Bayesian Checks

library(zoib)  
library(tidyverse)  
library(GGally)  
library(ggpubr)  
library(kableExtra)  
library(mice)  
library(parallel)  
  
theme\_set(theme\_pubr(legend = "bottom"))

# read imputed data

nnns\_imputed<- readRDS("../Haojia\_work/nnns\_imputed.rds")  
  
dat <- lapply(1:20, function(i) complete(nnns\_imputed, i))

# Use ZOIB package

## ZOIB Model

## Fit ZOIB model

set.seed(11282023)  
  
tictoc::tic()  
  
# Define a function for model fitting  
fit\_model <- function(d) {  
 zoib(  
 Percent\_of\_feeds\_taken\_by\_mouth\_at\_discharge ~  
 Pre\_Op\_NNNS\_attention\_score +  
 Length\_of\_intubation\_days +  
 Cardiac\_Anatomy +  
 Age\_at\_Surgery\_days +  
 Female #x1 design matrix  
 | 1 | #x2 design matrix  
 Pre\_Op\_NNNS\_attention\_score +  
 Length\_of\_intubation\_days +  
 Cardiac\_Anatomy +  
 Age\_at\_Surgery\_days +  
 Female | #X3 design matrix  
 Pre\_Op\_NNNS\_attention\_score +  
 Length\_of\_intubation\_days +  
 Cardiac\_Anatomy +  
 Age\_at\_Surgery\_days +  
 Female, #x4 design matrix  
 data = d,  
 n.response = 1,  
 zero.inflation = TRUE,  
 one.inflation = TRUE,  
 link.mu = "logit",  
 link.x0 = "logit",  
 link.x1 = "logit",  
 random = 0,  
 n.chain = 4,  
 n.iter = 3000,  
 n.thin = 2,  
 n.burn = 200,  
 seeds = c(11, 29, 20, 23)  
 )  
}  
model\_results <- lapply(dat, fit\_model)  
# Save results  
saveRDS(model\_results, "pre\_op\_models.rds")  
  
tictoc::toc()

set.seed(11282023)  
  
tictoc::tic()  
  
# Define a function for model fitting  
fit\_model <- function(d) {  
 zoib(  
 Percent\_of\_feeds\_taken\_by\_mouth\_at\_discharge ~  
 Post\_Op\_NNNS\_attention\_score +  
 Length\_of\_intubation\_days +  
 Cardiac\_Anatomy +  
 Age\_at\_Surgery\_days +  
 Female #x1 design matrix  
 | 1 | #x2 design matrix  
 Post\_Op\_NNNS\_attention\_score +  
 Length\_of\_intubation\_days +  
 Cardiac\_Anatomy +  
 Age\_at\_Surgery\_days +  
 Female | #X3 design matrix  
 Post\_Op\_NNNS\_attention\_score +  
 Length\_of\_intubation\_days +  
 Cardiac\_Anatomy +  
 Age\_at\_Surgery\_days +  
 Female, #x4 design matrix  
 data = d,  
 n.response = 1,  
 zero.inflation = TRUE,  
 one.inflation = TRUE,  
 link.mu = "logit",  
 link.x0 = "logit",  
 link.x1 = "logit",  
 random = 0,  
 n.chain = 4,  
 n.iter = 3000,  
 n.thin = 2,  
 n.burn = 200,  
 seeds = c(11, 29, 20, 23)  
 )  
}  
  
# Parallelize model fitting  
model\_results <- lapply(dat, fit\_model)  
  
# Save results  
saveRDS(model\_results, "post\_op\_models.rds")  
  
tictoc::toc()

## Interpreting output:

b: vector of estimates from Eqn 1; that is, g(mu) = xb\*b +z\*gamma

d: vector of estimates from Eqn 2; that is, log(eta) = xd\*d+z\*gamma

b0: vector of estimates from Eqn 3; that is, g(p0) = x0\*b0 +z\*gamma

b1: vector of estimates from Eqn ;4 that is, g(p1) = x1\*b1+z\*gamma

# Pool chains

post\_op\_models =readRDS(file="post\_op\_models.rds")  
pre\_op\_models =readRDS(file="pre\_op\_models.rds")  
  
post\_op\_coeff = list()  
pre\_op\_coeff = list()  
for(i in 1:length(post\_op\_models)){  
 pre\_op\_coeff[[i]] = pre\_op\_models[[i]]$coeff  
 post\_op\_coeff[[i]] = post\_op\_models[[i]]$coeff  
}  
  
pooled\_pre\_op = runjags::combine.mcmc(mcmc.objects = pre\_op\_coeff, collapse.chains = FALSE)  
pooled\_post\_op = runjags::combine.mcmc(mcmc.objects = post\_op\_coeff, collapse.chains = FALSE)  
  
saveRDS(pooled\_pre\_op, "pooled\_pre\_op.rds")  
saveRDS(pooled\_post\_op, "pooled\_post\_op.rds")

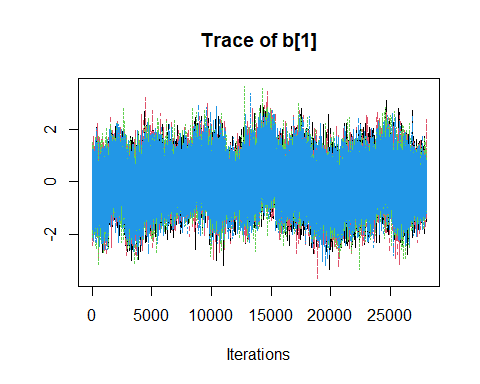
pooled\_pre\_op = readRDS("pooled\_pre\_op.rds")  
pooled\_post\_op = readRDS("pooled\_post\_op.rds")

