Appendix

Yunran Chen

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```
library(tibble)
library(dplyr)
library(purrr)
library(tidyr)
library(ggplot2)
library(stringr)
library(BAS)
library("R2jags")
library(knitr)

bioassay.read = read.table("http://stat.duke.edu/sites/stat.duke.edu/files/bioassay.txt",
                        header=T,stringsAsFactors = FALSE) %>% as.tibble()

bioassay=bind_cols(map_df(bioassay.read %>% select(uterus,weight,EE,ZM),~.x %>% as.numeric(.)),
                   map_df(bioassay.read %>% select(protocol,lab,group),~.x %>% as.factor(.))
                   ) %>% as.tibble()
bioassay.fac=bioassay %>% mutate(EE=as.factor(EE),ZM=as.factor(ZM))
X.fac=model.matrix(data=bioassay.fac,object =~ EE+ZM+lab+protocol+weight+EE:protocol+ZM:protocol+EE:lab
```

Containing Part I to Part IV

I use three different ways to settle down the problems. For part I(MLE), I mainly use t-test and F-test. For part II(BMA with hyper-g-n prior), I mainly use the posterior model probability, inclusive probability and the posterior pdf for each predictor. For part III(jags), I would just use visualization (Credible Interval) to illustrate. Actually, for each part, we can use boxplot to illustrate for convenience and directly. The long table and graph would be attached at the end of the document.

Part IV

The three method can get the same result for

Uterotrophic bioassay successful overall at identifying effects. Some labs fail to detect such effects. The dose response vary across labs. All three methods agree that "Huntingd","Poulenc" stands out as being different from each other. The protocols differ in their sensitivity to detect the effects. Protocol B is recommeded.

The main difference:

1.The frequentists act more strict. For "outliers", they show less tolerence. For the changing dose point, they require more.(EE3 v.s. EE1) Generally, Baysian methods take uncertainty into consideration which behave more "moderate".

Method 3 (jags) showing more tolerence for "outliers" than Method 2 (bma) than Method 1 (MLE). This is because I adopted a prior with heavy tail in Method 3. Some "outliers" considered by Method1 may be "normal" in method 2,3("Bayer"). Some "outlier" considered by method 2 may be "normal" in method 1,3.("TNO")

2.It is easy for frequentist to get the estimation of parameters. But it is complex to construct suitable test. Although it is really time-consuming to get the posterior distribution of parameters. But it would be easier to analysis based on the data. And the solution seems more natural.

Improvements:

1.I use different methods to answer the questions in three parts. So it may be hard to compare.

2. For PartIII, I should adopt a prior for selecting the variable to decrease the computation.

Part I

summary

```r
##1)We can consider `weight` and `uterus` as continuous variable. All other variables only have seperate
summary(bioassay)
```

```
##      uterus          weight             EE               ZM
##  Min.   : 10.4   Min.   : 27.7   Min.   : 0.000   Min.   :0.0000
##  1st Qu.: 32.8   1st Qu.: 48.4   1st Qu.: 0.010   1st Qu.:0.0000
##  Median : 80.0   Median : 56.1   Median : 0.300   Median :0.0000
##  Mean   :100.8   Mean   :106.7   Mean   : 1.875   Mean   :0.1009
##  3rd Qu.:124.4   3rd Qu.:200.2   3rd Qu.: 3.000   3rd Qu.:0.0000
##  Max.   :468.3   Max.   :341.0   Max.   :10.000   Max.   :1.0000
##  NA's   :4       NA's   :2
##  protocol       lab           group
##  A:1032   Hatano  : 264   2      : 246
##  B: 792   InEnvTox: 264   5      : 246
##  C: 594   Nihon   : 264   6      : 246
##  D: 263   Mitsubis: 263   7      : 246
##           Citijapa: 198   8      : 246
##           Sumitomo: 198   9      : 246
##           (Other) :1230   (Other):1205
```

```r
bioassay %>% select(EE) %>% table()
```

```
## .
##    0 0.01 0.03  0.1  0.3    1    3   10
##  486  234  239  246  246  246  738  246
```

