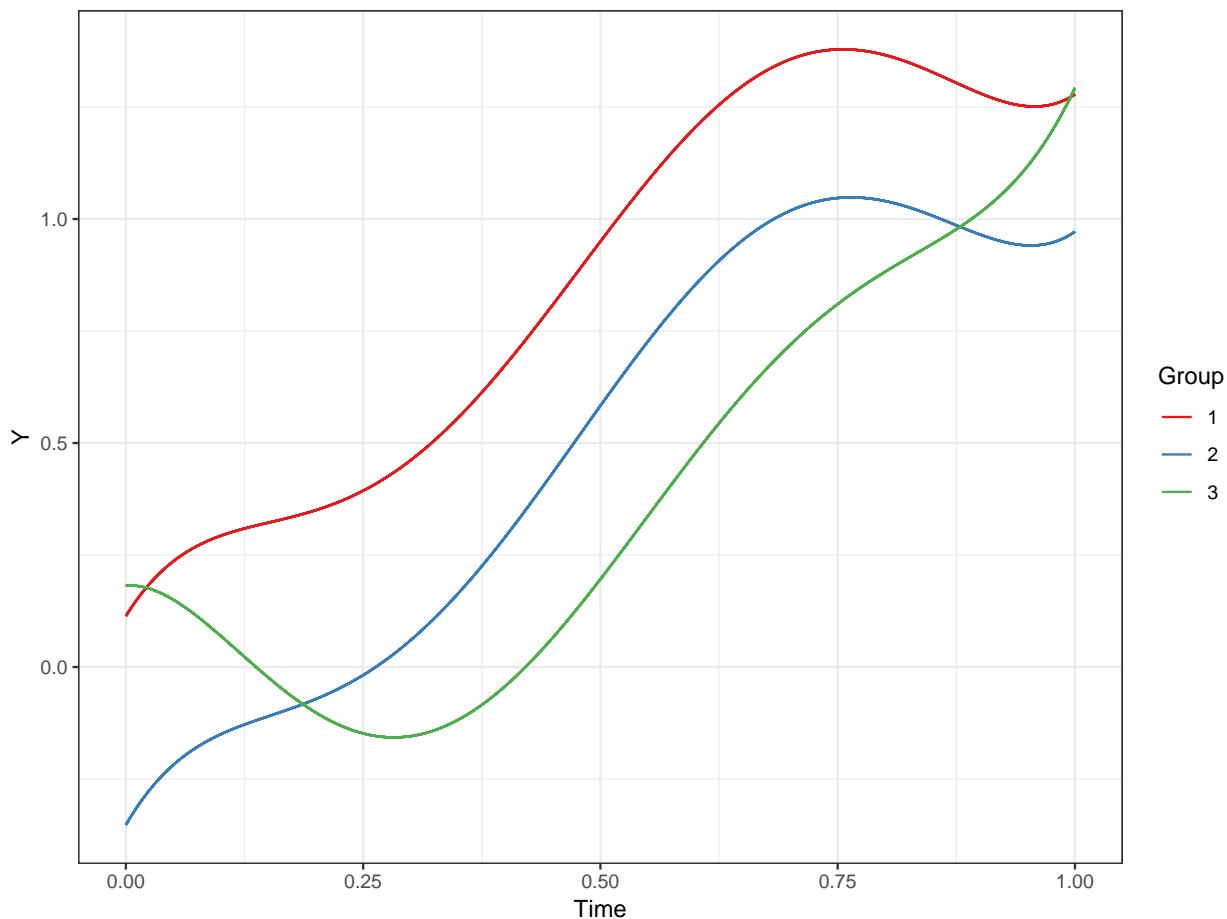
Analyze Using lm()

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)

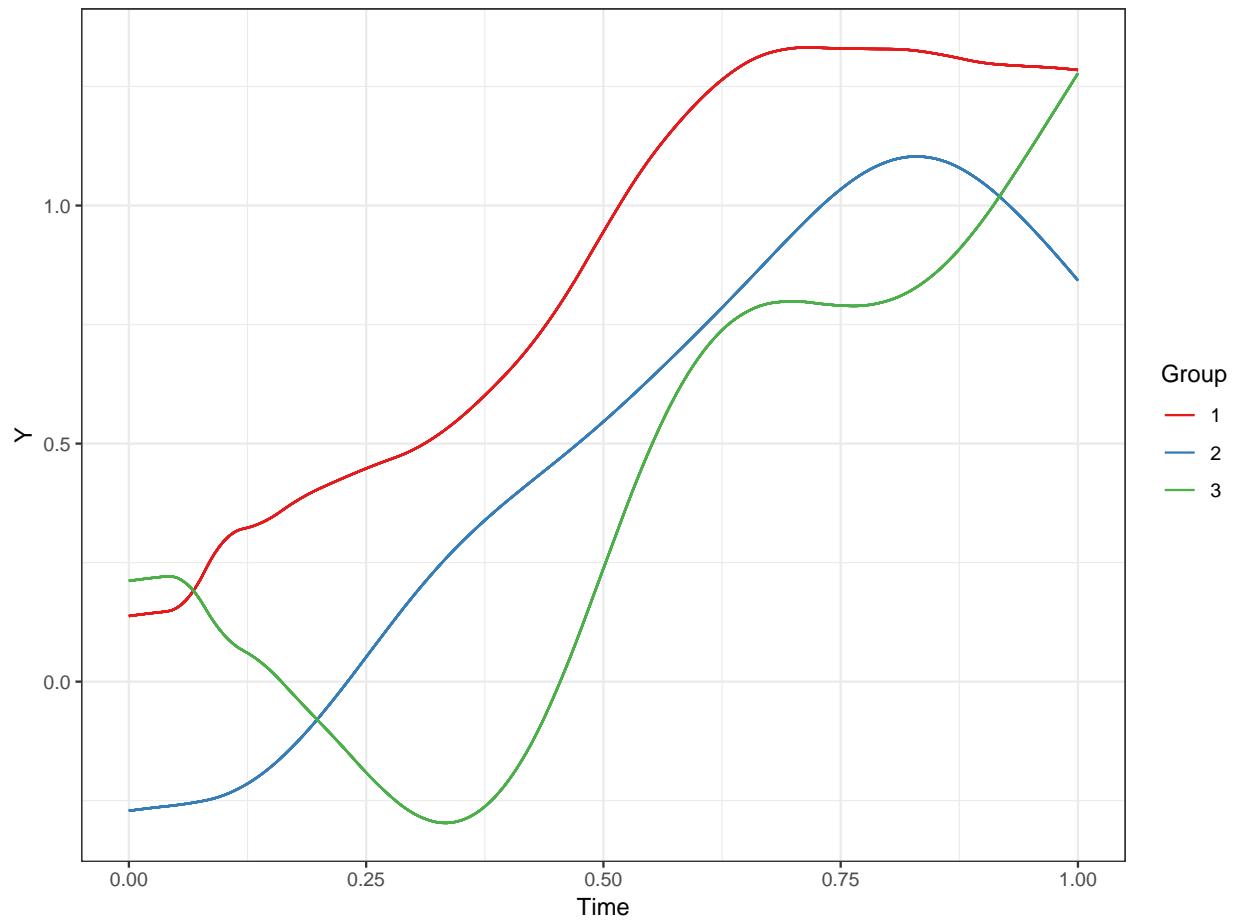
## Extract the model coefficients
coefs = c(unlist(mod$coefficients$fixed), unlist(mod$coefficients$random) )

## 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]   9.498e-01 0.002903 4.106e-05   1.340e-04
## beta[2]   8.132e-01 0.004973 7.034e-05   4.719e-04
## beta[3]   -8.580e-02 0.004365 6.174e-05   2.753e-04
## beta[4]   -3.804e-01 0.006321 8.941e-05   7.817e-04
## beta[5]   9.643e-05 0.001491 2.109e-05   8.517e-05
## beta[6]   7.417e-02 0.001845 2.610e-05   2.193e-04
## beta[7]   -3.666e-01 0.003712 5.250e-05   1.040e-04
## beta[8]   -7.538e-01 0.003636 5.144e-05   1.072e-04
## beta[9]   4.628e-02 0.002483 3.512e-05   4.559e-05
## beta[10]  -1.558e-02 0.002521 3.565e-05   4.562e-05
## beta[11]  -6.656e-03 0.002768 3.915e-05   7.937e-05
## beta[12]  2.676e-01 0.002693 3.810e-05   7.608e-05
## sigma    7.858e-02 0.000711 1.006e-05   1.077e-05
##
## 2. Quantiles for each variable:
##
##           2.5%        25%        50%        75%     97.5%
## beta[1]   0.944260  0.9477764  0.9497352  0.951737  0.955594
## beta[2]   0.803412  0.8098141  0.8131476  0.816708  0.822589
## beta[3]   -0.094575 -0.0887183 -0.0857545 -0.082858 -0.077459
## beta[4]   -0.392439 -0.3849208 -0.3805110 -0.375950 -0.368040
## beta[5]   -0.002822 -0.0009153  0.0000842  0.001093  0.003028
## beta[6]   0.070567  0.0728579  0.0742003  0.075519  0.077659
## beta[7]   -0.373809 -0.3691779 -0.3665755 -0.364060 -0.359382
## beta[8]   -0.760932 -0.7561885 -0.7538406 -0.751333 -0.746719

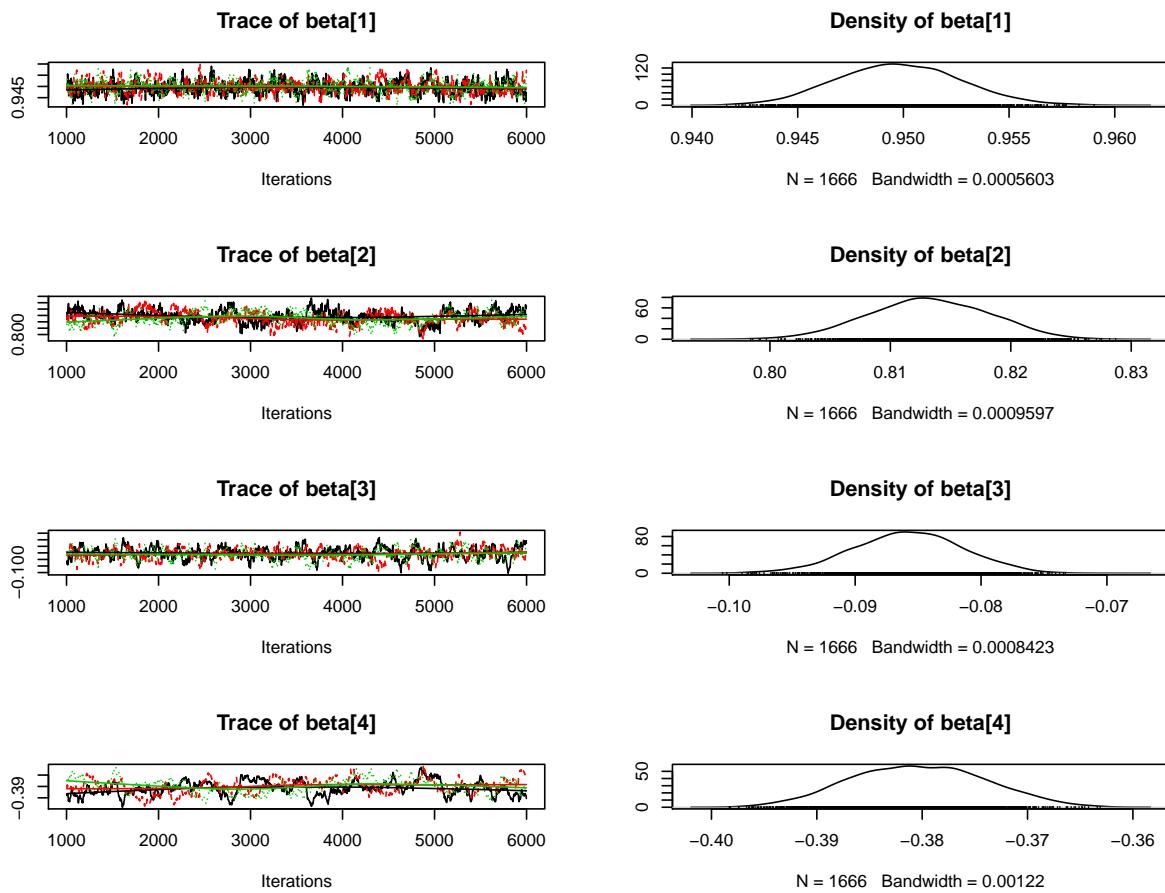
```

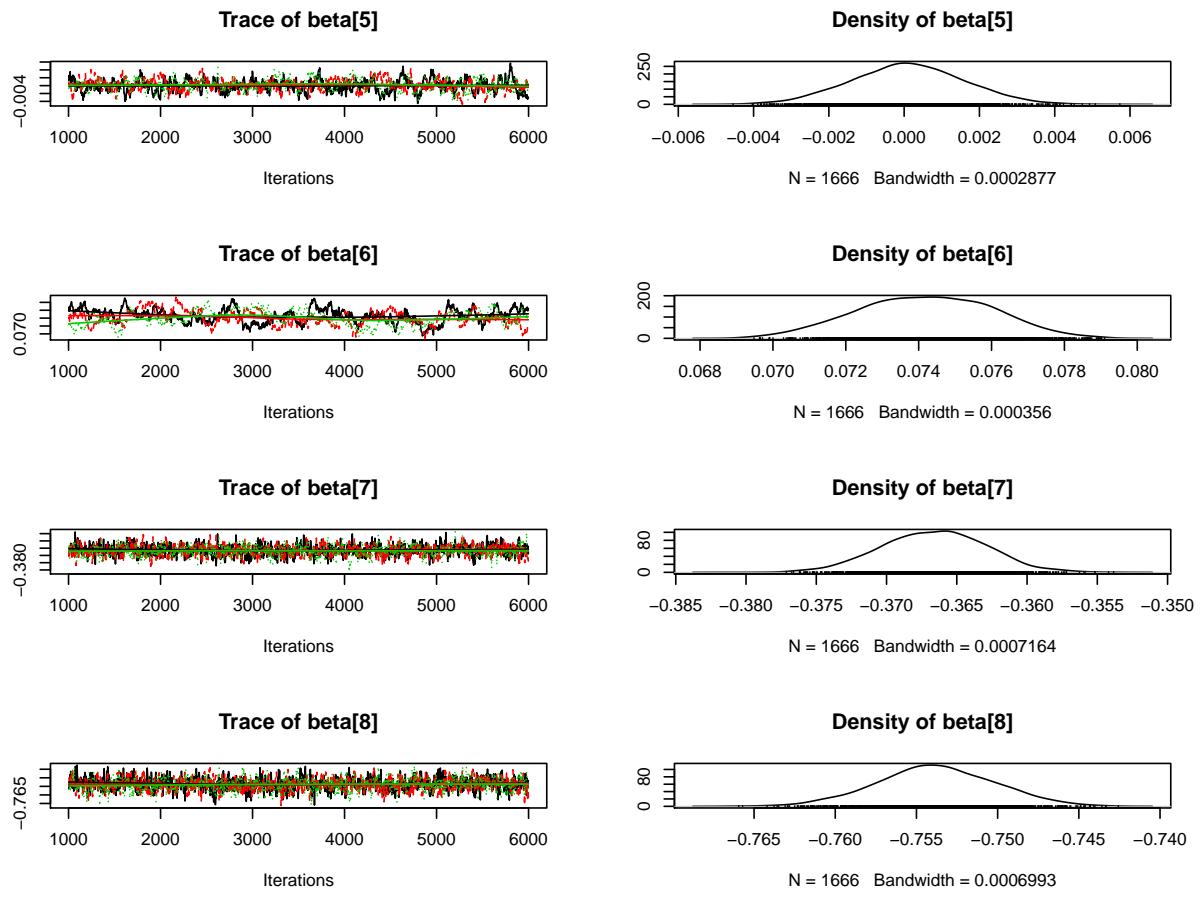
```