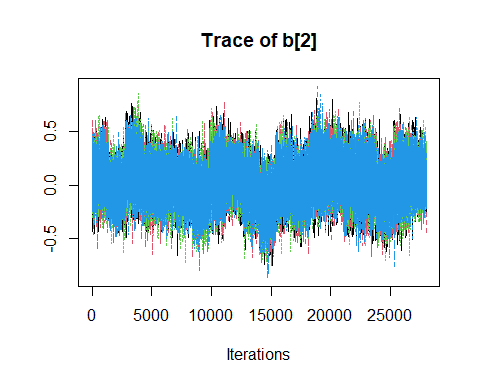
## Check convergence

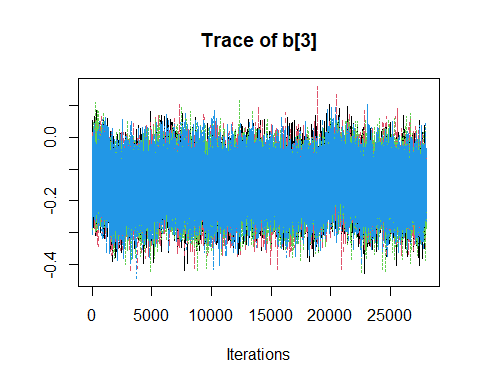
### Traceplots

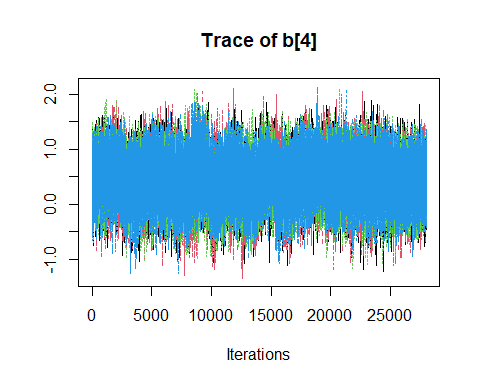
#### Pre-op

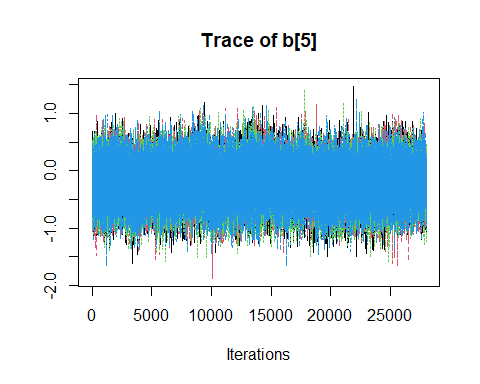
pooled\_pre\_op |> traceplot()