```r
bioassay %>% select(ZM) %>% table()
```

```
## .
##    0  0.1    1
## 2189  246  246
```

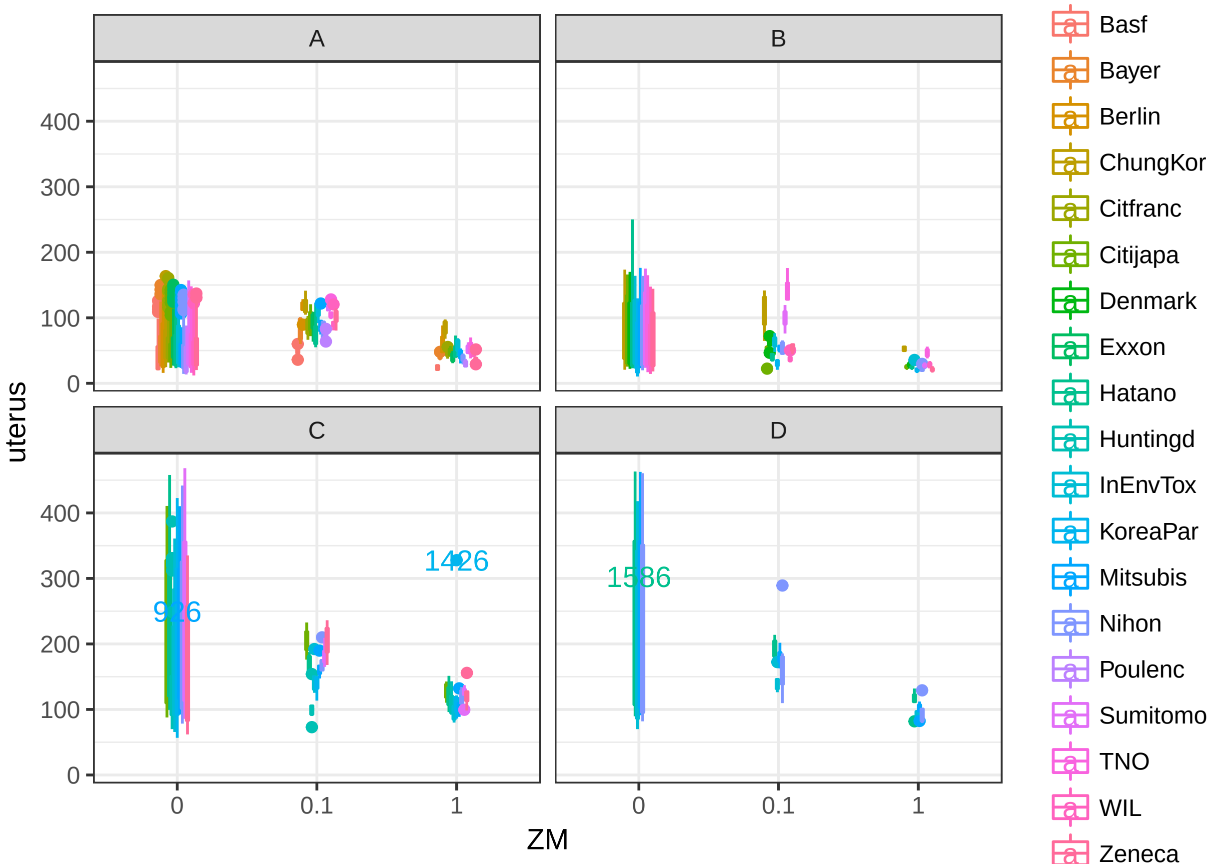
```r
##2)There are significant interaction among variables. Because each labs adopted differet treatment.
table(bioassay$EE,bioassay.fac$lab)
```

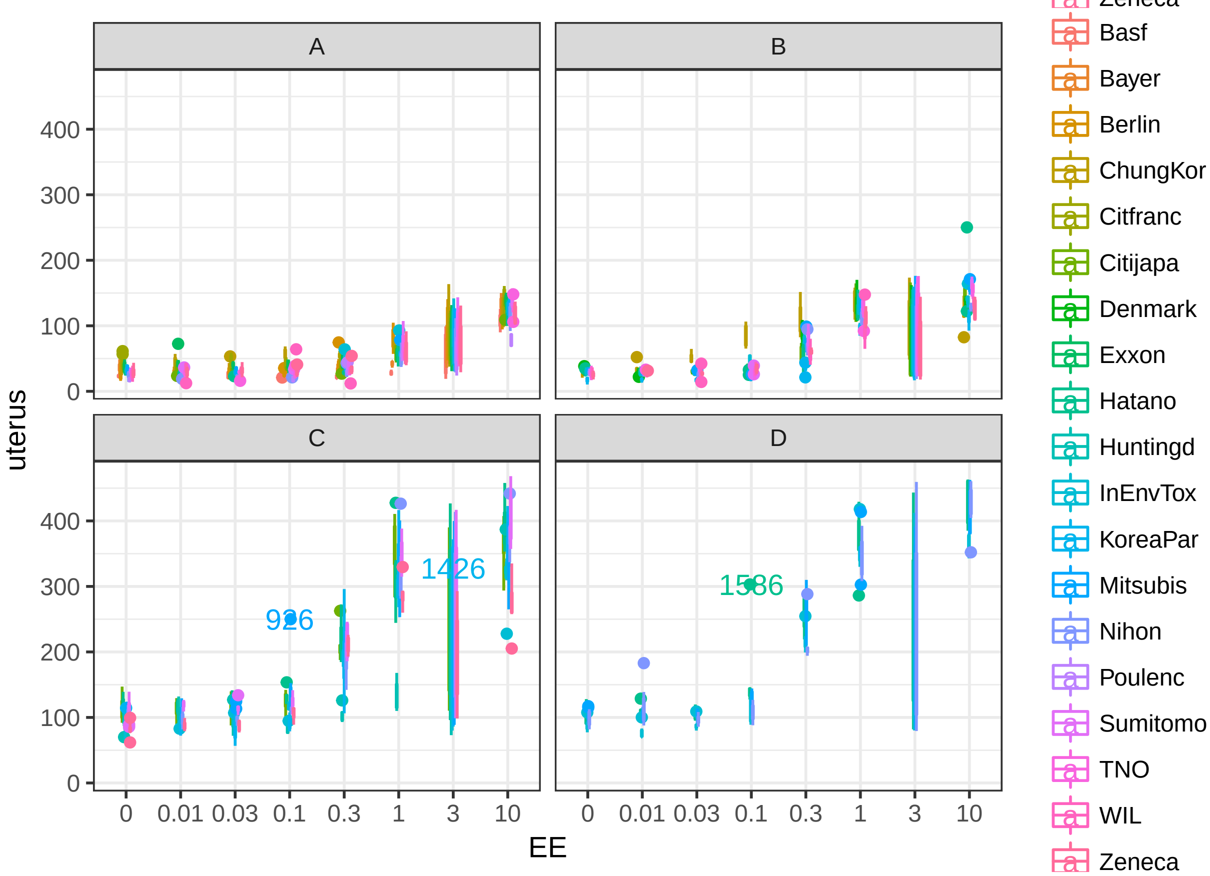
```
##
##        Basf Bayer Berlin ChungKor Citfranc Citijapa Denmark Exxon Hatano
##   0      12    12     12       24       12       36      12     6     48
##   0.01    0     0      6       12        6       18       6     6     24
##   0.03    6     0      6       12        6       18       6     6     24
##   0.1     6     6      6       12        6       18       6     6     24
##   0.3     6     6      6       12        6       18       6     6     24
##   1       6     6      6       12        6       18       6     6     24
##   3      18    18     18       36       18       54      18    18     72
##   10      6     6      6       12        6       18       6     6     24
##
##        Huntingd InEnvTox KoreaPar Mitsubis Nihon Poulenc Sumitomo TNO WIL
```

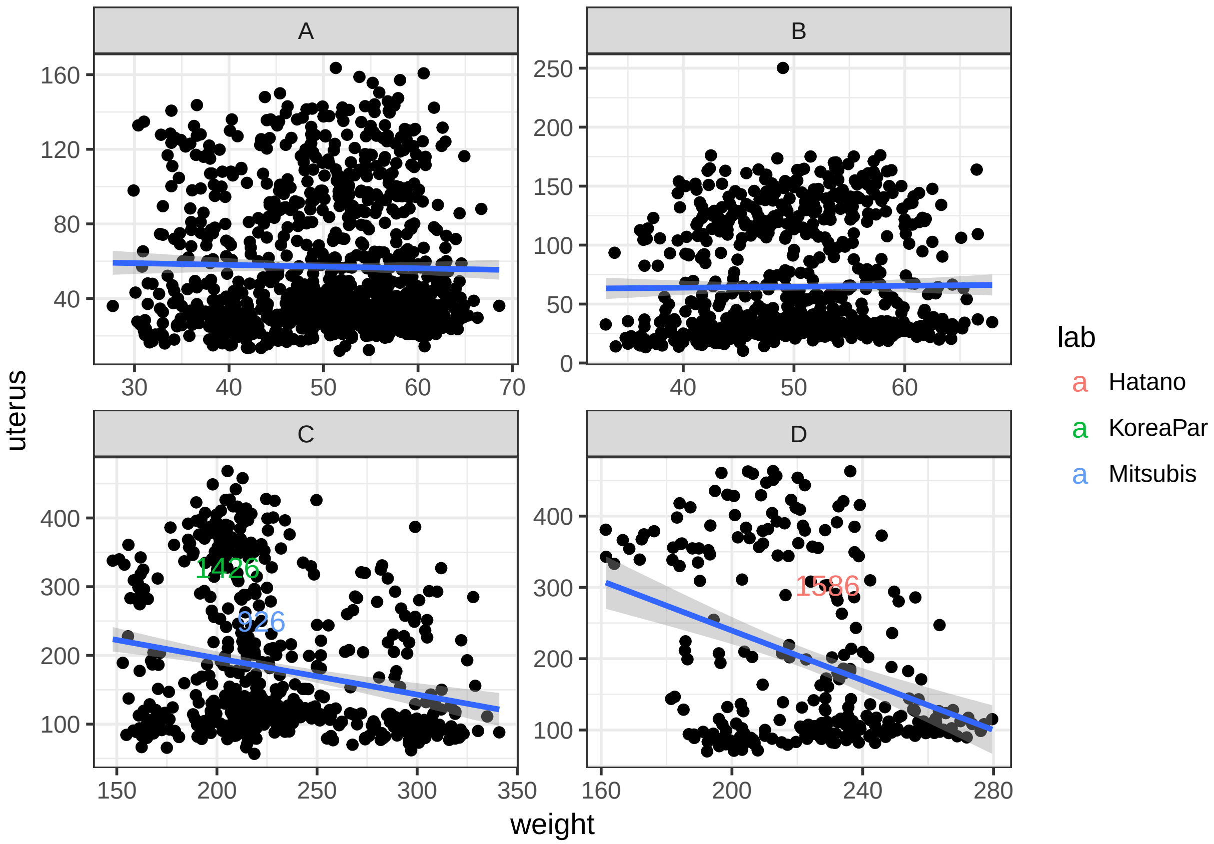
```
##   0          12        48        24        48     48       12        36   24   24
##   0.01        6        24        12        24     24        6        18   12   12
##   0.03        6        24        12        23     24        6        18   12   12
##   0.1         6        24        12        24     24        6        18   12   12
##   0.3         6        24        12        24     24        6        18   12   12
##   1           6        24        12        24     24        6        18   12   12
##   3          18        72        36        72     72       18        54   36   36
##   10          6        24        12        24     24        6        18   12   12
##
##        Zeneca
##   0        36
##   0.01     18
##   0.03     18
##   0.1      18
##   0.3      18
##   1        18
##   3        54
##   10       18
```