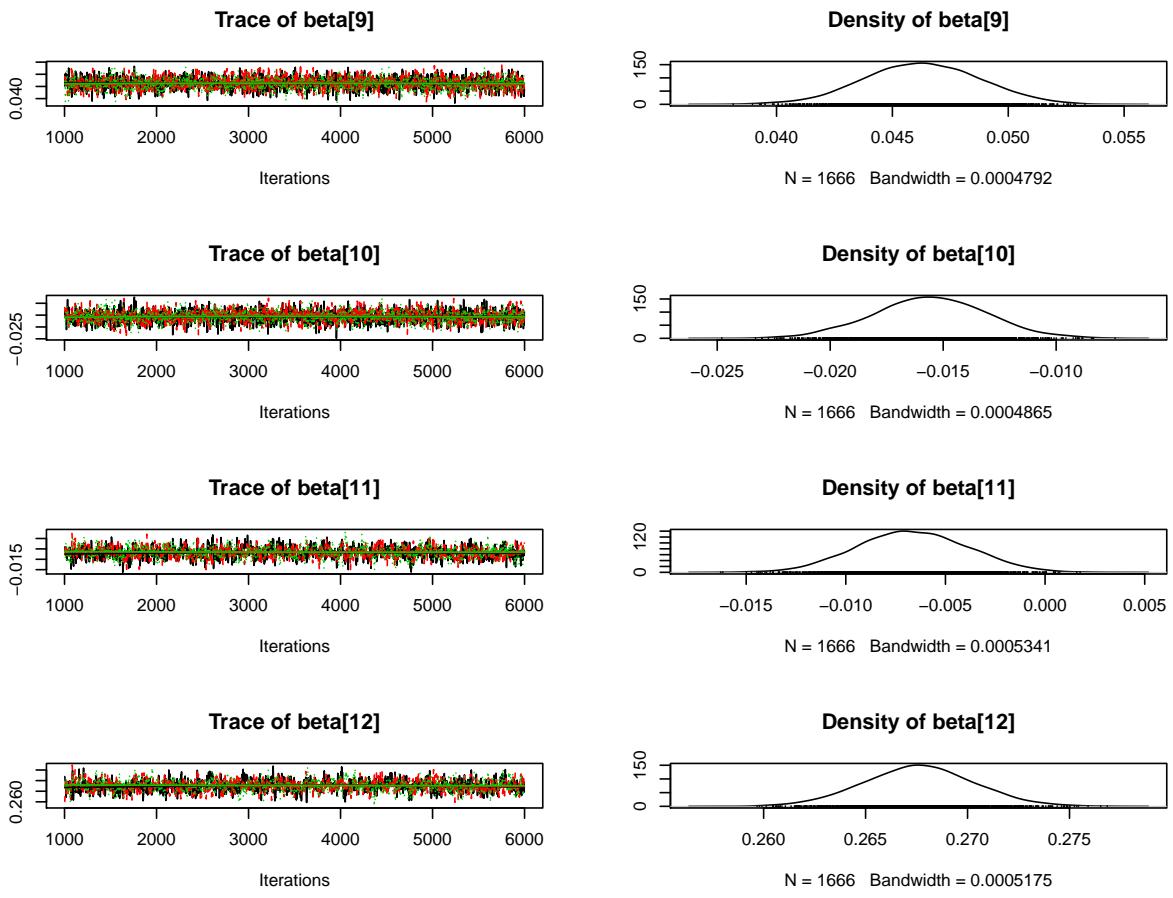
## beta[9]    0.041386  0.0445910  0.0462803  0.047979  0.051110
## beta[10]   -0.020537 -0.0172463 -0.0155750 -0.013855 -0.010602
## beta[11]   -0.011910 -0.0085735 -0.0067087 -0.004766 -0.001247
## beta[12]    0.262336  0.2658226  0.2676153  0.269416  0.272976
## sigma      0.077191  0.0781095  0.0785591  0.079062  0.080005

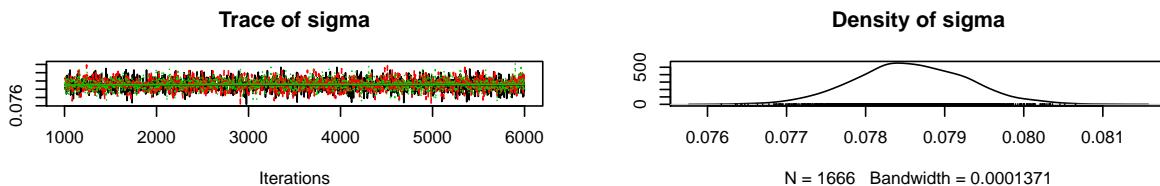
plot(samp)

```









```

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

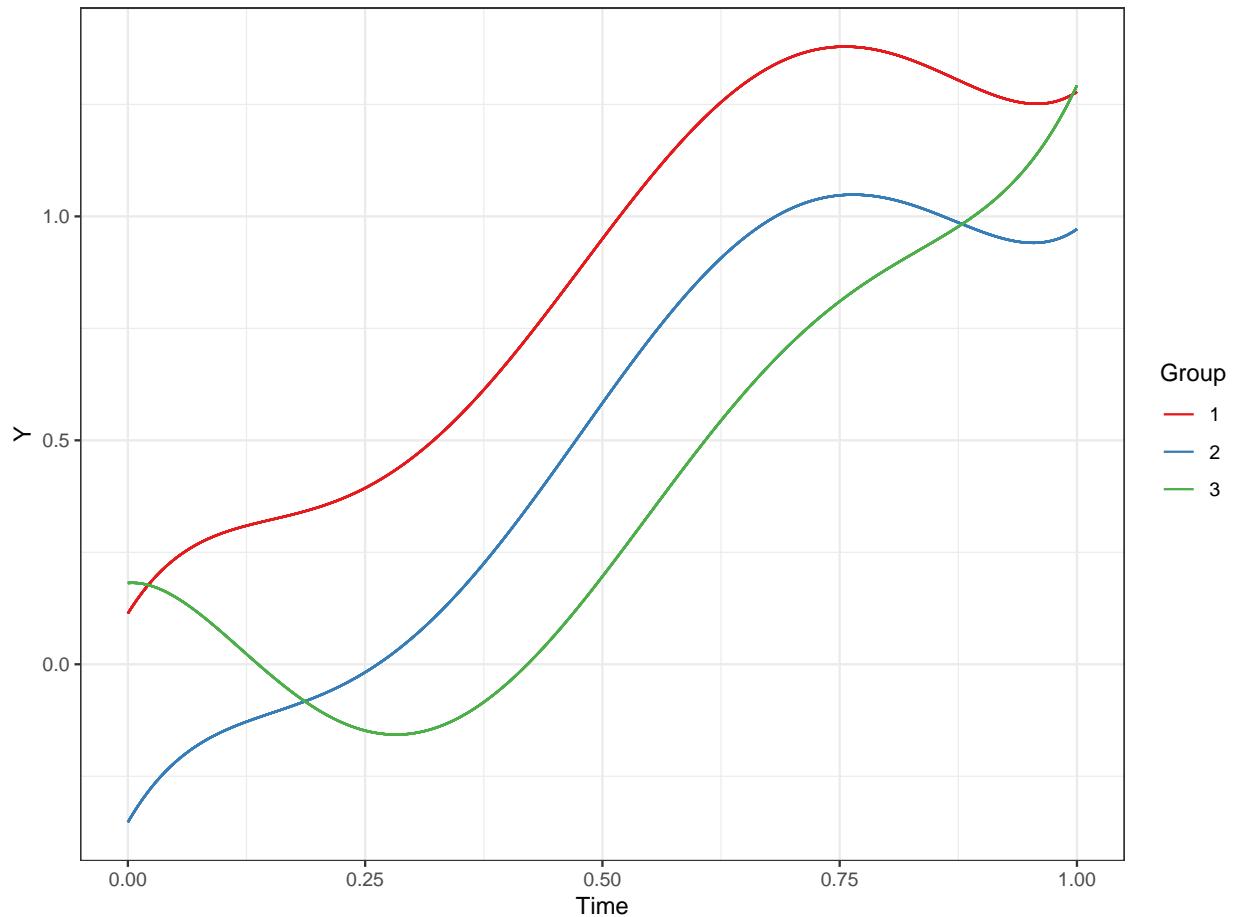
## Extract the beta estimates
betas = coefs$Mean[ row.names(coefs) %in% paste0( paste0("beta[",1:12), "]") ]

## 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] 0.1162596 0.039824 5.633e-04      0.011363
## alpha[2] 0.0812388 0.048139 6.809e-04      0.004754
## alpha[3] 0.0023003 0.019449 2.751e-04      0.005334
## alpha[4] -0.0055698 0.060813 8.602e-04      0.010247
## alpha[5] -0.0273928 0.052383 7.409e-04      0.013810
## alpha[6] -0.1074374 0.062800 8.883e-04      0.024469
## alpha[7] -0.0857162 0.052892 7.482e-04      0.011453
## alpha[8] -0.0888489 0.055029 7.784e-04      0.009588
## alpha[9]  0.0628334 0.103071 1.458e-03      0.045371
## alpha[10] 0.0537579 0.104428 1.477e-03      0.034318
## alpha[11] 0.1209571 0.124411 1.760e-03      0.053709
## alpha[12] -0.1005982 0.076320 1.080e-03      0.025305
## alpha[13] -0.1147686 0.157147 2.223e-03      0.020615
## alpha[14] -0.3559387 0.293318 4.149e-03      0.074946
## alpha[15] -0.6977843 0.309648 4.380e-03      0.109194
## alpha[16] -0.2365078 0.351442 4.971e-03      0.071223
## alpha[17]  0.2518026 0.377191 5.335e-03      0.176725
## alpha[18]  0.9691836 0.623452 8.819e-03      0.371438
## alpha[19]  0.5521195 0.440448 6.230e-03      0.164400
## alpha[20] -0.7565838 0.635987 8.996e-03      0.263575
## alpha[21] -0.7066760 1.033065 1.461e-02      0.418911
## alpha[22]  1.9469904 1.694540 2.397e-02      0.507226
## alpha[23] -1.5070931 2.175567 3.077e-02      0.383041
## alpha[24]  0.7286818 2.890781 4.089e-02      0.340278
## alpha[25]  0.1361500 0.024920 3.525e-04      0.009748
## alpha[26]  0.1018134 0.026775 3.787e-04      0.007929
## alpha[27]  0.1047418 0.032269 4.564e-04      0.005176

```