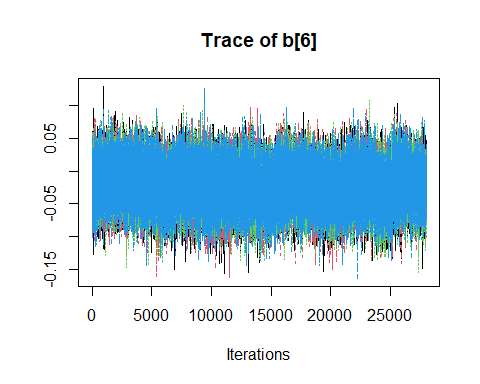


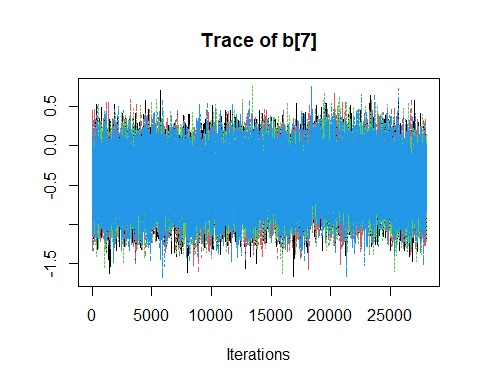


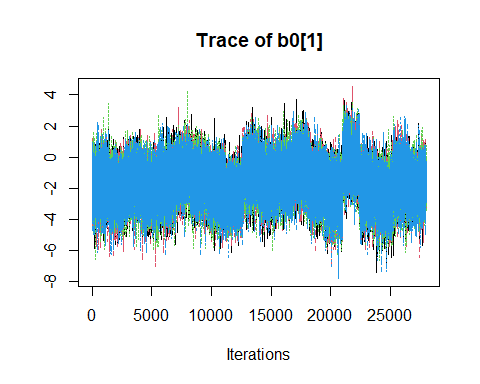


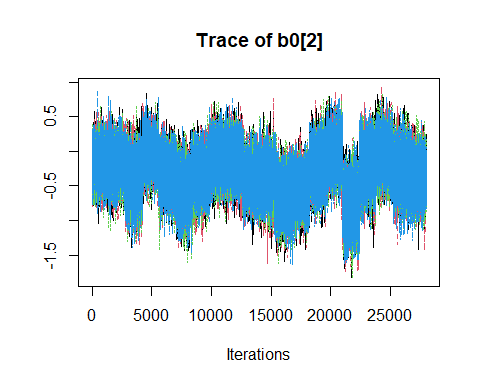


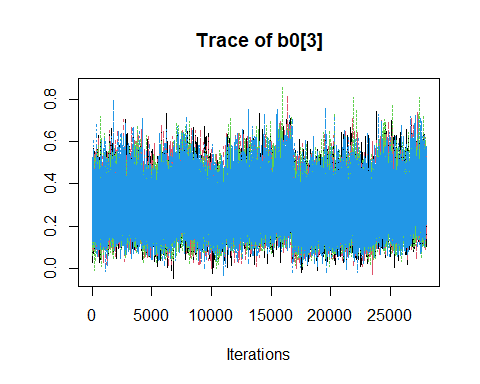


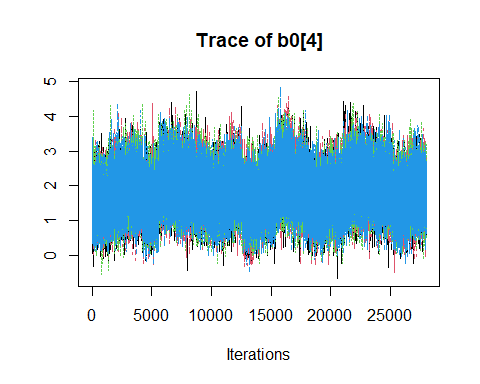


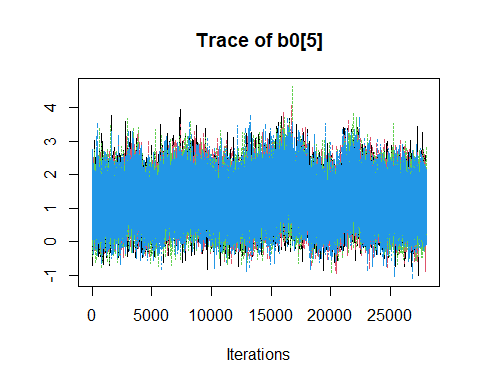


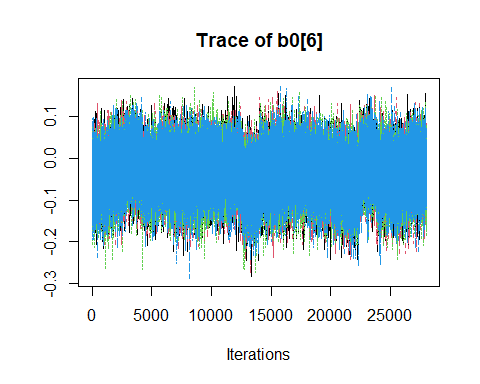


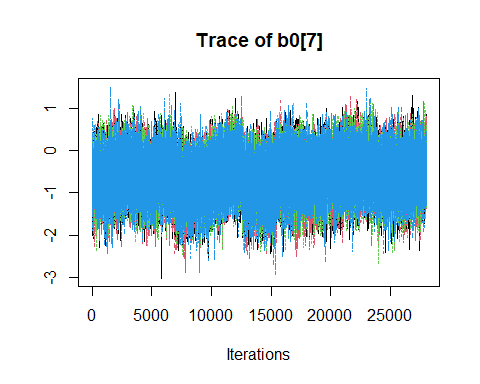


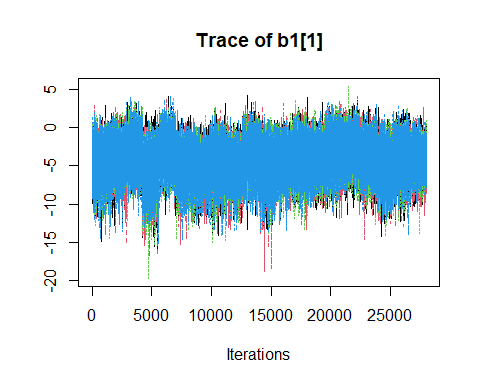


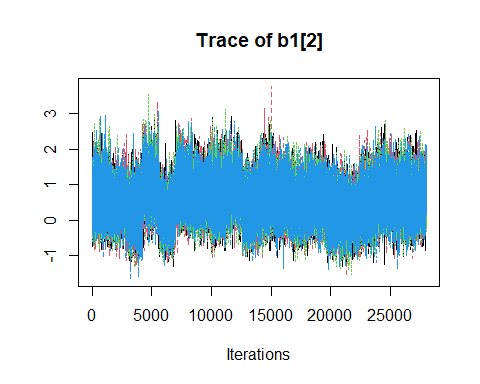


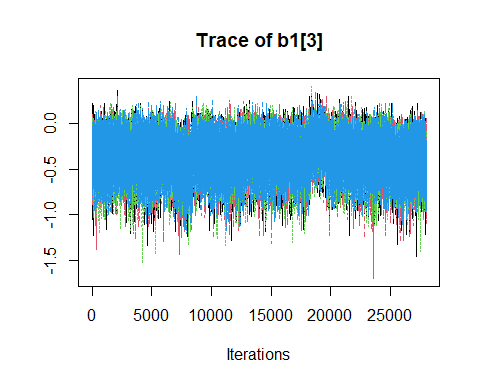