```
##visualization for points
#ggplot(data=bioassay,mapping = aes(y = lab,x = protocol,color=as.factor(ZM)))+
#  geom_jitter(alpha=0.5)
#ggplot(data=bioassay.fac,mapping = aes(y = lab,x = ZM,color=protocol))+
#  geom_jitter(alpha=0.5)
#ggplot(data=bioassay,mapping = aes(y = lab,x = protocol,color=as.factor(EE)))+
#  geom_jitter(alpha=0.5)
#ggplot(data=bioassay,mapping = aes(y = lab,x = protocol,color=as.factor(EE)))+
#     geom_count(alpha=0.5,position = "jitter")
```

EDA


A
B
C
D
uterus
0
100
200
300
400
926
1426
1586
0
0.1
1
ZM
Basf
Bayer
Berlin
ChungKor
Citfranc
Citijapa
Denmark
Exxon
Hatano
Huntingd
InEnvTox
KoreaPar
Mitsubis
Nihon
Poulenc
Sumitomo
TNO
WIL
Zeneca


A
B
C
D
uterus
0
100
200
300
400
926
1426
1586
0
0.01
0.03
0.1
0.3
1
3
10
EE
Basf
Bayer
Berlin
ChungKor
Citfranc
Citijapa
Denmark
Exxon
Hatano
Huntingd
InEnvTox
KoreaPar
Mitsubis
Nihon
Poulenc
Sumitomo
TNO
WIL
Zeneca



Model and Results