```

## alpha[28]  0.1125364  0.036978 5.231e-04      0.011159
## alpha[29] -0.0003799  0.061069 8.638e-04      0.021194
## alpha[30] -0.1202876  0.088043 1.245e-03      0.024056
## alpha[31] -0.24448329 0.130929 1.852e-03      0.035674
## alpha[32] -0.3086444  0.148085 2.095e-03      0.032618
## alpha[33] -0.4091620  0.120622 1.706e-03      0.012744
## alpha[34] -0.2056296  0.087731 1.241e-03      0.023211
## alpha[35] -0.0729451  0.197812 2.798e-03      0.104340
## alpha[36]  0.2465318  0.223348 3.159e-03      0.098220
## alpha[37]  0.5902134  0.259238 3.667e-03      0.111290
## alpha[38]  0.6073840  0.136093 1.925e-03      0.044130
## alpha[39]  0.3855411  0.421311 5.959e-03      0.230972
## alpha[40] -0.6544915  0.777551 1.100e-02      0.381821
## alpha[41] -0.8970813  0.547178 7.740e-03      0.192690
## alpha[42] -1.3821884 0.843964 1.194e-02      0.402015
## alpha[43]  0.9203881  1.770704 2.505e-02      1.170407
## alpha[44]  0.8516159  1.740964 2.463e-02      0.613072
## alpha[45] -0.6824377  4.336988 6.135e-02      3.568719
## alpha[46] -0.7176114  5.464382 7.729e-02      2.848422
## alpha[47]  1.5311469  5.907083 8.356e-02      1.990404
## alpha[48] -0.3481189  6.199916 8.770e-02      1.509658
## alpha[49] -0.2321412  0.051681 7.310e-04      0.021598
## alpha[50] -0.2491400  0.052588 7.439e-04      0.023419
## alpha[51] -0.1898735  0.031862 4.507e-04      0.011501
## alpha[52] -0.0842308  0.015683 2.218e-04      0.006170
## alpha[53]  0.0719569  0.063655 9.004e-04      0.026415
## alpha[54]  0.3564686  0.137660 1.947e-03      0.058662
## alpha[55]  0.5892549  0.138223 1.955e-03      0.057087
## alpha[56]  0.6609249  0.155523 2.200e-03      0.056209
## alpha[57]  0.7518156  0.101651 1.438e-03      0.033975
## alpha[58]  0.5843744  0.185954 2.630e-03      0.051680
## alpha[59] -0.0131337  0.318004 4.498e-03      0.150344
## alpha[60] -1.1045172  0.497080 7.031e-03      0.219930
## alpha[61] -1.7771111  0.496498 7.023e-03      0.192190
## alpha[62] -2.0265421  0.280319 3.965e-03      0.081375
## alpha[63] -1.3960528  0.819941 1.160e-02      0.466706
## alpha[64]  0.8676368  1.466609 2.075e-02      0.714003
## alpha[65]  3.5038016  1.366324 1.933e-02      0.479456
## alpha[66]  2.4426347  2.129385 3.012e-02      1.240093
## alpha[67] -0.4661451  3.931032 5.560e-02      2.084203
## alpha[68] -5.4036842  3.288187 4.651e-02      1.211755
## alpha[69]  3.4742624  9.947726 1.407e-01      7.158253
## alpha[70]  2.9356767  13.156251 1.861e-01      9.221146
## alpha[71] -5.3850237  12.647719 1.789e-01      4.954127
## alpha[72]  3.3137875  12.139663 1.717e-01      3.390474
## beta[1]   0.6460561  0.015556 2.200e-04      0.002956
## beta[2]  -0.4664607  0.006809 9.632e-05      0.001112
## beta[3]  -0.1514627  0.027548 3.897e-04      0.009521
## beta[4]   0.5352347  0.030282 4.283e-04      0.005607
## beta[5]   0.1783599  0.013081 1.850e-04      0.001684
## sigma    0.0589147  0.009865 1.395e-04      0.003908
##
## 2. Quantiles for each variable:
##

```

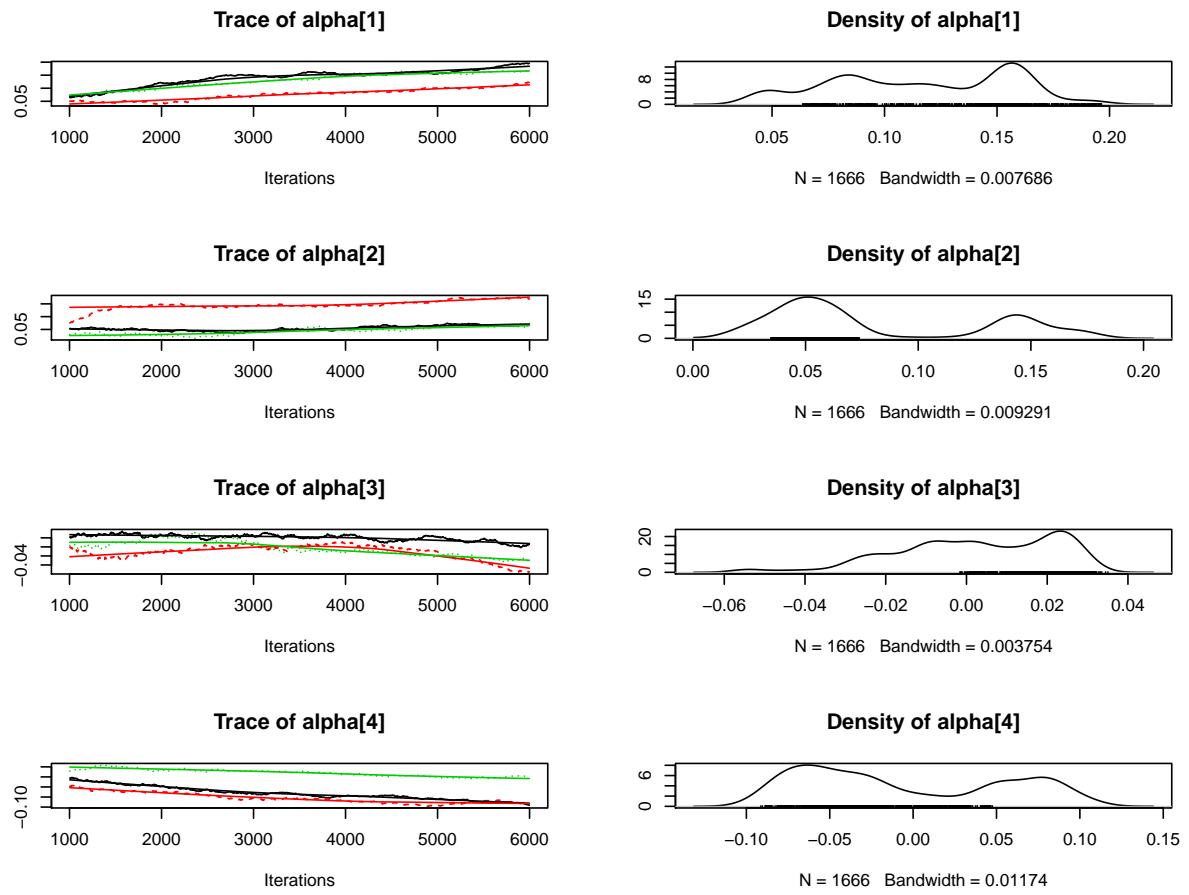
	2.5%	25%	50%	75%	97.5%
## alpha[1]	0.045356	0.083573	0.11690	0.154397	0.180397
## alpha[2]	0.023718	0.045906	0.06073	0.140195	0.171210
## alpha[3]	-0.040805	-0.010746	0.00299	0.020331	0.029549
## alpha[4]	-0.087839	-0.059293	-0.02453	0.053840	0.099543
## alpha[5]	-0.096341	-0.065354	-0.03781	0.006937	0.080334
## alpha[6]	-0.227597	-0.147116	-0.10914	-0.067687	0.005001
## alpha[7]	-0.190432	-0.127076	-0.08006	-0.037251	-0.013479
## alpha[8]	-0.180552	-0.129174	-0.10214	-0.039827	0.008526
## alpha[9]	-0.116091	-0.004498	0.05696	0.151537	0.247037
## alpha[10]	-0.135636	-0.032897	0.04528	0.144181	0.216750
## alpha[11]	-0.109230	0.029832	0.13153	0.235318	0.302429
## alpha[12]	-0.278322	-0.145475	-0.09807	-0.048810	0.061336
## alpha[13]	-0.357321	-0.224031	-0.15635	0.059170	0.143776
## alpha[14]	-0.820816	-0.621699	-0.42031	-0.094360	0.150425
## alpha[15]	-1.246077	-0.979621	-0.59420	-0.415041	-0.272633
## alpha[16]	-0.853179	-0.439832	-0.28562	0.132783	0.291712
## alpha[17]	-0.265358	-0.042101	0.17689	0.495916	1.047093
## alpha[18]	0.216146	0.553463	0.78888	1.136239	2.566605
## alpha[19]	-0.264410	0.167792	0.61363	0.936035	1.229411
## alpha[20]	-2.338403	-1.019136	-0.67321	-0.322675	0.294799
## alpha[21]	-2.373039	-1.453474	-0.78759	-0.192181	1.753285
## alpha[22]	-1.503879	0.717670	2.08781	2.980428	5.296444
## alpha[23]	-6.270523	-2.943541	-1.33563	0.041807	2.373063
## alpha[24]	-4.726074	-1.243160	0.55863	2.583534	6.873914
## alpha[25]	0.086152	0.117259	0.14049	0.154272	0.175279
## alpha[26]	0.057906	0.079487	0.09738	0.125432	0.144357
## alpha[27]	0.044452	0.075157	0.11158	0.127663	0.159324
## alpha[28]	0.051123	0.077539	0.11042	0.143907	0.179292
## alpha[29]	-0.104154	-0.061513	0.01313	0.049958	0.090115
## alpha[30]	-0.290187	-0.192100	-0.12221	-0.028235	0.012155
## alpha[31]	-0.490805	-0.334624	-0.22907	-0.154518	-0.035970
## alpha[32]	-0.588353	-0.390995	-0.30008	-0.208547	-0.048246
## alpha[33]	-0.538268	-0.505850	-0.47530	-0.278700	-0.174719
## alpha[34]	-0.346636	-0.265466	-0.22301	-0.158171	0.018745
## alpha[35]	-0.399913	-0.231278	-0.07103	0.089074	0.290542
## alpha[36]	-0.208545	0.102589	0.25865	0.406552	0.607714
## alpha[37]	-0.009379	0.424504	0.67222	0.747283	0.971265
## alpha[38]	0.273276	0.533626	0.63998	0.713633	0.778495
## alpha[39]	-0.411962	0.042463	0.42137	0.752345	1.045167
## alpha[40]	-1.770126	-1.394220	-0.68583	0.059298	0.644791
## alpha[41]	-1.676082	-1.255027	-0.97532	-0.610532	0.382092
## alpha[42]	-2.714890	-1.987659	-1.49938	-0.898482	0.343801
## alpha[43]	-1.929442	-0.909437	1.21517	2.409380	3.600694
## alpha[44]	-2.784873	-0.339084	0.86908	2.086568	4.026108
## alpha[45]	-6.438545	-4.745384	-1.78345	3.776050	6.394502
## alpha[46]	-9.385634	-5.963812	-0.58666	4.551358	7.188324
## alpha[47]	-12.173726	-2.756472	2.26161	6.645158	10.110995
## alpha[48]	-9.497878	-4.907350	-1.26930	2.729232	15.272586
## alpha[49]	-0.322173	-0.271945	-0.24154	-0.193163	-0.135631
## alpha[50]	-0.343206	-0.283708	-0.24960	-0.215650	-0.143012
## alpha[51]	-0.227814	-0.218099	-0.19964	-0.166614	-0.125416
## alpha[52]	-0.105421	-0.096480	-0.08736	-0.074870	-0.045038
## alpha[53]	-0.034085	0.013992	0.07077	0.126697	0.178567

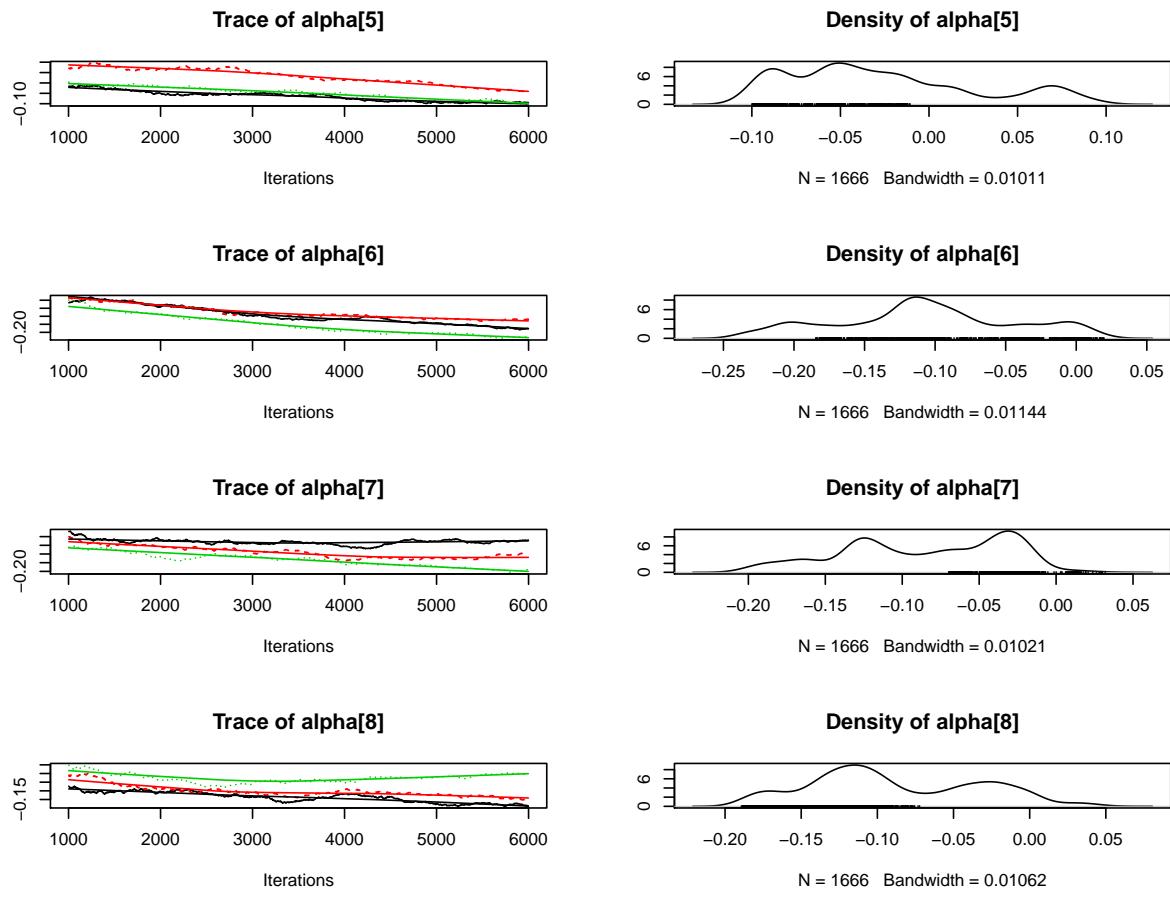
```