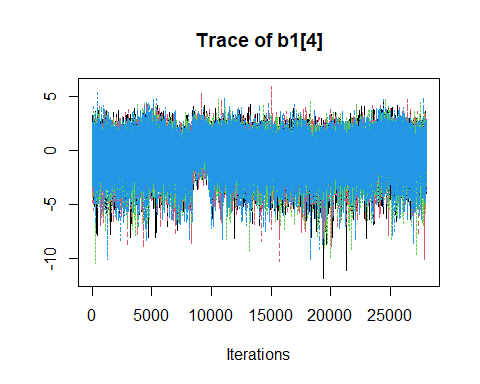


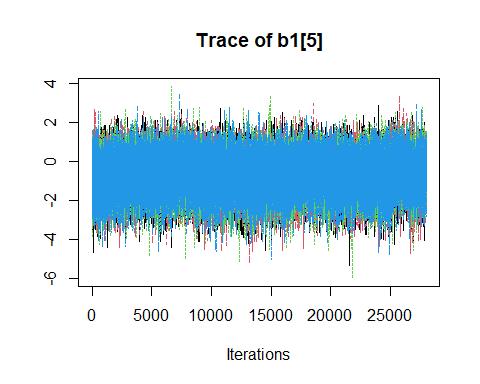


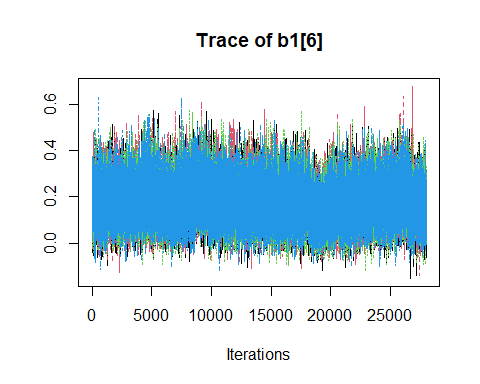


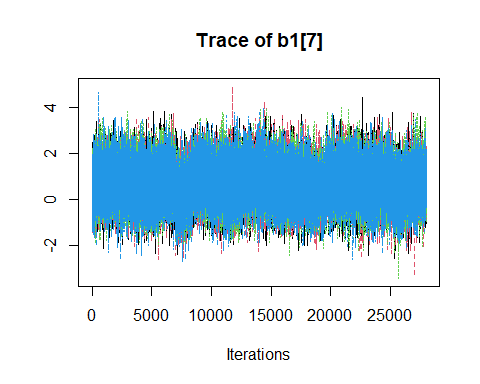


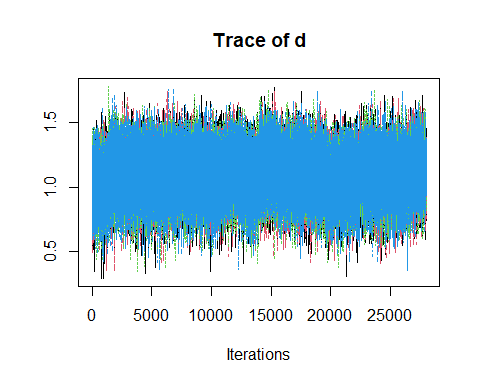






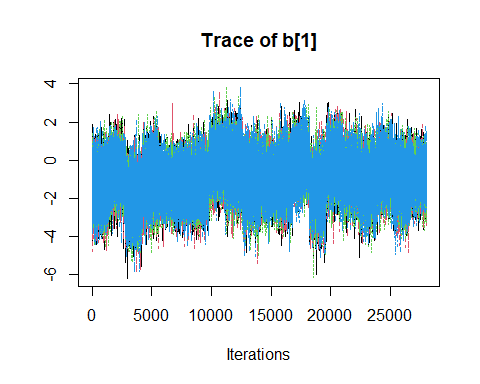


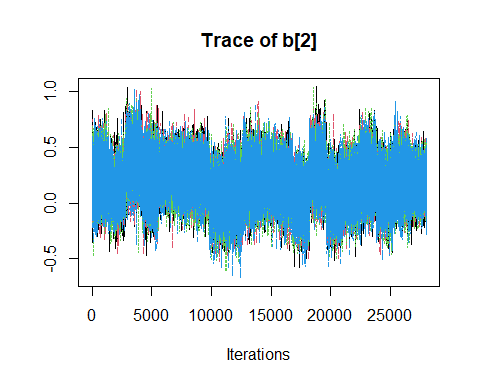


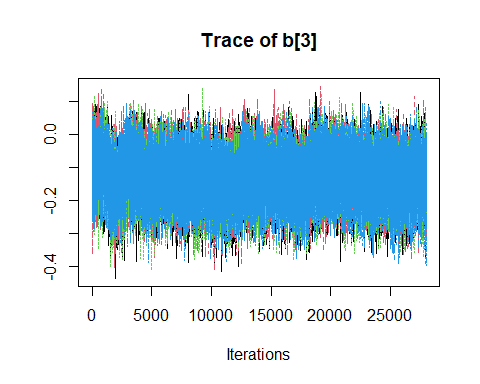


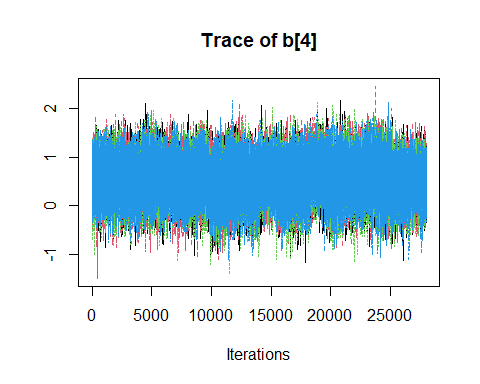
#### Post-op

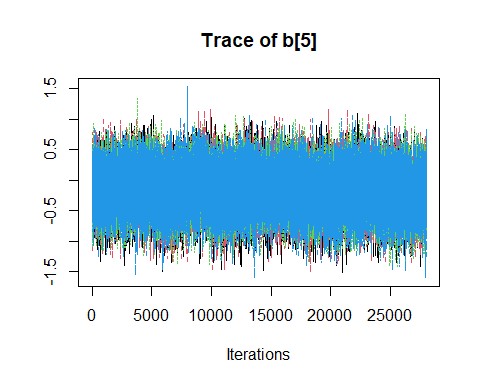
pooled\_post\_op |> traceplot()