```
lm.full.fac=lm(data = bioassay.fac[-c(1586,926),],formula = uterus~EE+ZM+lab+protocol+weight+EE:protocol

#plot(lm.full.fac) ##use the plot to check model assumption. (detect outliers, normality, influential p

#bioassay.fac %>% select(EE,ZM) %>% table() -- there is imbalanced distribution

#summary(lm.full.fac)
#Adjusted R-squared:  0.9538

##if consider EE,ZM as numeric
#lm.full.q=lm(data = bioassay,formula = #uterus~poly(EE,2)+poly(ZM,2)+lab+protocol+weight+EE:protocol+Z
#anova(lm.full.q)
#summary(lm.full.q) #0.8286 #p=69
```

```
eff.tbl=function(lm.obj){
  if (is.matrix(lm.obj)){
    ind.mat=matrix(0,nrow=ncol(lm.obj),ncol=7)
    colnames(ind.mat)=c("EE","ZM","lab","protocol","EEdose","ZMdose","interaction")
    ind.mat=cbind(coef=lm.obj%>%colnames(.),ind.mat)
  }else{
    ind.mat=matrix(0,nrow=nrow(summary(lm.obj)$coefficients),ncol=7)
    colnames(ind.mat)=c("EE","ZM","lab","protocol","EEdose","ZMdose","interaction")
    ind.mat=cbind(coef=summary(lm.obj)$coefficients%>%rownames(.),ind.mat)
  }
```

```r
  ind.mat[str_detect(ind.mat[,1],"EE"),"EE"]=1
  ind.mat[str_detect(ind.mat[,1],"ZM"),"ZM"]=1
  ind.mat[str_detect(ind.mat[,1],"EE.*protocol"),"interaction"]=1
  ind.mat[str_detect(ind.mat[,1],"ZM.*protocol"),"interaction"]=1
  ind.mat[str_detect(ind.mat[,1],"EE.*lab"),"interaction"]=1
  ind.mat[str_detect(ind.mat[,1],"ZM.*lab"),"interaction"]=1
  for (dose in c(bioassay.fac$EE %>% levels())){
     ind.mat[str_detect(ind.mat[,1],paste0("EE",dose)),"EEdose"]=dose
  }
  for (dose in c(bioassay.fac$ZM %>% levels())){
     ind.mat[str_detect(ind.mat[,1],paste0("ZM",dose)),"ZMdose"]=dose
  }
  for (lab in c(bioassay.fac$lab %>% levels())){
     ind.mat[str_detect(ind.mat[,1],paste0("lab",lab)),"lab"]=lab
  }
  for (protocol in c(bioassay.fac$protocol %>% levels())){
     ind.mat[str_detect(ind.mat[,1],paste0("protocol",protocol)),"protocol"]=protocol
  }
  ind.tbl=ind.mat%>% as.tibble()
  return(ind.tbl)
}

t.test=function(lm.obj,str.ee,str.lab,str.ori){
ind.tbl=eff.tbl(lm.obj)
cov.coef=vcov(lm.obj)
p=nrow(ind.tbl)
i.levels=bioassay.fac %>% pull(str.ori) %>% levels() #original colnames in bioassay.fac
i.n=i.levels %>% length(.)
lambda=matrix(nrow=i.n,ncol=nrow(ind.tbl))
lab.ee=t.value=p.value=denominator=nominator=numeric(i.n)

for (i in 1:i.n){
  lambda[i,]=((ind.tbl[str.lab]==i.levels[i])&(ind.tbl[str.ee]=="1"))|((ind.tbl[str.ee]=="1")&(ind.tbl[
  lab.ee[i]=summary(lm.obj)$coefficients[lambda[i,],"Estimate"] %>% sum()
  denominator[i]=(cov.coef[lambda[i,],lambda[i,]]) %>% sum() %>% sqrt()
  nominator[i]=lab.ee[i] %>% abs()
  t.value[i]=(nominator[i])/(denominator[i])
  p.value[i]=pt(q = t.value[i],df = summary(lm.obj)$df[2],lower.tail = FALSE)
}

res=list(t.test=tibble(i.levels,p.value,estimator=lab.ee),value=tibble(i.levels,variance=denominator,es
return(res)
}
```

a.1

uterotrophic bioassay successful overal at identifying effects of EE and ZM. F-test for EE,ZM are significant. For the significant coefficients, all EE are positive, ZM are negative.