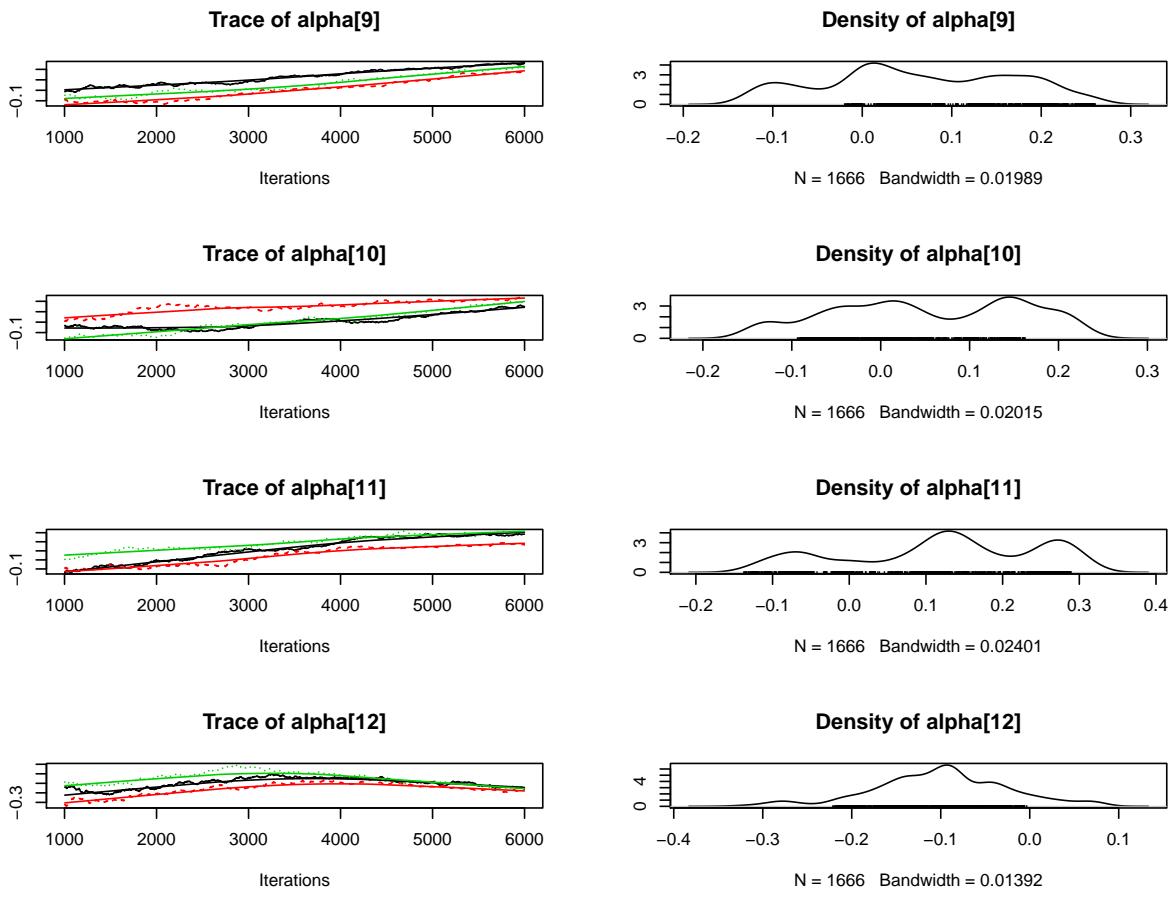
## alpha[54]  0.070070  0.250878  0.36222  0.457720  0.603026
## alpha[55]  0.321802  0.488002  0.61784  0.701736  0.797696
## alpha[56]  0.336480  0.555561  0.68967  0.755108  0.932524
## alpha[57]  0.504245  0.698743  0.75312  0.840324  0.877574
## alpha[58]  0.222848  0.455992  0.58706  0.730047  0.896404
## alpha[59] -0.595758 -0.265845 -0.03326  0.237671  0.562808
## alpha[60] -1.872235 -1.528806 -1.20354 -0.729657 -0.139014
## alpha[61] -2.453618 -2.187461 -1.85613 -1.480568 -0.683856
## alpha[62] -2.511045 -2.250225 -2.01467 -1.856963 -1.404509
## alpha[63] -2.638813 -2.207031 -1.43015 -0.654191 -0.009962
## alpha[64] -2.090824 -0.334844  1.21859  2.193449  2.748953
## alpha[65] -0.103778  3.090716  3.91727  4.220405  5.311936
## alpha[66] -1.804263  0.583423  2.88977  4.198703  5.344830
## alpha[67] -5.436112 -3.726139 -1.85489  2.741530  7.084632
## alpha[68] -10.098362 -8.396288 -6.03258 -2.590422  1.005256
## alpha[69] -13.931502 -6.312723  7.69026 12.160052 14.733726
## alpha[70] -14.900675 -9.899244  1.57862 16.304196 23.495720
## alpha[71] -23.692213 -18.093769 -4.55522  5.119609 21.277819
## alpha[72] -29.935682 -3.293444  4.04375 13.271258 19.861001
## beta[1]   0.609042  0.639129  0.64964  0.657965  0.666336
## beta[2]  -0.478260 -0.471477 -0.46690 -0.462041 -0.452504
## beta[3]  -0.213004 -0.170179 -0.14411 -0.129690 -0.114210
## beta[4]   0.466262  0.520393  0.53982  0.560134  0.575471
## beta[5]   0.151870  0.169014  0.17891  0.188783  0.199944
## sigma    0.046991  0.050512  0.05633  0.065673  0.081440