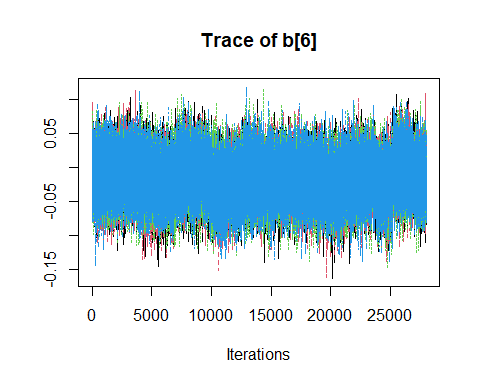


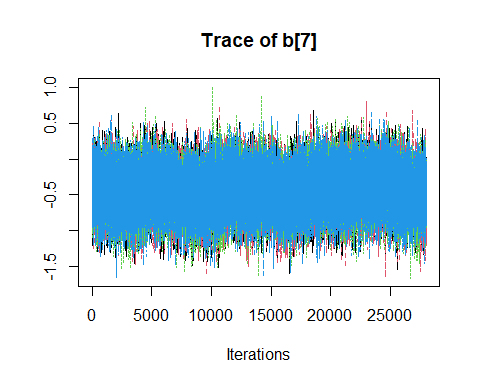


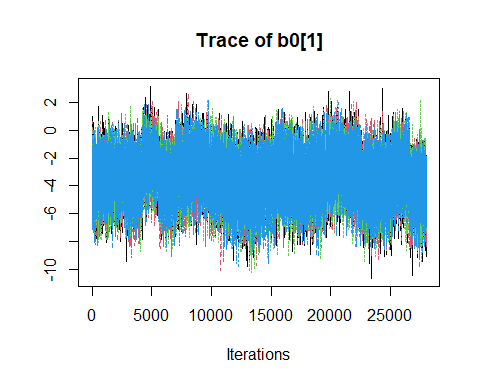


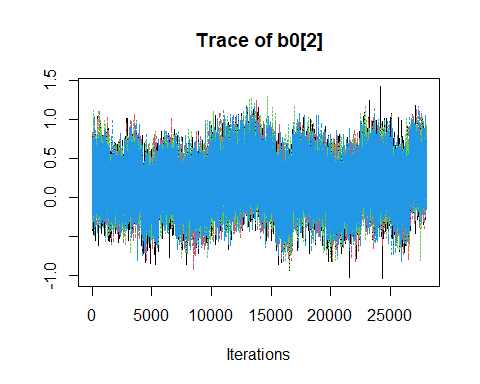


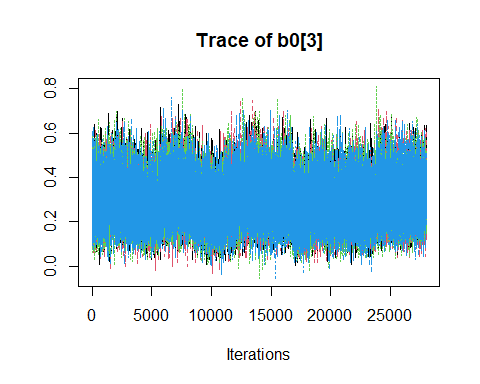


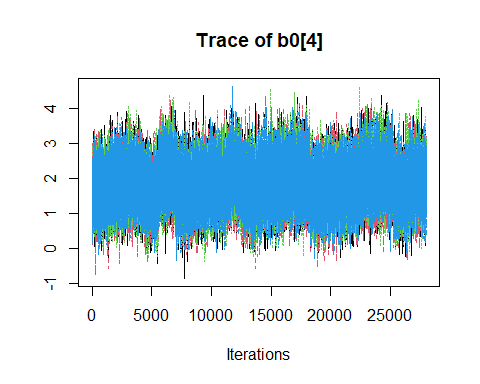


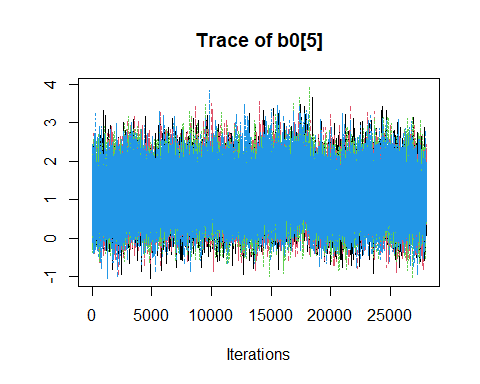


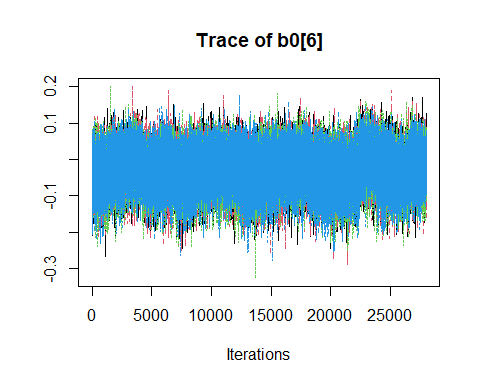


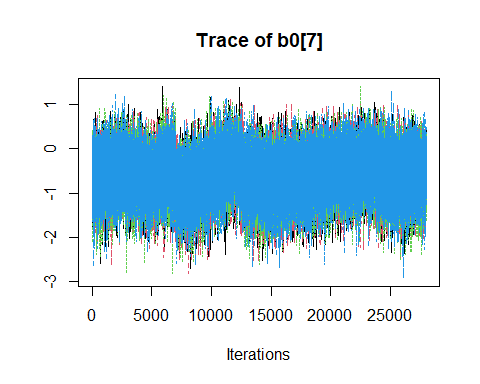


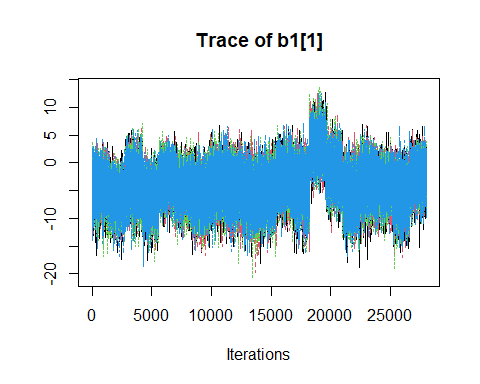


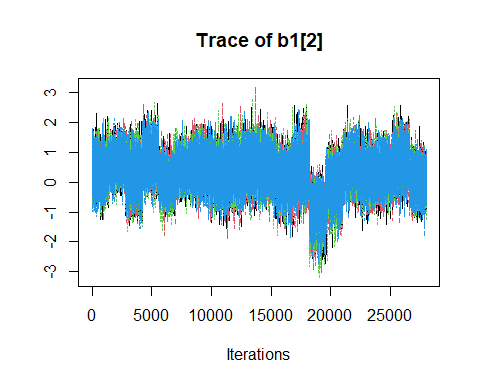


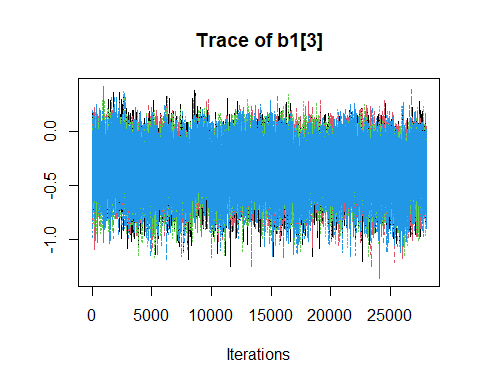