```r
#0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1



anova(lm.full.fac)
```

```
## Analysis of Variance Table
```

```
##
## Response: uterus
##                Df   Sum Sq Mean Sq   F value    Pr(>F)
## EE              7 6493181  927597 2437.9005 < 2.2e-16 ***
## ZM              2 2091034 1045517 2747.8158 < 2.2e-16 ***
## lab            18 2399373  133298  350.3335 < 2.2e-16 ***
## protocol        3 7374975 2458325 6460.9417 < 2.2e-16 ***
## weight          1  116191  116191  305.3720 < 2.2e-16 ***
## EE:protocol    21 2228787  106133  278.9368 < 2.2e-16 ***
## ZM:protocol     6  964465  160744  422.4660 < 2.2e-16 ***
## EE:lab        123  307285    2498    6.5659 < 2.2e-16 ***
## ZM:lab         36  105732    2937    7.7190 < 2.2e-16 ***
## Residuals    2457  934864     380
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```
coefs=rownames(summary(lm.full.fac)$coefficients)

res=summary(lm.full.fac)$coefficients %>%
  cbind(coef=coefs,.) %>%
  as.tibble() #get the coefficients matrix

colnames(res)=c("coef","estimate","std_error","t_value","p_value")

res %>% filter(as.numeric(p_value)<0.05) %>% slice(1:10)
```

```
## # A tibble: 10 x 5
##           coef          estimate          std_error          t_value
##          <chr>             <chr>              <chr>            <chr>
##  1 (Intercept)  17.5174725602682   6.0832664338643  2.87961619809253
##  2         EE3  69.3169543543242  9.89986651384673  7.00180696955581
##  3        EE10  85.6474733135621  9.90017366264282  8.65110817568213
##  4       ZM0.1 -44.2697077991087  11.2619188955346  -3.9309204949666
##  5         ZM1 -68.4662160221504   11.261889153971 -6.07946101103372
##  6 labChungKor  17.0236675479605  7.21540009027292  2.35935184951284
##  7 labCitfranc  19.9168751325116   8.1423844433654  2.44607403040768
##  8   protocolC  56.9794121460095  5.40377846249726  10.5443649367664
##  9   protocolD  47.3180475238927  6.15630309938495  7.68611401355793
## 10      weight 0.101351933549335 0.0269475706902319   3.7610786780893
## # ... with 1 more variables: p_value <chr>
```

a.2 do some labs fail to detect such effects

There are some labs fail to detect such effects, as follows:"Huntingd""Bayer""ChungKor""TNO""Zeneca". Or just pick out the labs with significant p value at "EE:lab_i" but opposite t value. ("Huntingd""Bayer""Zeneca")

```
a.2.ee=t.test(lm.full.fac,"EE","lab","lab")$t.test
a.2.ee
```

```
## # A tibble: 19 x 3
##    i.levels      p.value estimator
##       <chr>        <dbl>     <dbl>
##  1     Basf 2.937598e-05  164.2023
##  2    Bayer 1.297653e-05  148.7924
##  3   Berlin 8.081249e-10  270.6481
##  4 ChungKor 9.973079e-14  244.7607
##  5 Citfranc 3.911202e-05  176.8314
```

```
##   6 Citijapa 2.504636e-12  197.9101
##   7  Denmark 1.725524e-06  227.4437
##   8    Exxon 2.001695e-04  211.2410
##   9   Hatano 2.850135e-17  221.4205
## 10 Huntingd 1.178475e-05 -211.9685
## 11 InEnvTox 7.907738e-15  202.7865
## 12 KoreaPar 2.228704e-06  167.7607
## 13 Mitsubis 4.957299e-15  204.5481
## 14    Nihon 1.228075e-14  201.2653
## 15  Poulenc 1.477856e-04  161.9877
## 16 Sumitomo 3.479523e-21  269.7772
## 17      TNO 1.605547e-11  224.8464
## 18      WIL 1.125449e-07  171.9591
## 19   Zeneca 1.077435e-08  160.2037
```

```
a.2.ee %>% filter(((p.value<0.05)&(estimator<0))|(p.value>0.05))# %>% pull(i.levels)
```

```
## # A tibble: 1 x 3
##   i.levels      p.value estimator
##      <chr>        <dbl>     <dbl>
## 1 Huntingd 1.178475e-05 -211.9685
```

```
a.2.zm=t.test(lm.full.fac,"ZM","lab","lab")$t.test
a.2.zm
```

```
## # A tibble: 19 x 3
##    i.levels      p.value  estimator
##       <chr>        <dbl>      <dbl>
##   1     Basf 4.220254e-09 -112.73592
##   2    Bayer 6.804663e-02  -29.08390
##   3   Berlin 4.049193e-06  -87.23322
##   4 ChungKor 6.389885e-02  -22.01560
##   5 Citfranc 1.763902e-04  -69.79584
##   6 Citijapa 2.304572e-09  -73.19550
##   7  Denmark 6.965919e-05  -81.37726
##   8    Exxon 6.126571e-07  -94.87320
##   9   Hatano 1.954502e-19 -103.41602
## 10 Huntingd 3.707009e-04   73.75550
## 11 InEnvTox 2.959297e-12  -79.17206
## 12 KoreaPar 1.941093e-04  -56.54709
## 13 Mitsubis 3.288518e-20 -105.47859
## 14    Nihon 7.278050e-20 -104.46423
## 15  Poulenc 4.017327e-02  -34.12421
## 16 Sumitomo 4.094885e-13  -89.55271
## 17      TNO 1.913899e-01  -12.61549
## 18      WIL 9.920550e-04  -44.74128
## 19   Zeneca 2.106639e-01   10.00848
```