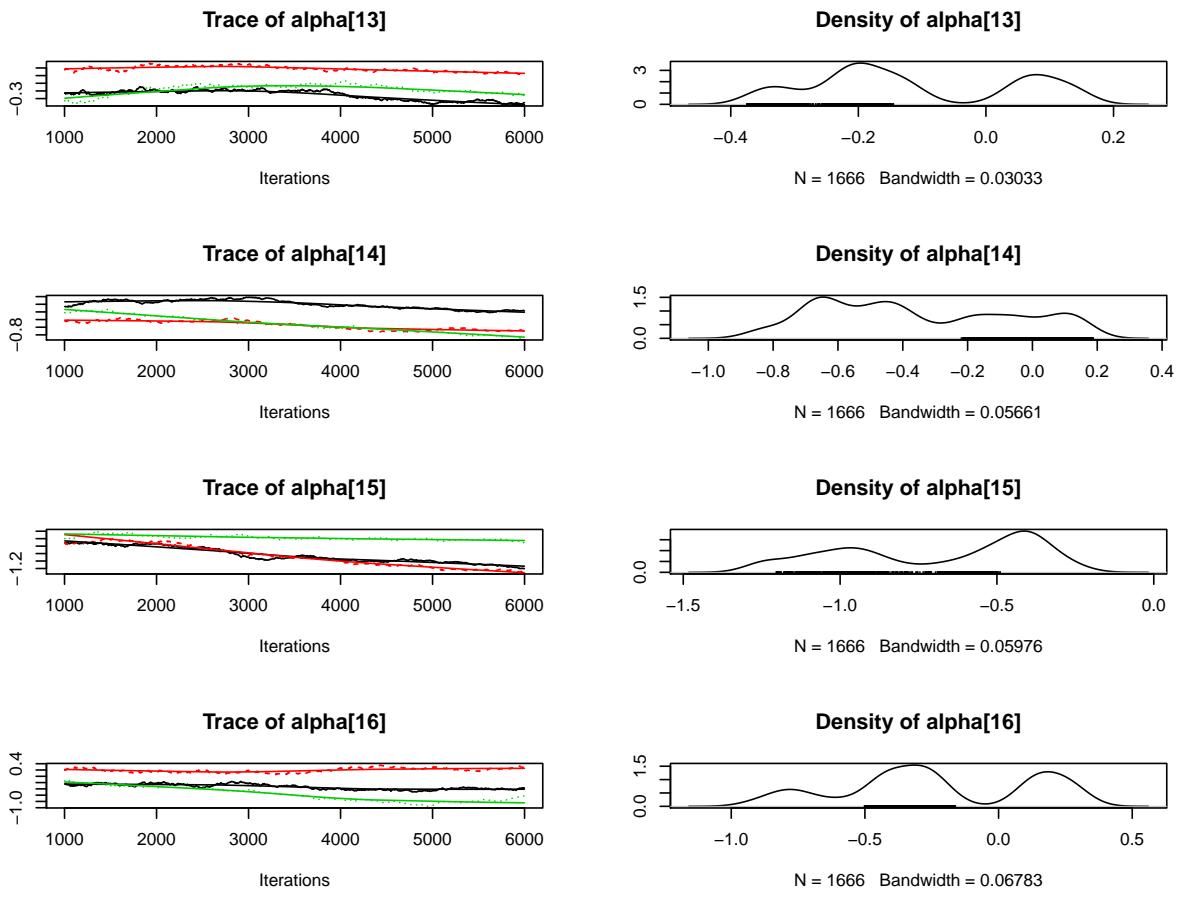
```

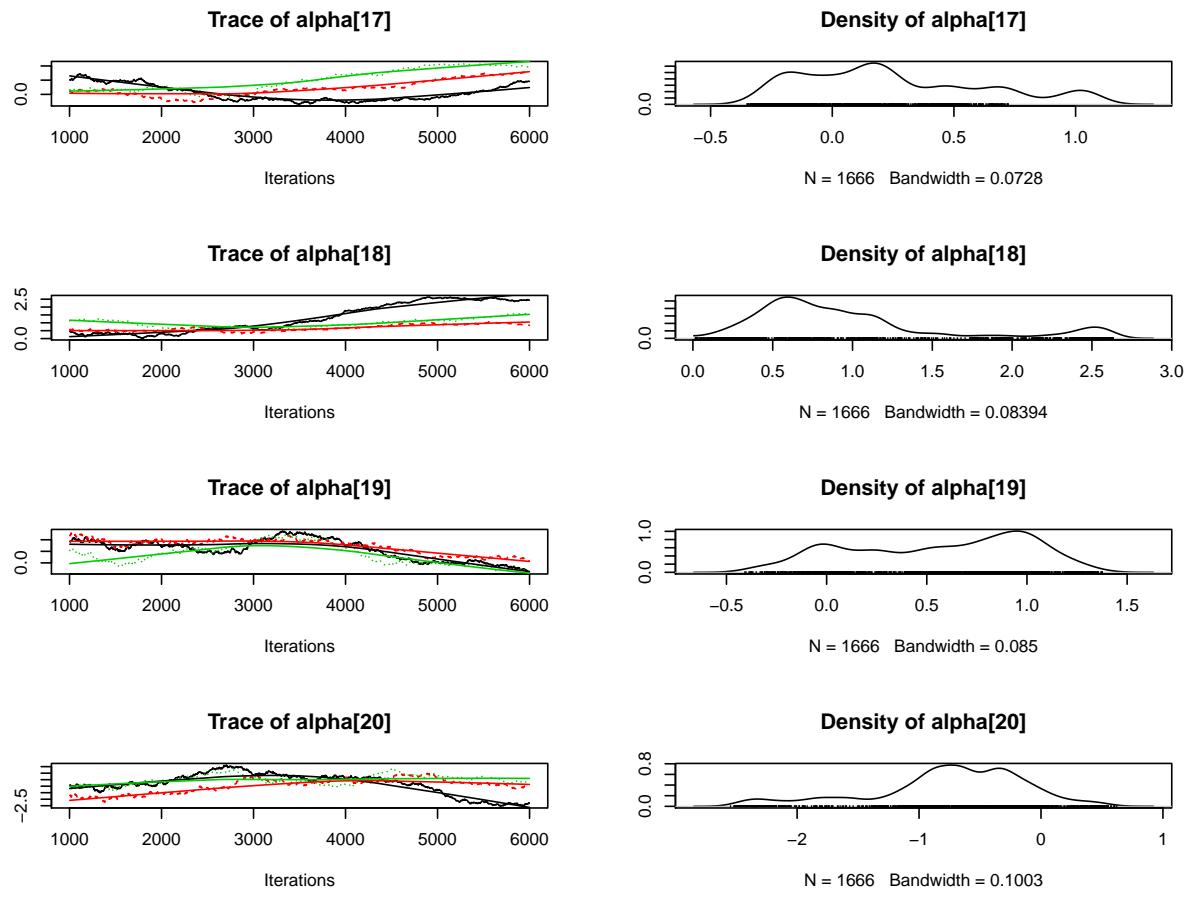
```
plot(samp)
```

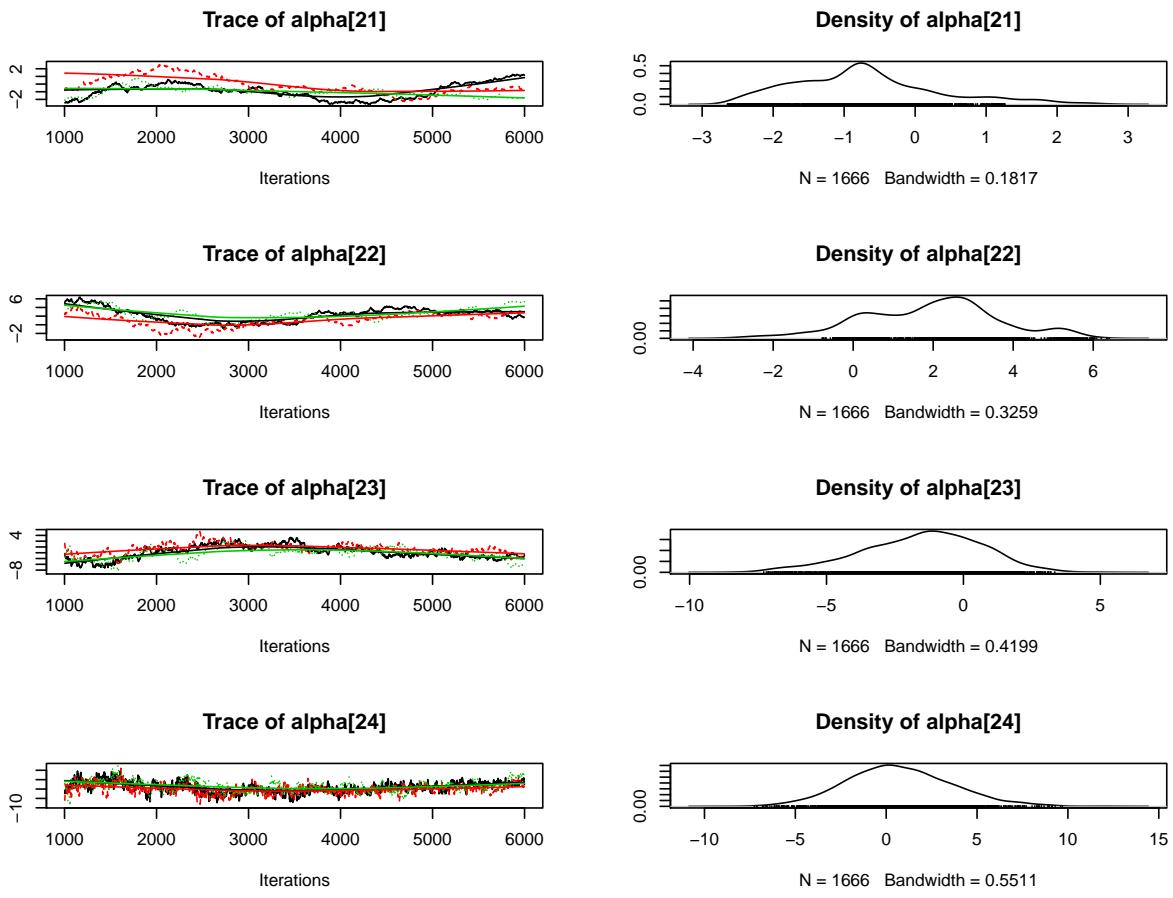


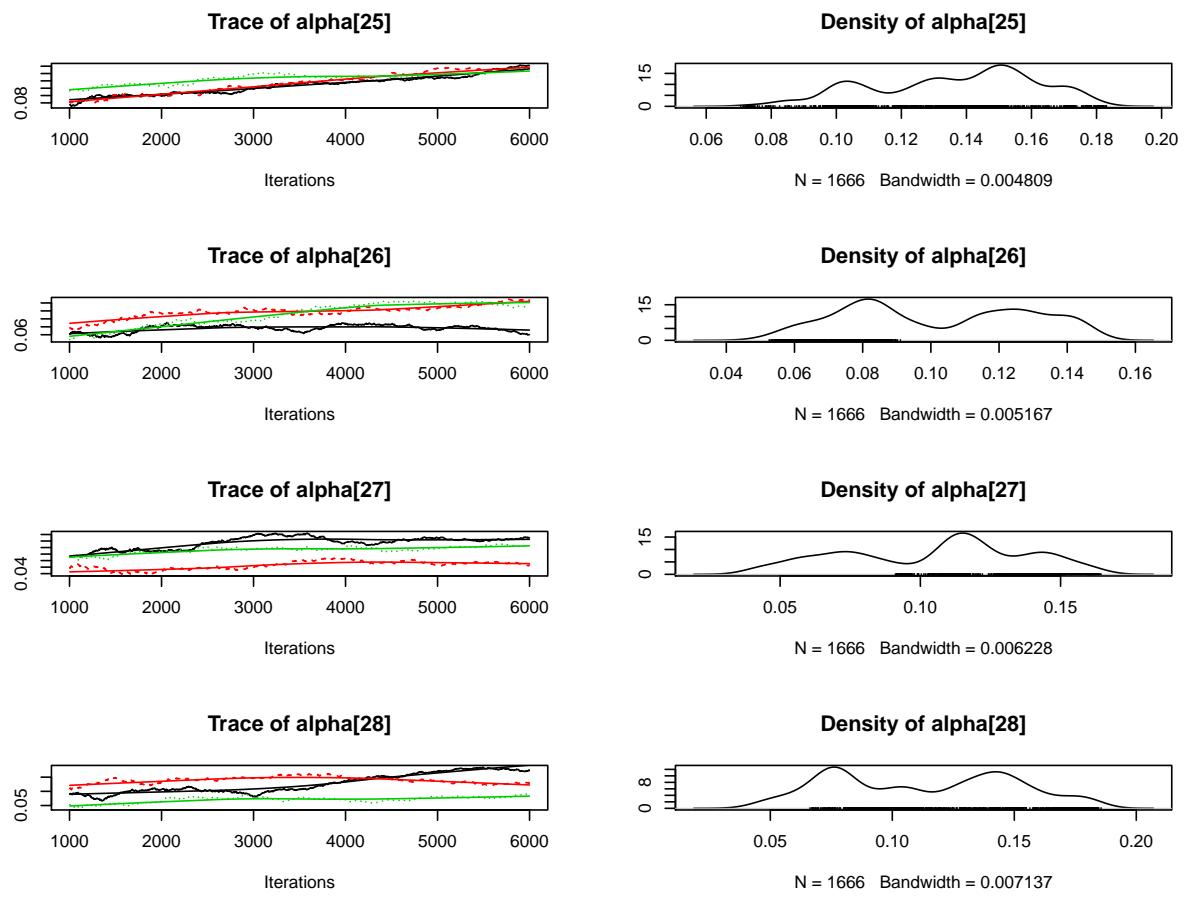


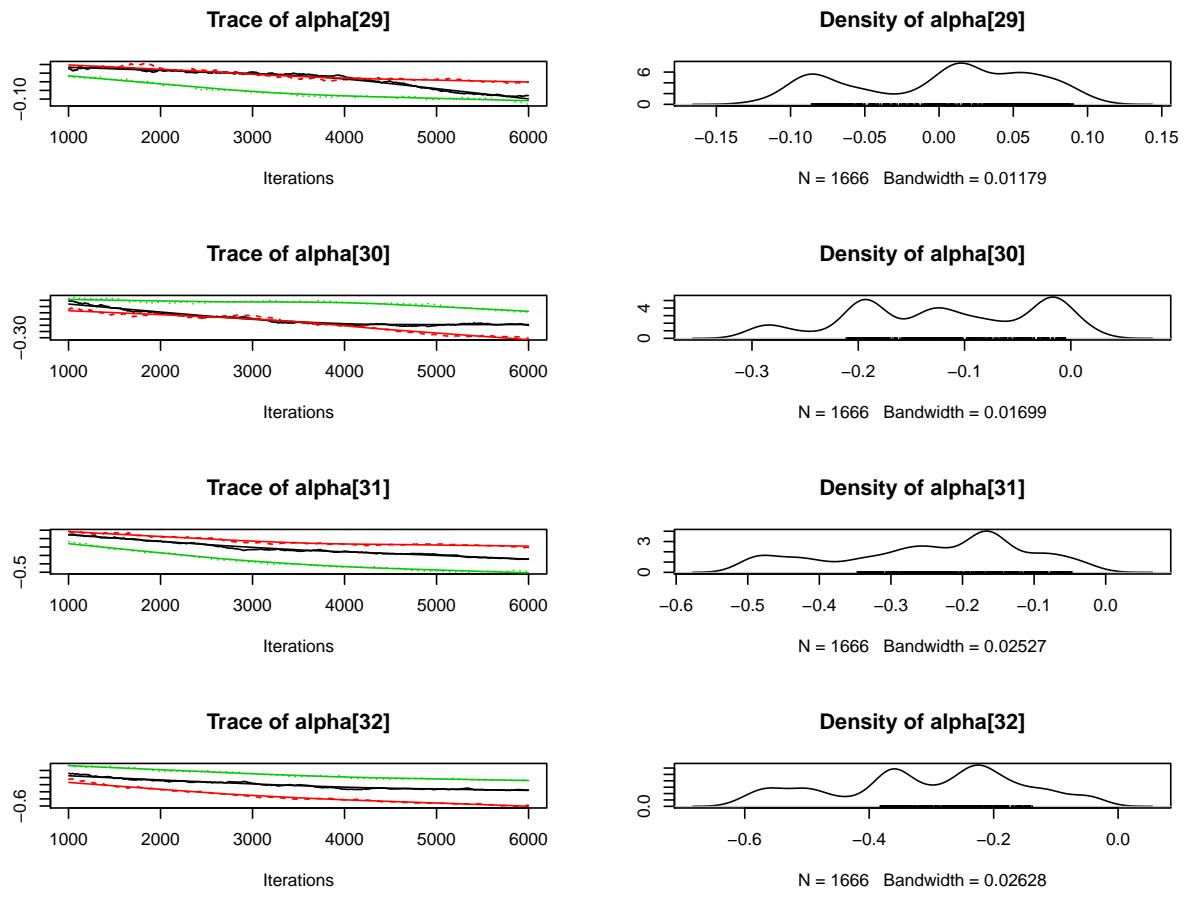


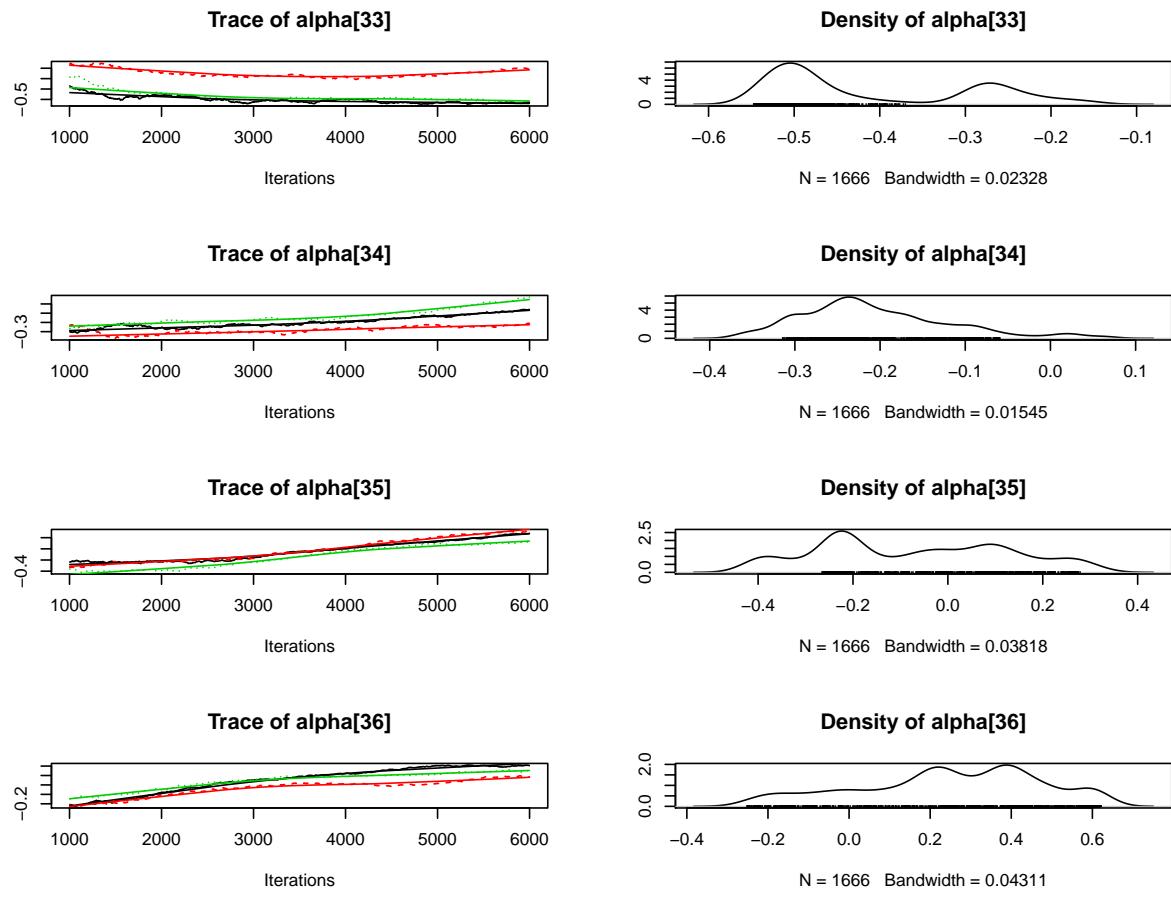


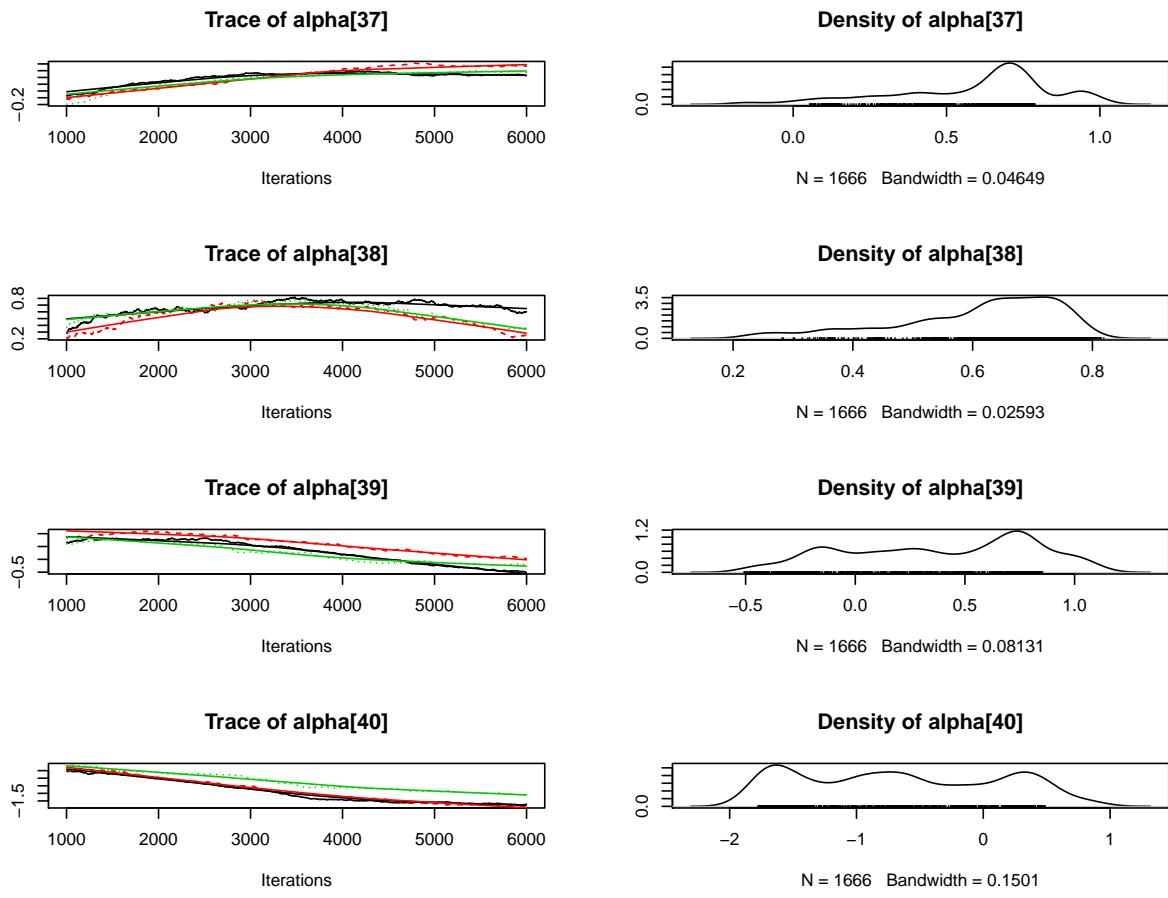


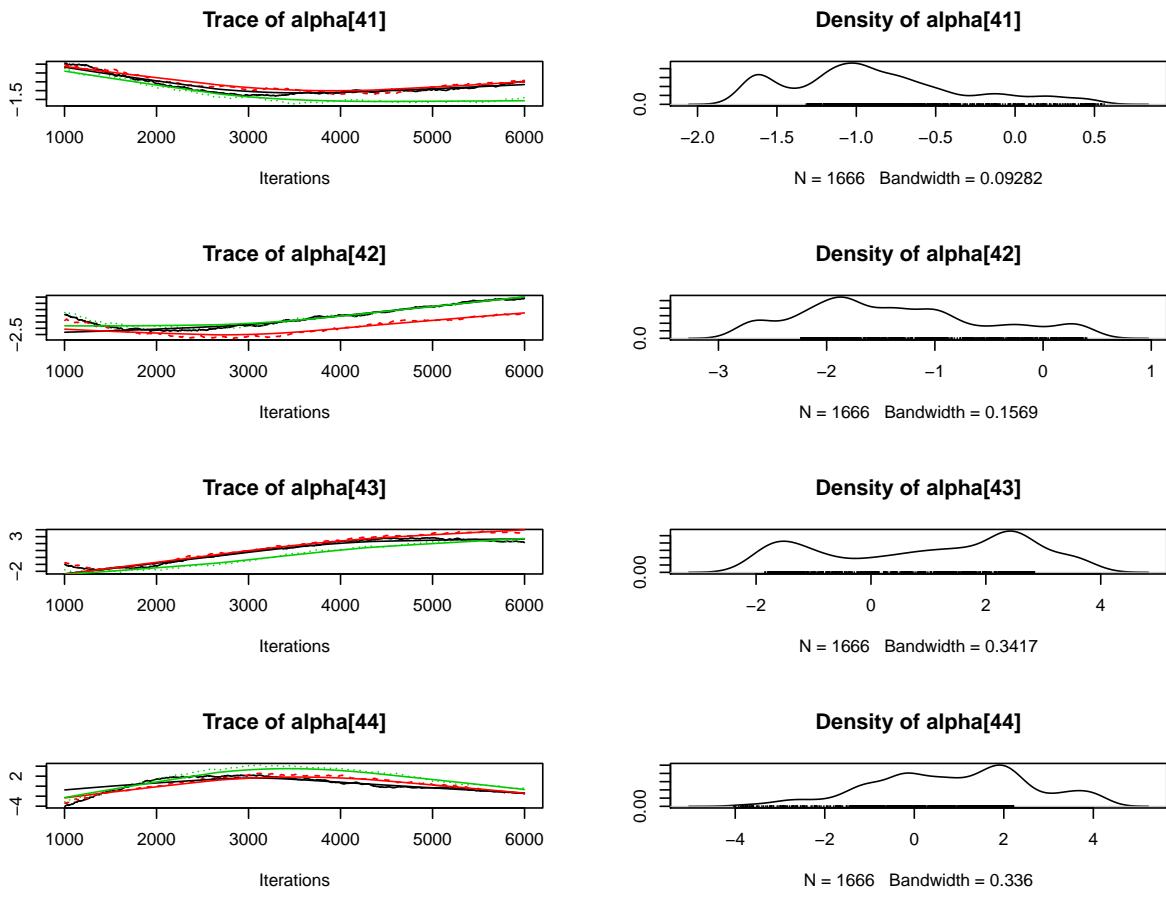


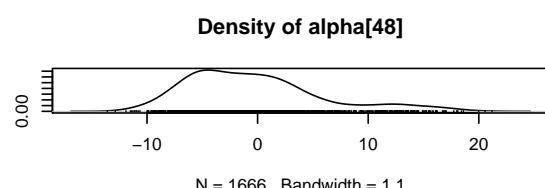
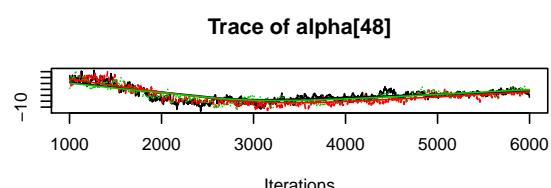