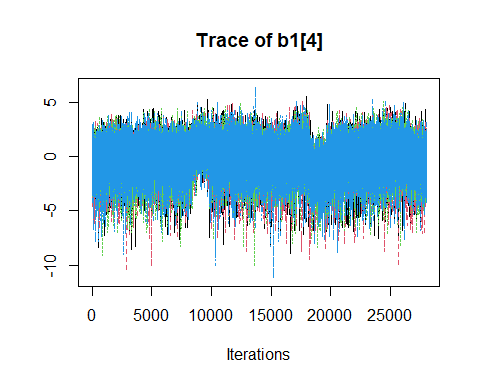


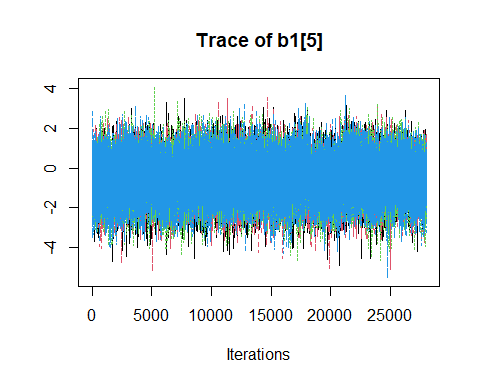


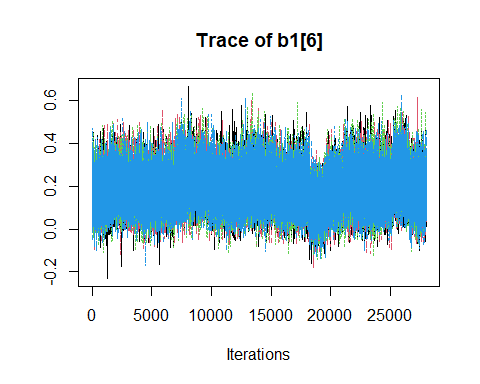


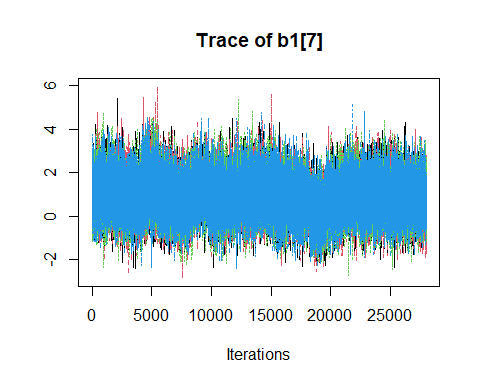


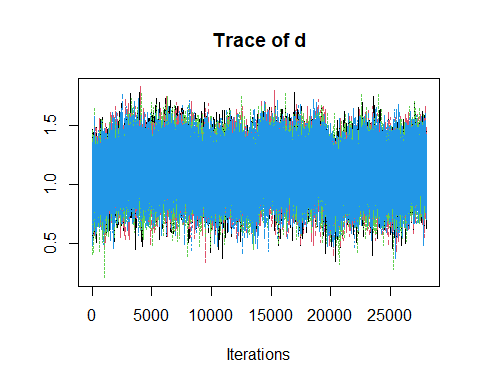








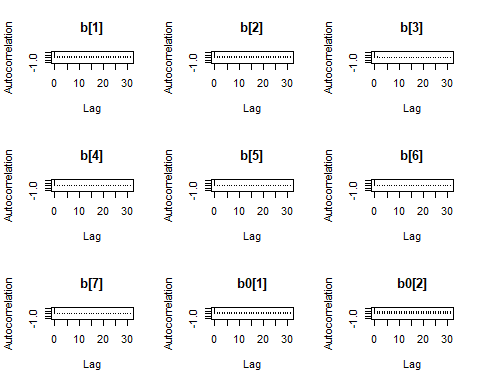


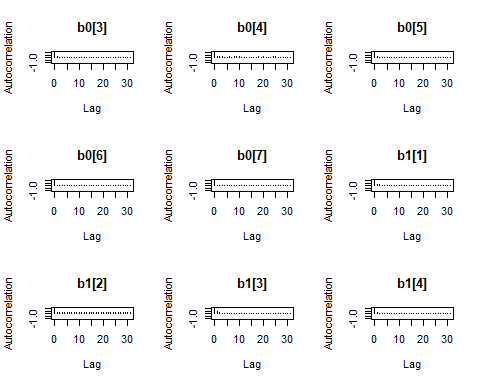


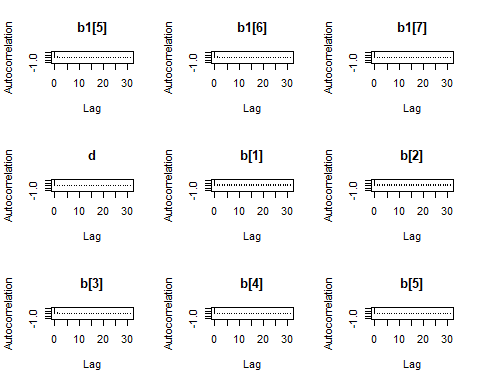
### Autocorrelation plots

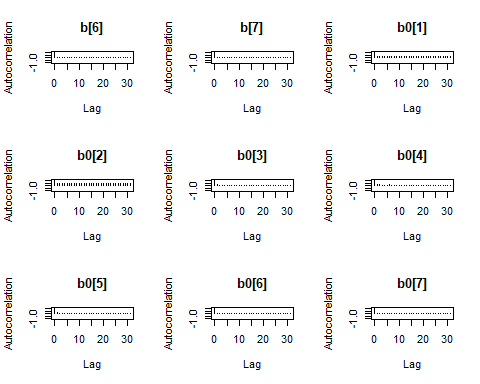
#### Pre-op

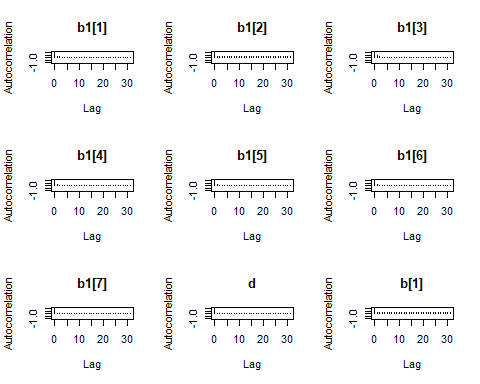
pooled\_pre\_op |> autocorr.plot()