```
a.2.zm %>% filter(((p.value<0.05)&(estimator>0))|(p.value>0.05))#%>% pull(i.levels)
```

```
## # A tibble: 5 x 3
##   i.levels      p.value estimator
##      <chr>        <dbl>     <dbl>
## 1    Bayer 0.0680466340 -29.08390
## 2 ChungKor 0.0638988547 -22.01560
## 3 Huntingd 0.0003707009  73.75550
```

```
## 4      TNO 0.1913899445 -12.61549
## 5   Zeneca 0.2106639006  10.00848
```

```r
res %>% filter(str_detect(res$coef,"EE.*lab")) %>%
   filter(p_value<0.05,t_value<0)
```

```
## # A tibble: 3 x 5
##                coef           estimate        std_error            t_value
##               <chr>              <chr>            <chr>              <chr>
## 1      EE3:labBayer -28.2023694053915 13.8970614794358 -2.02937645826235
## 2 EE0.1:labHuntingd  -30.049402348541 14.7449822505579  -2.0379408966331
## 3     EE3:labZeneca -23.5618392029676 11.6930187049281 -2.01503476540555
## # ... with 1 more variables: p_value <chr>
```

```r
res %>% filter(str_detect(res$coef,"ZM.*lab")) %>%
   filter(p_value<0.05,t_value<0)
```

```
## # A tibble: 0 x 5
## # ... with 5 variables: coef <chr>, estimate <chr>, std_error <chr>,
## #   t_value <chr>, p_value <chr>
```

a.3 the change dose for EE? vary across labs?

From the output of summary(See the end of part I). The change dose for EE is EE3. Dose larger than this is significant, less than this is not significant. The value varies across labs. Because for different labs, the dose changing points is different. For example, SUmitomo. EE0.3 may be the changing dose point. For Huntingd, EE0.1 may be the changing dose point.

b. does the dose reponse vary across labs? are there certain labs stands out as being different? From the output of summary. There exist several significant interaction cofficients, meaning dose reponse vary across labs. The labs Berlin and Sumitomo stands out as being different.(with pvalue$<$0.001 for EE:labs). The labs Bayer,Poulenc,Zeneca stands out as being different.(with pvalue$<$0.005 for ZM:labs)

```r
res %>% filter(str_detect(res$coef,"EE.*lab")) %>%
  filter(p_value<0.001)
```

```
## # A tibble: 2 x 5
##              coef          estimate        std_error           t_value
##             <chr>             <chr>            <chr>             <chr>
## 1   EE1:labBerlin 49.4837223304949 13.8970357690877 3.56073936576932
## 2 EE1:labSumitomo 42.0319864090083 11.6927892205068 3.59469290144157
## # ... with 1 more variables: p_value <chr>
```

```r
res %>% filter(str_detect(res$coef,"ZM.*lab")) %>%
  filter(p_value<0.005)
```

```
## # A tibble: 3 x 5
##                coef          estimate        std_error           t_value
##               <chr>             <chr>            <chr>             <chr>
## 1   ZM0.1:labBayer 50.8727460593738 15.9269030374418 3.19413924601535
## 2 ZM0.1:labPoulenc 49.0113737477311 15.9267123836315 3.07730638735599
## 3    ZM1:labZeneca 44.7841287734452  13.358278781101 3.35253736707494
## # ... with 1 more variables: p_value <chr>
```

c.Do the protocols differ in sensitivity to detect? Which one recommend?

From the result from anova. The protocols differ. And the variance of protocol C,D is super large. Protocol A and B would be recommended.

```r
anova(lm.full.fac)["EE:protocol", ]
```

```
## Analysis of Variance Table
##
## Response: uterus
##             Df  Sum Sq Mean Sq F value    Pr(>F)
## EE:protocol 21 2228787  106133  278.94 < 2.2e-16 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```r
anova(lm.full.fac)["ZM:protocol", ]
```

```
## Analysis of Variance Table
##
## Response: uterus
##             Df Sum Sq Mean Sq F value    Pr(>F)
## ZM:protocol  6 964465  160744  422.47 < 2.2e-16 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```r
res %>% filter(str_detect(res$coef,"^protocol"))
```

```
## # A tibble: 3 x 5
##        coef          estimate        std_error            t_value
##       <chr>             <chr>            <chr>              <chr>
## 1 protocolB -2.16077131127482  2.4955877941489 -0.865836624277823
## 2 protocolC  56.9794121460095 5.40377846249726   10.5443649367664
## 3 protocolD  47.3180475238927 6.15630309938495   7.68611401355793
## # ... with 1 more variables: p_value <chr>
```