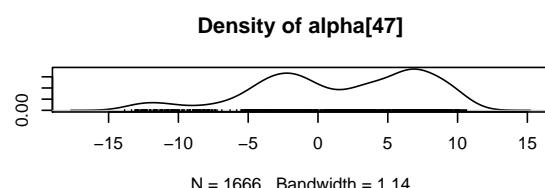
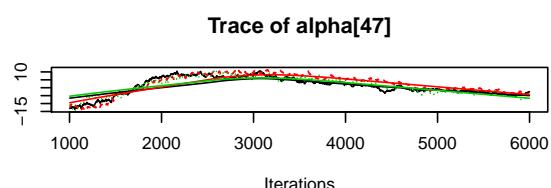
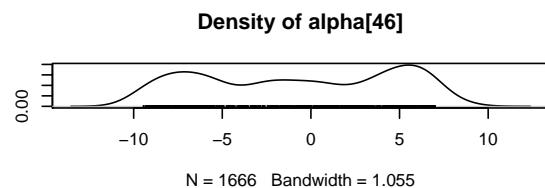
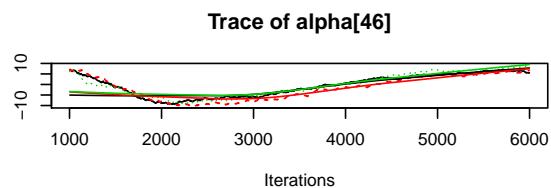
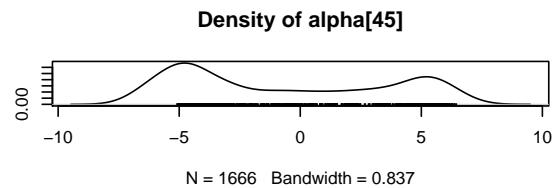
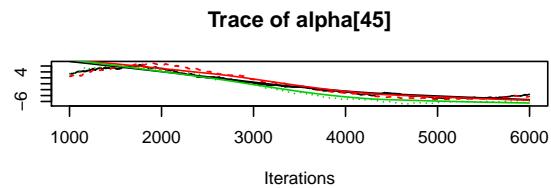


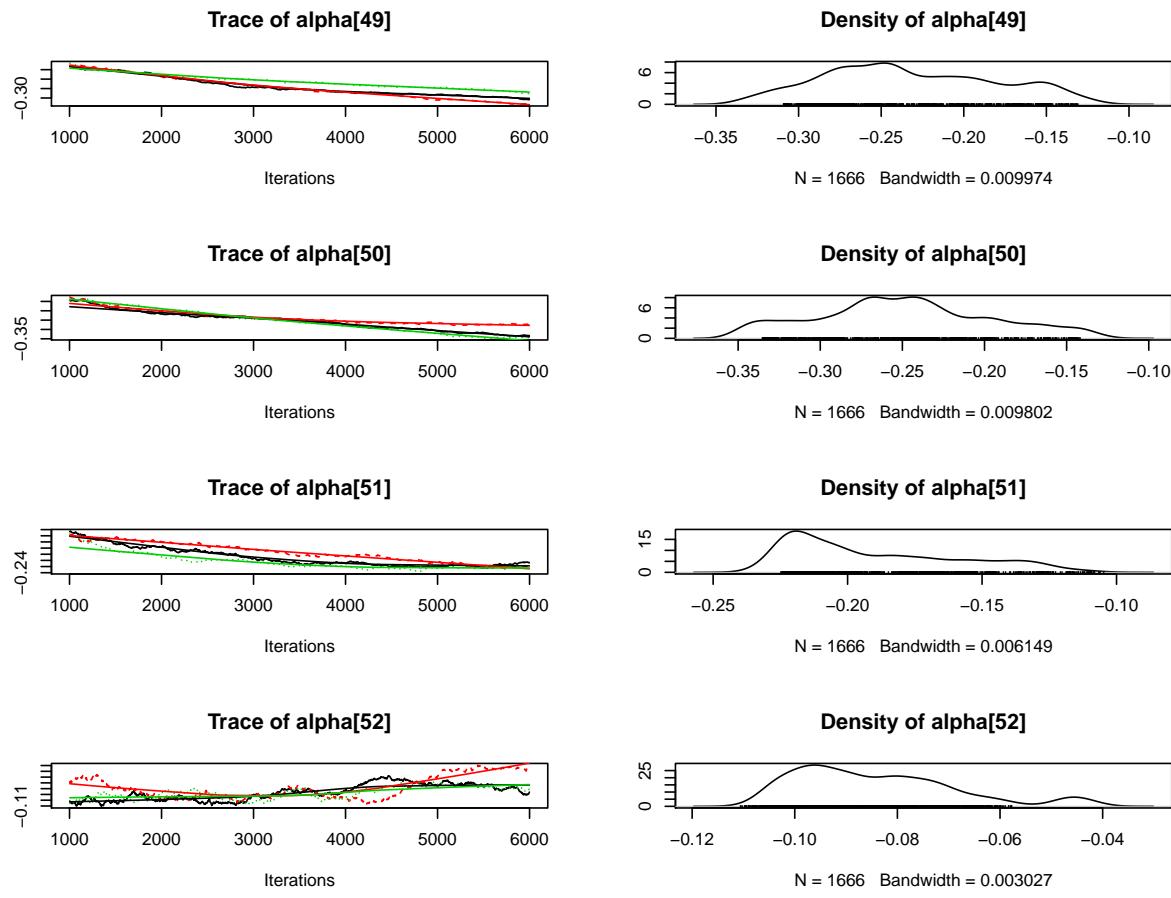


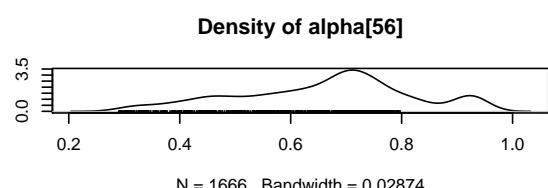
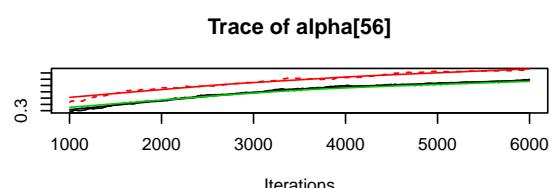
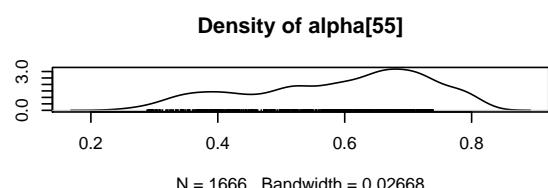
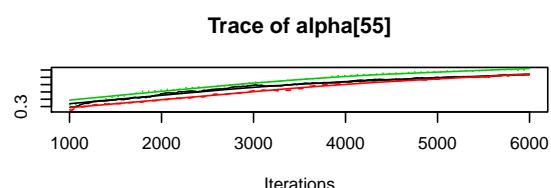