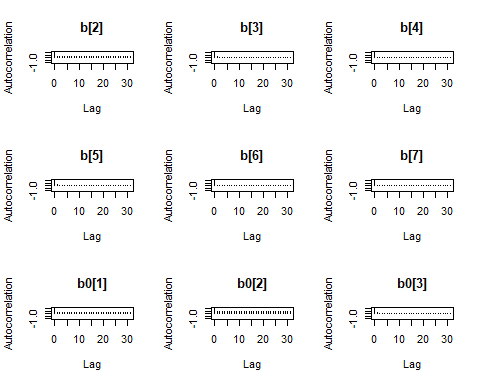


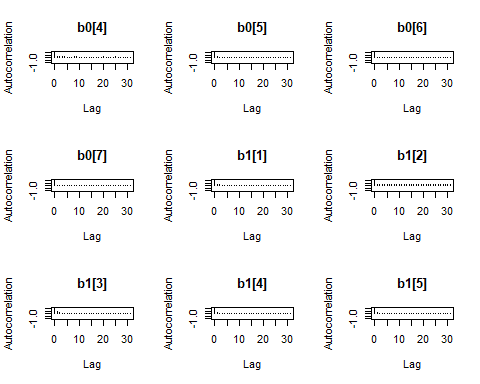


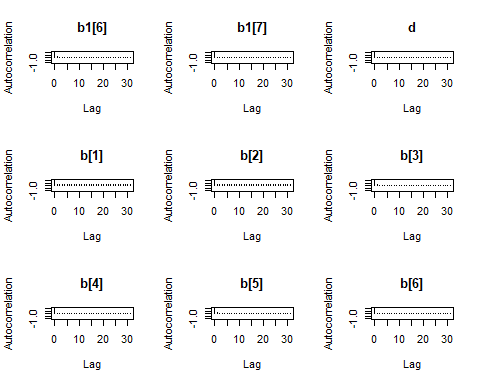


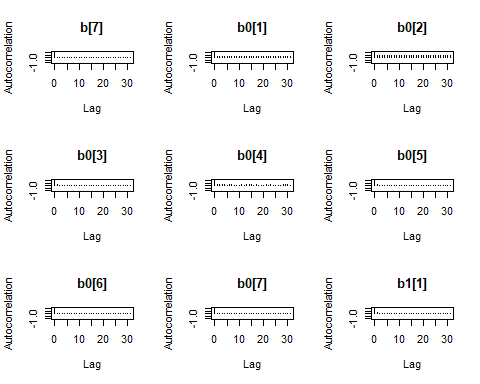


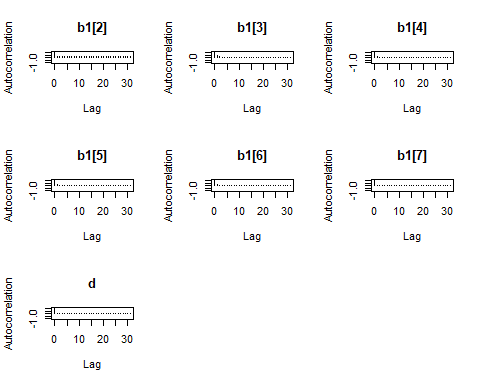






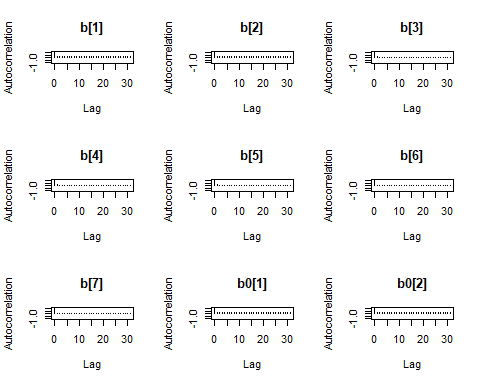


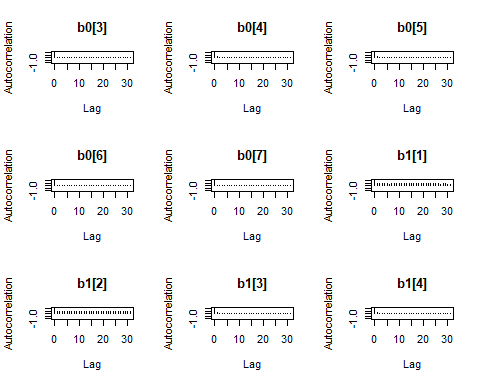


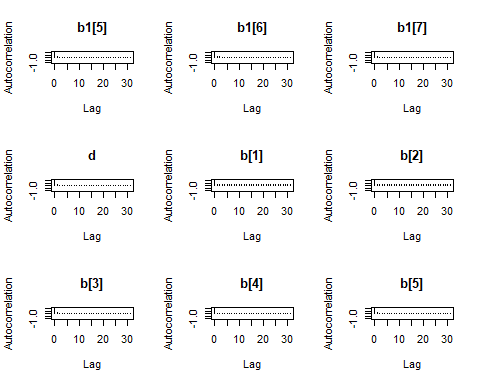


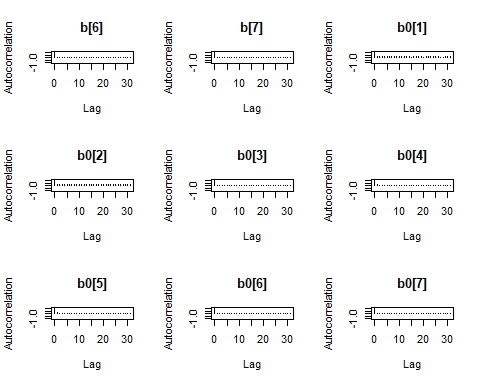
#### Post-op

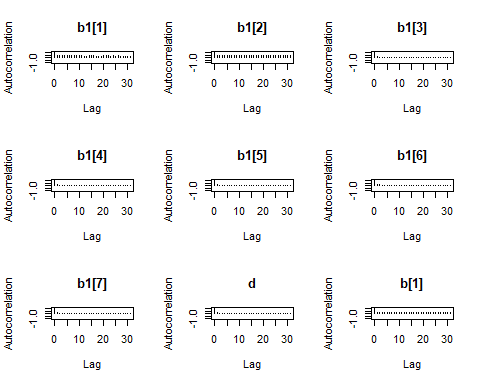
pooled\_post\_op |> autocorr.plot()

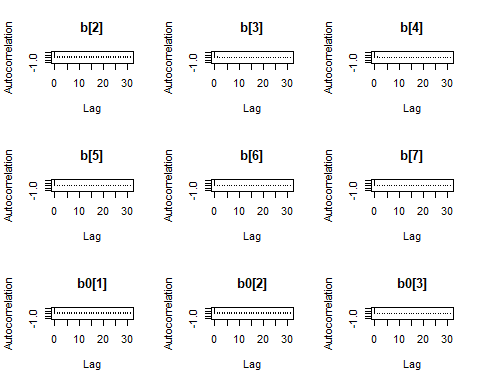


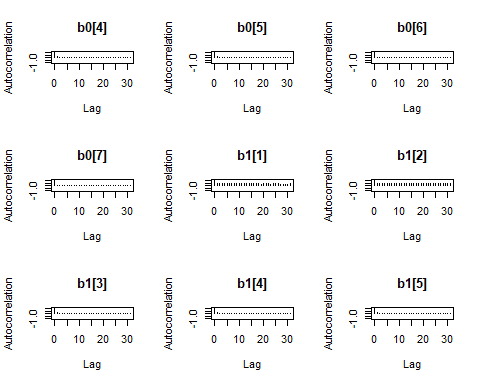


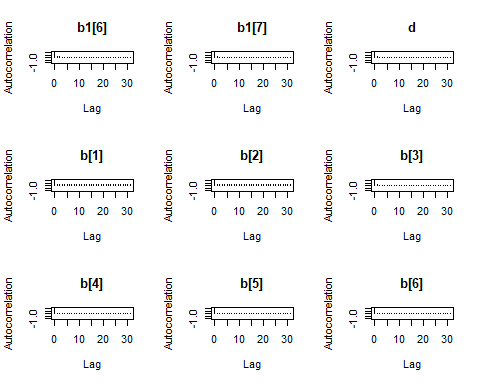


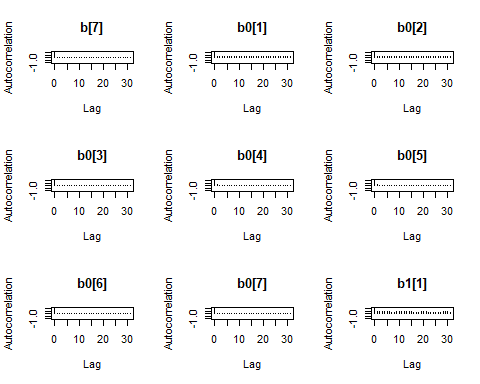


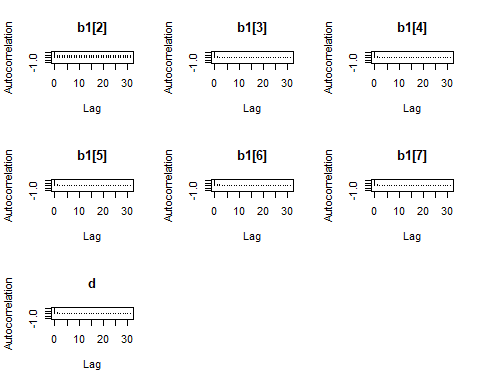












# Summary table

summary\_pooled\_pre\_op = pooled\_pre\_op |> summary()  
summary\_pooled\_post\_op = pooled\_post\_op |> summary()  
  
rnames = c("Baseline","Attention Score","Length of Intubation (d)",  
 "Single Ventricle w/ Arch Obstruction","Two Ventricles w/ Arch Obstruction",  
 "Age", "Female")  
  
pre\_mean = summary\_pooled\_pre\_op$statistics[,"Mean"]  
pre\_lb = summary\_pooled\_pre\_op$quantiles[,"2.5%"]   
pre\_ub = summary\_pooled\_pre\_op$quantiles[,"97.5%"]  
  