```r
res %>% filter(str_detect(res$coef,"EE.*protocol"))
```

```
## # A tibble: 21 x 5
##                coef           estimate        std_error             t_value
##               <chr>              <chr>            <chr>               <chr>
##  1 EE0.01:protocolB   1.19108136858824 4.31635717989136   0.275945969934356
##  2 EE0.03:protocolB     3.541307048283 4.31635426940738   0.820439386401249
##  3  EE0.1:protocolB   7.45488173303661 4.31641616363892    1.72709985562463
##  4  EE0.3:protocolB   35.0983219034887 4.31635334591939    8.13147559772188
##  5    EE1:protocolB   58.2145220892542 4.31639052433566    13.4868524432724
##  6    EE3:protocolB   34.4029534792872 4.31637929244136    7.97032678280428
##  7   EE10:protocolB   17.5749522283604 4.32796829285087    4.06078580968154
##  8 EE0.01:protocolC -0.323072655511128  4.9003836743018 -0.0659280327779425
##  9 EE0.03:protocolC   2.72255040119417 4.90038109624472   0.555579320816605
## 10  EE0.1:protocolC   14.0429742703248 4.92125955112887    2.85353254068942
## # ... with 11 more rows, and 1 more variables: p_value <chr>
```

```r
res %>% filter(str_detect(res$coef,"ZM.*protocol"))
```

```
## # A tibble: 6 x 5
##              coef          estimate        std_error           t_value
##             <chr>             <chr>            <chr>             <chr>
## 1 ZM0.1:protocolB  -61.037963794127 4.98061458836321  -12.255106816885
## 2   ZM1:protocolB -53.8667551088683 4.98057530455602 -10.8153680679405
## 3 ZM0.1:protocolC -158.414580874021 5.67997807489639 -27.8899986558329
## 4   ZM1:protocolC -171.324039321919 5.66139549748667  -30.261803719238
## 5 ZM0.1:protocolD -183.644764786495 7.20742931513241 -25.4799258871567
```

```
## 6   ZM1:protocolD -217.250601221133 7.20370581533531 -30.1581723060718
## # ... with 1 more variables: p_value <chr>
```

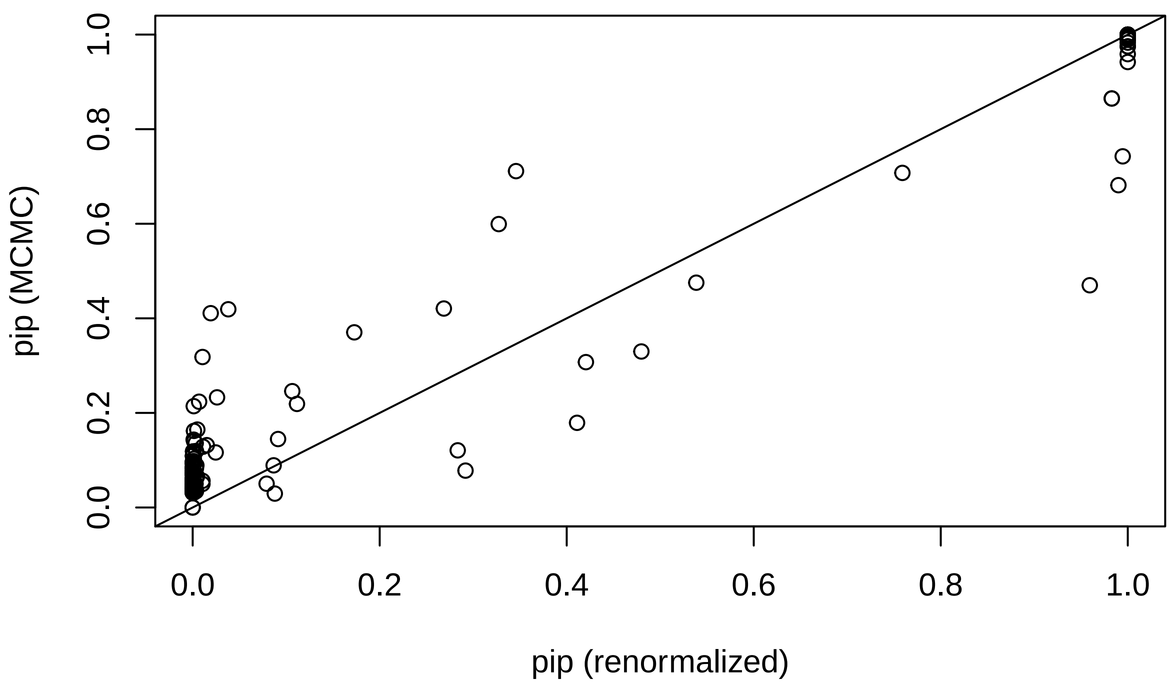
Part II

With the same model, using Bayesian Average Model to estimate the parameter with hyper-g-n prior(mixture prior). To answer the questions, I mainly concentrate on inclusion probability, posterior model probability and the shape of posterior distribution for β_i (or confidence interval).

```
n=nrow(bioassay.fac)

bas.fac.2=bas.lm(formula =uterus~EE+ZM+lab+protocol+weight+EE:protocol+ZM:protocol+EE:lab+ZM:lab,
                 data=bioassay.fac,
                 prior="hyper-g-n",
                 alpha=n,
                 #n.models=20000,
                 method = "MCMC",
                 thin=10,
                 #initprobs = "eplogp",
                 MCMC.iterations = 500000)
```

```
## Warning in bas.lm(formula = uterus ~ EE + ZM + lab + protocol + weight + :
## dropping 4 rows due to missing data
```