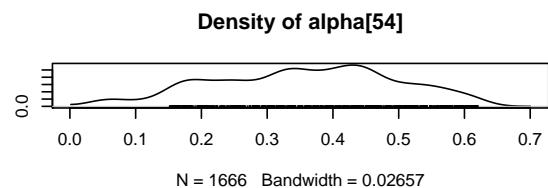
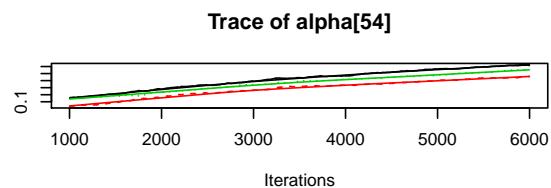
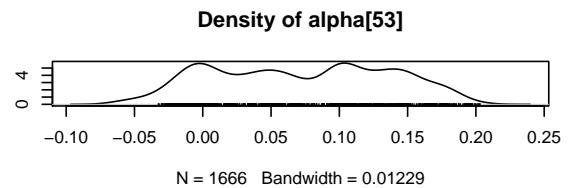
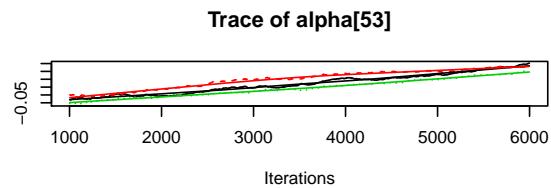


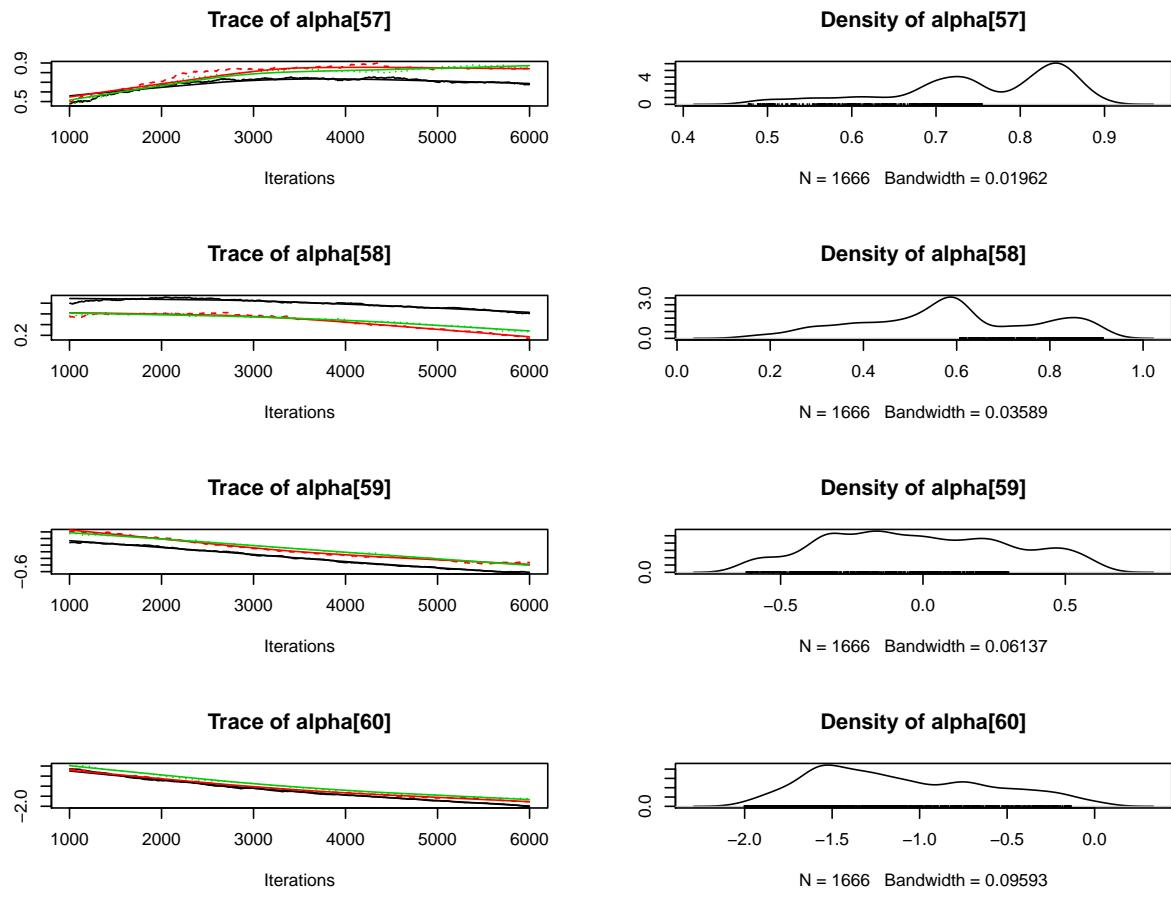


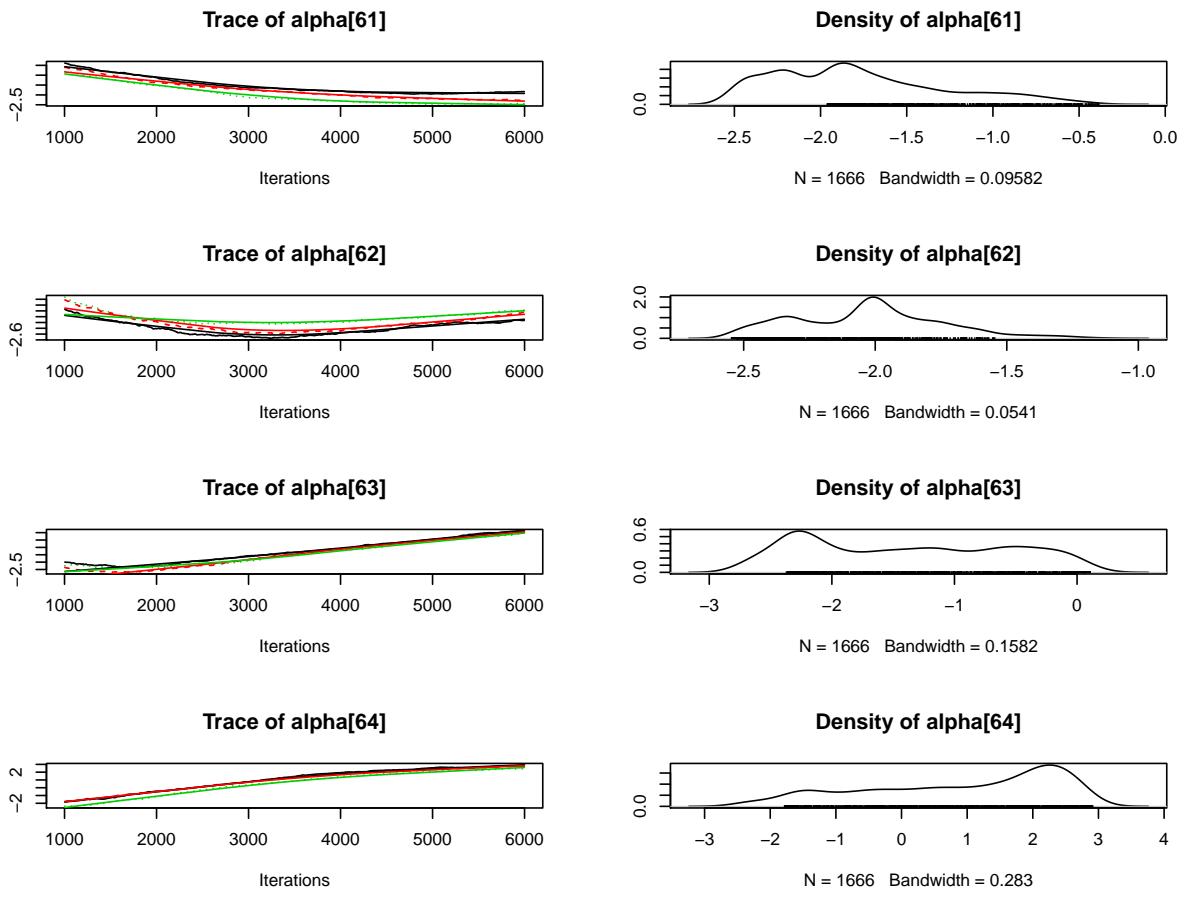


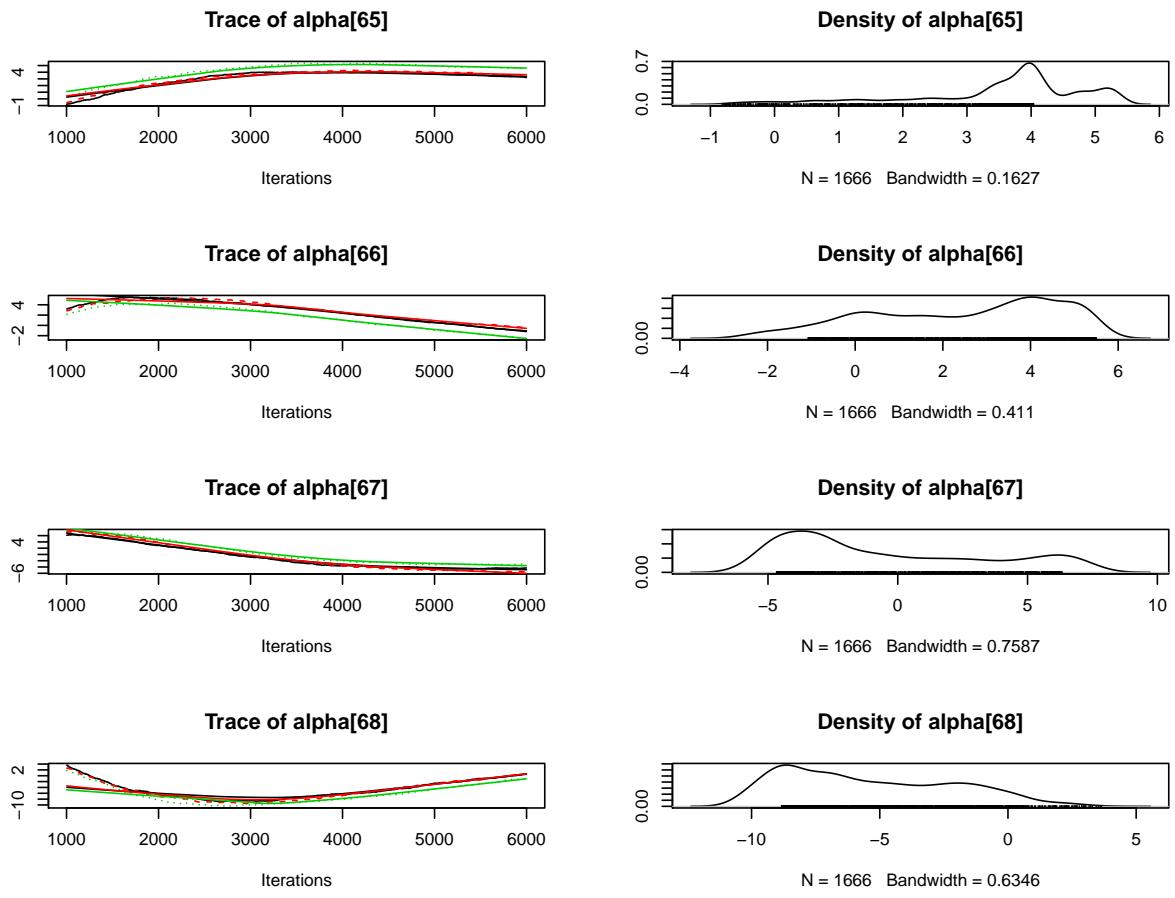


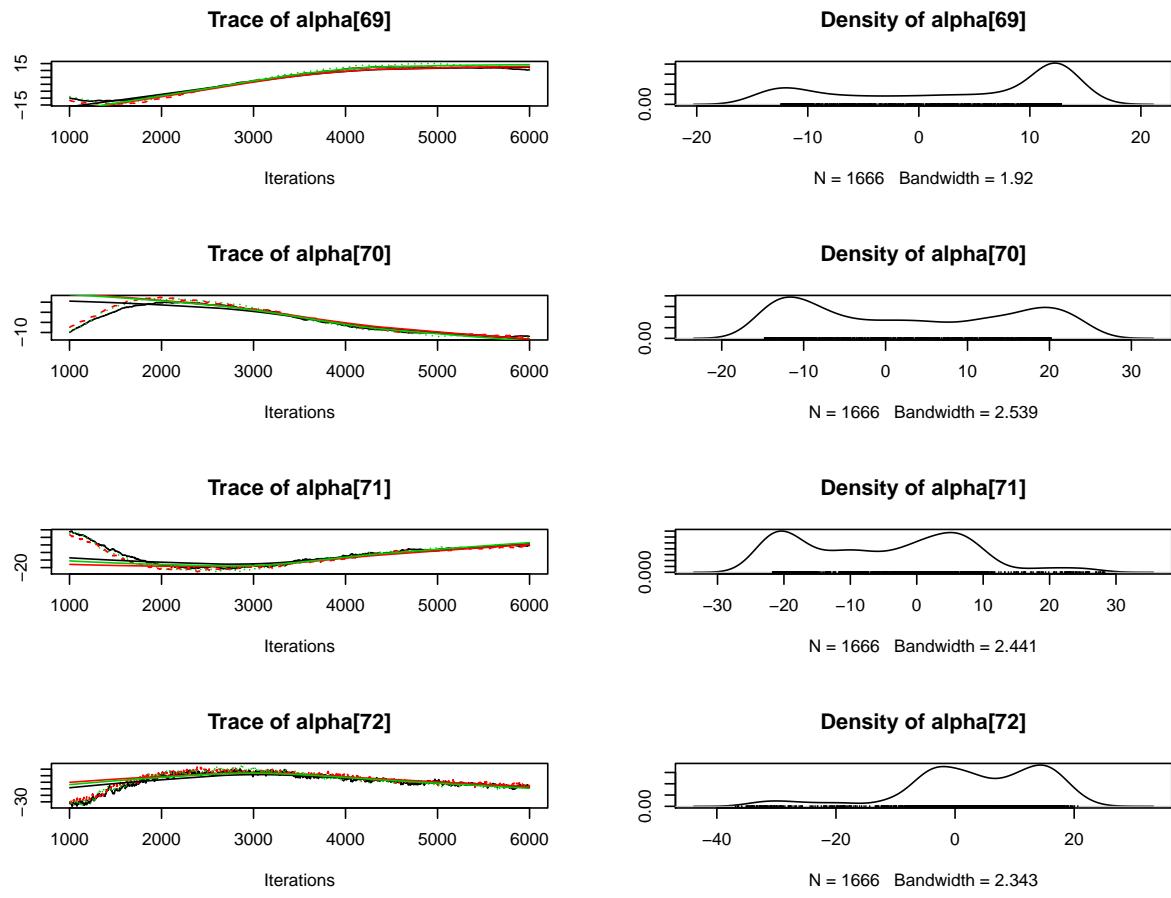


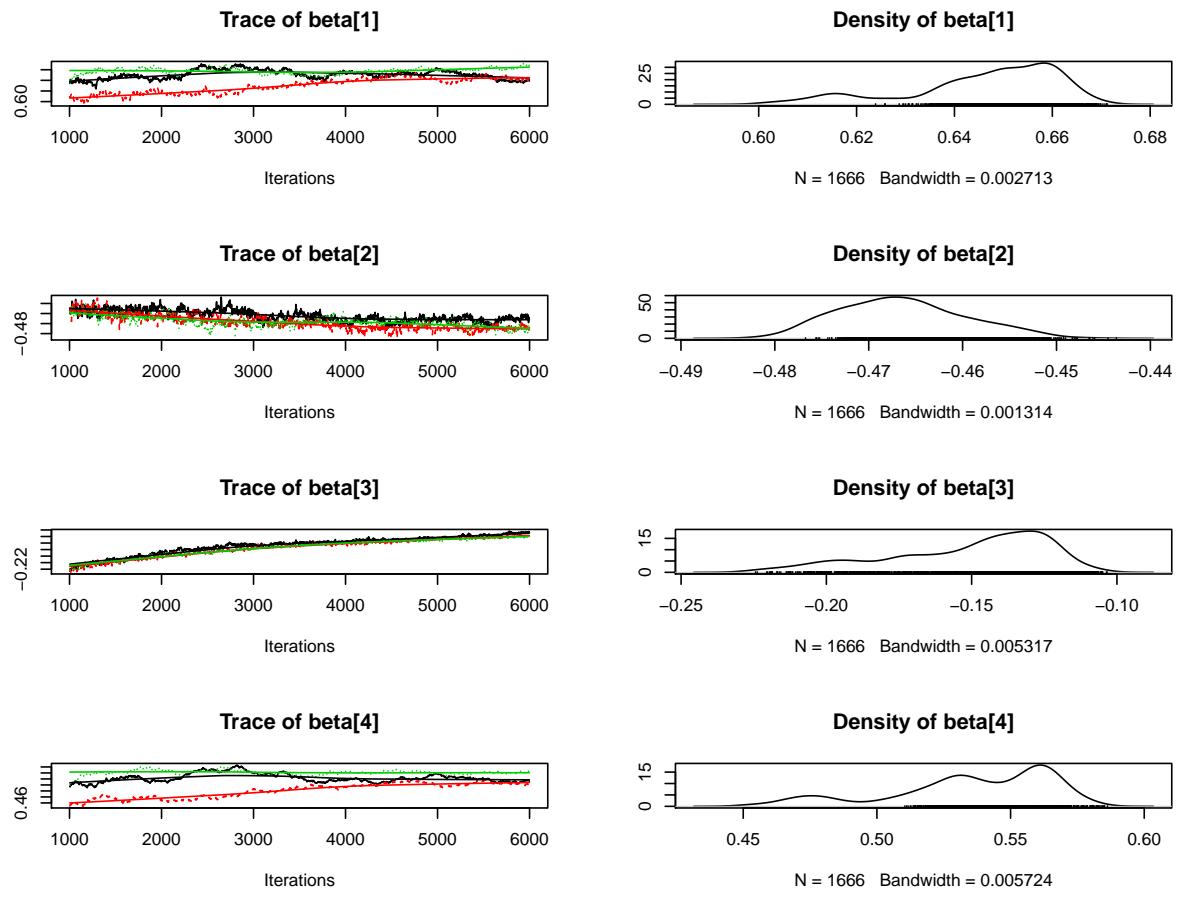


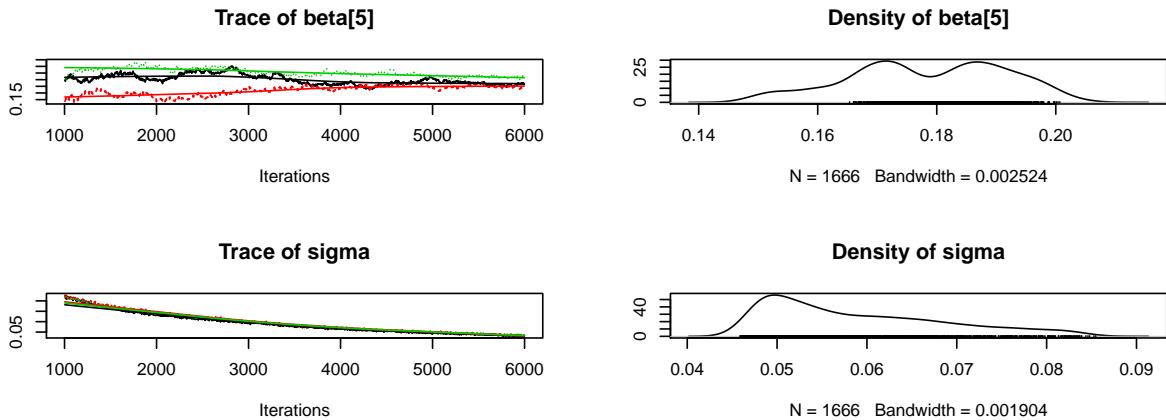