  
  
post\_mean = summary\_pooled\_post\_op$statistics[,"Mean"]  
post\_lb = summary\_pooled\_post\_op$quantiles[,"2.5%"]   
post\_ub = summary\_pooled\_post\_op$quantiles[,"97.5%"]   
  
  
pre\_b\_df= cbind("Mean"= pre\_mean[1:7] |> exp() |> round(2),  
 "2.5%"= pre\_lb[1:7] |> exp() |> round(2),  
 "97.5%" = pre\_ub[1:7] |> exp() |> round(2))  
  
pre\_b0\_df= cbind("Mean"= pre\_mean[8:14] |> exp() |> round(2),  
 "2.5%"= pre\_lb[8:14] |> exp() |> round(2),  
 "97.5%" = pre\_ub[8:14] |> exp() |> round(2))  
pre\_b1\_df= cbind("Mean"= pre\_mean[15:21] |> exp() |> round(2),  
 "2.5%"= pre\_lb[15:21] |> exp() |> round(2),  
 "97.5%" = pre\_ub[15:21] |> exp() |> round(2))  
  
pre\_df = cbind(pre\_b\_df,pre\_b0\_df,pre\_b1\_df)  
rownames(pre\_df) = rnames  
  
  
  
post\_b\_df= cbind("Mean"= post\_mean[1:7] |> exp() |> round(2),  
 "2.5%"= post\_lb[1:7] |> exp() |> round(2),  
 "97.5%" = post\_ub[1:7] |> exp() |> round(2))  
  
post\_b0\_df= cbind("Mean"= post\_mean[8:14] |> exp() |> round(2),  
 "2.5%"= post\_lb[8:14] |> exp() |> round(2),  
 "97.5%" = post\_ub[8:14] |> exp() |> round(2))  
post\_b1\_df= cbind("Mean "= post\_mean[15:21] |> exp() |> round(2),  
 "2.5%"= post\_lb[15:21] |> exp() |> round(2),  
 "97.5%" = post\_ub[15:21] |> exp() |> round(2))  
  
post\_df = cbind(post\_b\_df,post\_b0\_df,post\_b1\_df)  
rownames(post\_df) = rnames  
  
  
pre\_kable = pre\_df |>  
 kable(caption = "Odds Ratio of Percent Oral Feed Model Results (Pre-Operation)") |>  
 add\_header\_above(header = c("Predictor" = 1,  
 "Odds of Oral Feed \n when oral feed between 0 and 1" = 3,  
 "Odds of 0% Oral Feed" = 3,  
 "Odds of 100% Oral Feed" =3)) |>  
 add\_footnote(paste("Posterior variance is estimated to be ", pre\_mean[22] |> exp() |> round(2),  
 " (",pre\_lb[22] |> exp() |> round(2),",", pre\_ub[22]|> exp()|> round(2),")"))  
  
post\_kable = post\_df |>  
 kable(caption = "Odds Ratio of Percent Oral Feed Model Results (Post-Operation)") |>  
 add\_header\_above(header = c("Predictor" = 1,  
 "Odds of Oral Feed \n when oral feed between 0 and 1" = 3,  
 "Odds of 0% Oral Feed" = 3,  
 "Odds of 100% Oral Feed" =3)) |>  
 add\_footnote(paste("Posterior variance is estimated to be ", post\_mean[22] |> exp() |> round(2),  
 " (",post\_lb[22] |> exp() |> round(2),",", post\_ub[22]|> exp()|> round(2),")"))

## Pre-operation

pre\_kable

Odds Ratio of Percent Oral Feed Model Results (Pre-Operation)

| Predictor | Odds of Oral Feed when oral feed between 0 and 1 | | | Odds of 0% Oral Feed | | | Odds of 100% Oral Feed | | |
| --- | --- | --- | --- | --- | --- | --- | --- | --- | --- |
|  | Mean | 2.5% | 97.5% | Mean | 2.5% | 97.5% | Mean | 2.5% | 97.5% |
| Baseline | 0.96 | 0.21 | 4.47 | 0.20 | 0.02 | 2.32 | 0.02 | 0.00 | 1.11 |
| Attention Score | 1.02 | 0.71 | 1.47 | 0.74 | 0.37 | 1.35 | 1.74 | 0.63 | 5.34 |
| Length of Intubation (d) | 0.86 | 0.76 | 0.98 | 1.35 | 1.13 | 1.67 | 0.69 | 0.45 | 0.99 |
| Single Ventricle w/ Arch Obstruction | 1.57 | 0.71 | 3.36 | 6.19 | 1.90 | 22.14 | 0.76 | 0.03 | 10.62 |
| Two Ventricles w/ Arch Obstruction | 0.81 | 0.42 | 1.59 | 3.43 | 1.11 | 11.58 | 0.52 | 0.08 | 3.05 |
| Age | 0.98 | 0.92 | 1.04 | 0.97 | 0.87 | 1.07 | 1.19 | 1.02 | 1.43 |
| Female | 0.65 | 0.37 | 1.13 | 0.56 | 0.21 | 1.44 | 1.94 | 0.40 | 9.96 |
| a Posterior variance is estimated to be 3 ( 2.08 , 4.22 ) |  |  |  |  |  |  |  |  |  |

## Post-operation

post\_kable

Odds Ratio of Percent Oral Feed Model Results (Post-Operation)

| Predictor | Odds of Oral Feed when oral feed between 0 and 1 | | | Odds of 0% Oral Feed | | | Odds of 100% Oral Feed | | |
| --- | --- | --- | --- | --- | --- | --- | --- | --- | --- |
|  | Mean | 2.5% | 97.5% | Mean | 2.5% | 97.5% | Mean | 2.5% | 97.5% |
| Baseline | 0.39 | 0.04 | 3.29 | 0.03 | 0.00 | 0.67 | 0.02 | 0.00 | 37.09 |
| Attention Score | 1.20 | 0.82 | 1.75 | 1.19 | 0.71 | 2.01 | 1.33 | 0.34 | 4.09 |
| Length of Intubation (d) | 0.88 | 0.77 | 1.00 | 1.34 | 1.12 | 1.65 | 0.72 | 0.47 | 1.03 |
| Single Ventricle w/ Arch Obstruction | 1.72 | 0.77 | 3.71 | 6.20 | 1.94 | 21.52 | 0.84 | 0.02 | 13.07 |
| Two Ventricles w/ Arch Obstruction | 0.85 | 0.44 | 1.64 | 3.16 | 1.06 | 9.91 | 0.63 | 0.09 | 3.92 |
| Age | 0.98 | 0.92 | 1.05 | 0.97 | 0.87 | 1.07 | 1.21 | 1.02 | 1.45 |
| Female | 0.64 | 0.36 | 1.11 | 0.54 | 0.20 | 1.40 | 2.47 | 0.46 | 14.76 |
| a Posterior variance is estimated to be 3.07 ( 2.13 , 4.34 ) |  |  |  |  |  |  |  |  |  |