```

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

## 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.

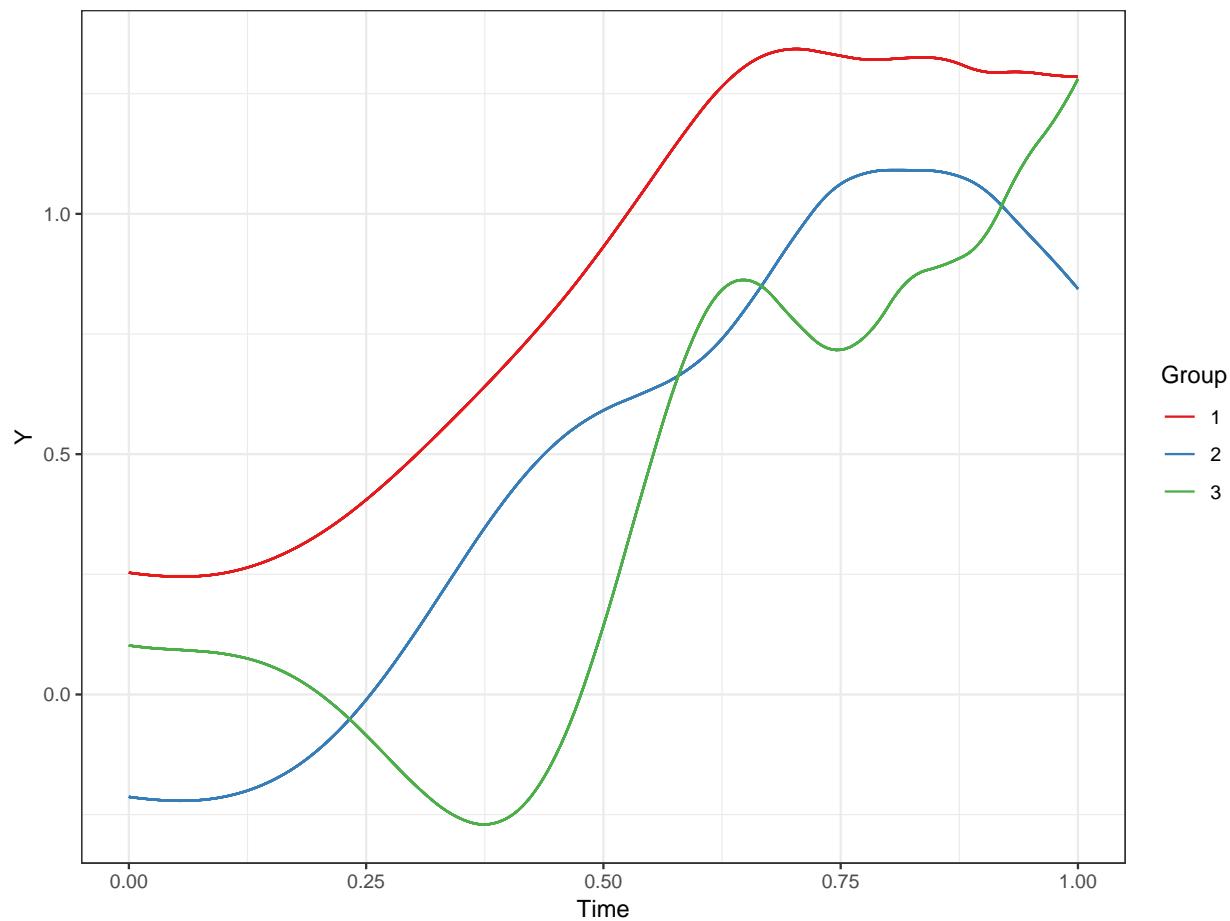
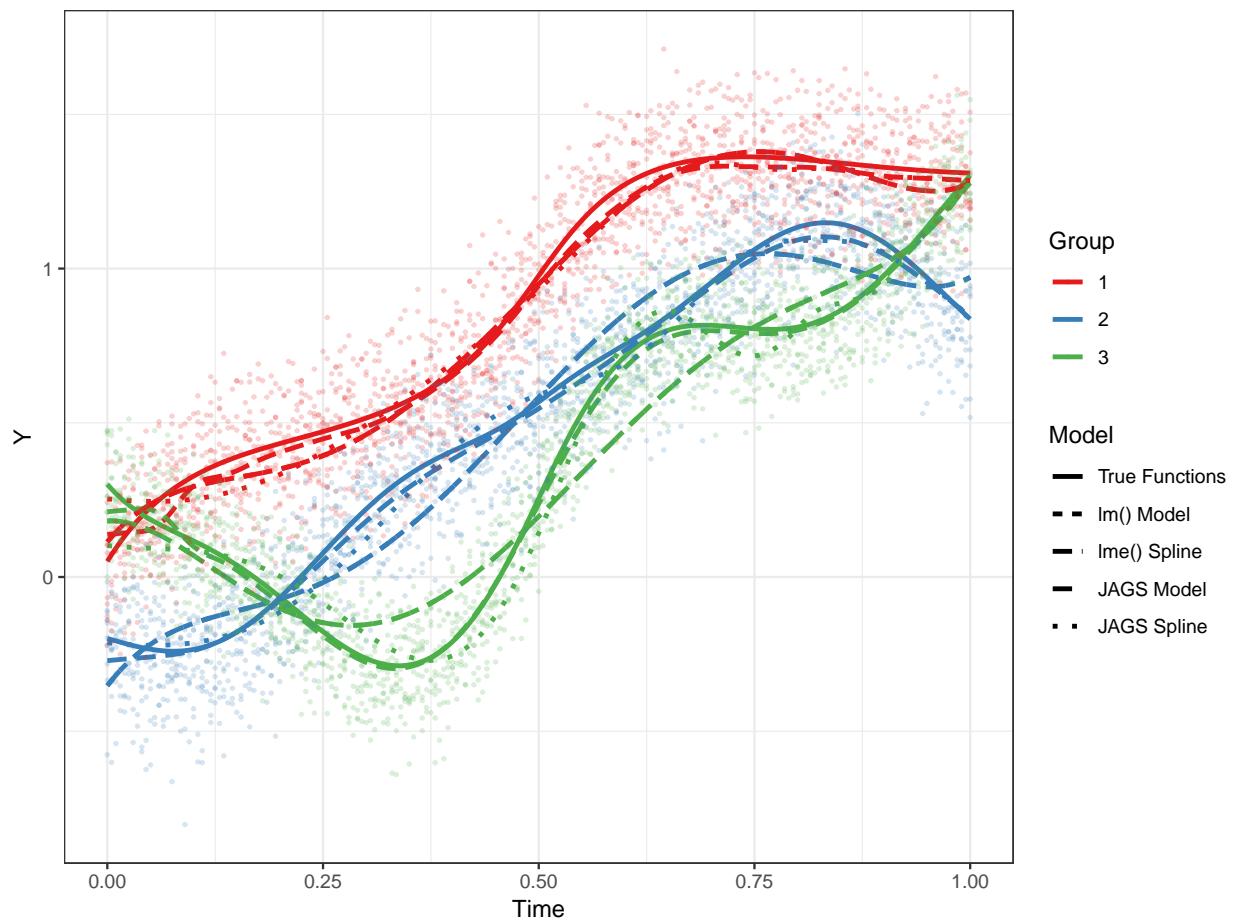


Figure 8: A comparison of the fitted effect functions from each model.



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_1.2-14     nlme_3.1-137      RColorBrewer_1.1-2
## [7] ggpplot2_3.1.0     knitr_1.20        MASS_7.3-51
##
## loaded via a namespace (and not attached):
## [1] Rcpp_0.12.19      nloptr_1.2.1      pillar_1.3.0      compiler_3.5.1
## [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_0.20-35
## [13] pkgconfig_2.0.2   rlang_0.3.0.1    rstudioapi_0.8    yaml_2.2.0
## [17] xfun_0.4          bindrcpp_0.2.2    stringr_1.3.1    withr_2.1.2
## [21] dplyr_0.7.7       rprojroot_1.3-2   grid_3.5.1       tidyselect_0.2.5
## [25] glue_1.3.0         R6_2.3.0          rmarkdown_1.10    minqa_1.2.4
## [29] purrrr_0.2.5      magrittr_1.5      splines_3.5.1    backports_1.1.2
## [33] scales_1.0.0       htmltools_0.3.6   rsconnect_0.8.8  assertthat_0.2.0
## [37] colorspace_1.3-2   labeling_0.3      tinytex_0.9       stringi_1.2.4
## [41] lazyeval_0.2.1     munsell_0.5.0     crayon_1.3.4
```