```
##diagonose
diagnostics(bas.fac.2,"pip")
```




```
##More iteration would be better
```

a.1 Similar to Part I, we want to test whether the coefficients before `EE` all equal to 0. Here I use sum posterior model probabiliters over all models that include `EE`, is 0.99982. Similar for ZM,is 0.99982. For the coefficients `EE` with high inclusion probability, all of them are larger than 0 with high probability. Simlar for `ZM`(negative). So the method successful overall at identifying effects.

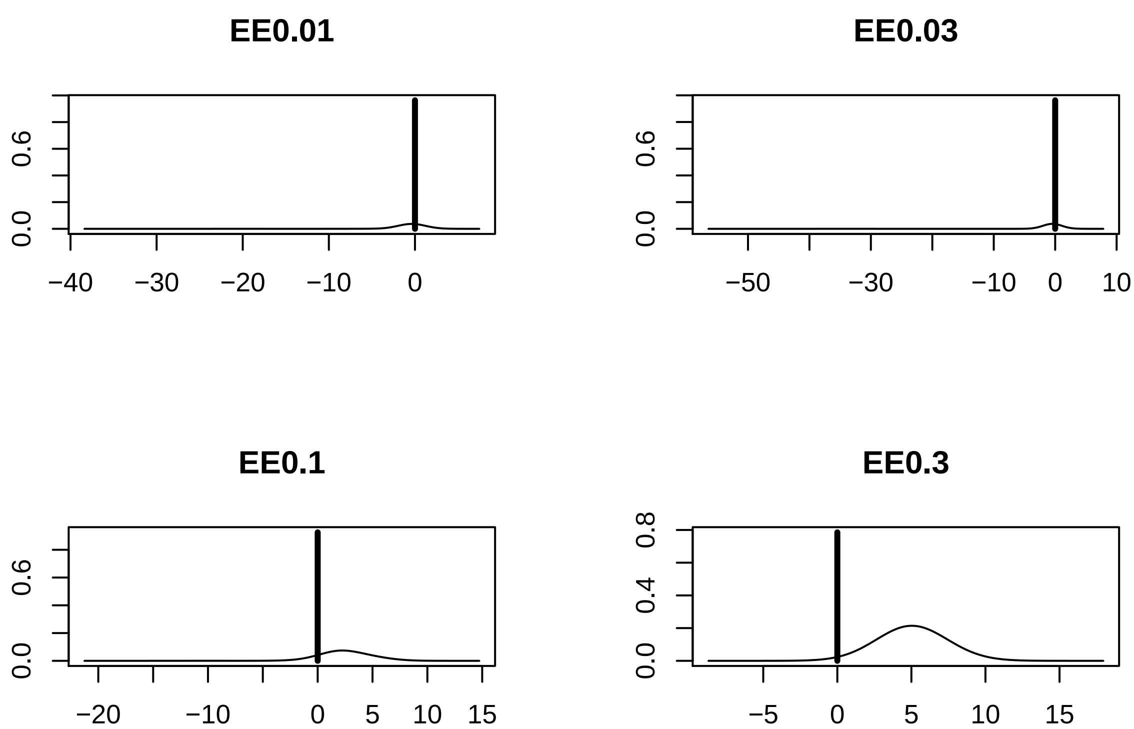
```r
a_1=function(str_ee){
  which.mat=list2matrix.which(bas.fac.2,)
  ind.tbl.bas=eff.tbl(X.fac) #part II model assumption is the same to part I
  head(ind.tbl.bas)
  ind.var=((ind.tbl.bas[str_ee]=="1")&(ind.tbl.bas$interaction=="0"))
  n.ind=sum(ind.var)
  poll.in=(which.mat[,ind.var] %*% rep(1,n.ind))>0
  res=list(prob=sum(poll.in*bas.fac.2$postprobs),ind=ind.var)
  return(res)
}



a_1("EE")$prob
```

```
## [1] 0.99992
```

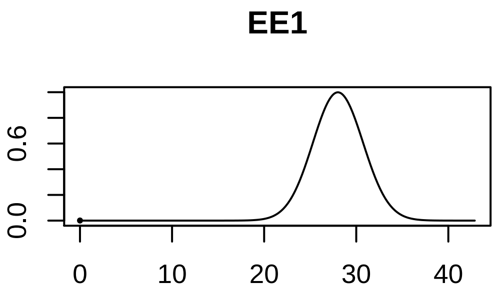
```r
a_1("ZM")$prob
```

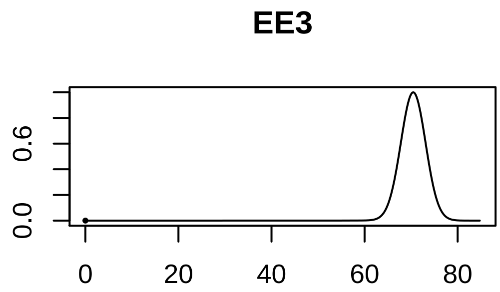
```
## [1] 0.9994198
```

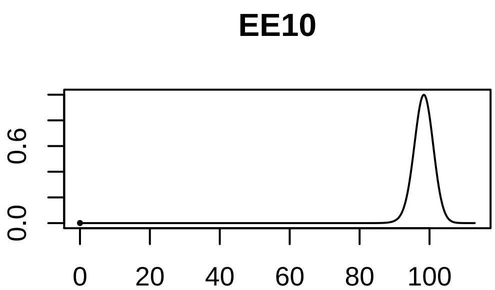
```r
#image(bas.fac.2)--to much predictor, cannot visualization
#plot(bas.fac.2)

par(mfrow=c(2,2))
ind.ee=which(a_1("EE")$ind)
coef(bas.fac.2) %>% plot(.,ask=F,subset=ind.ee)
```

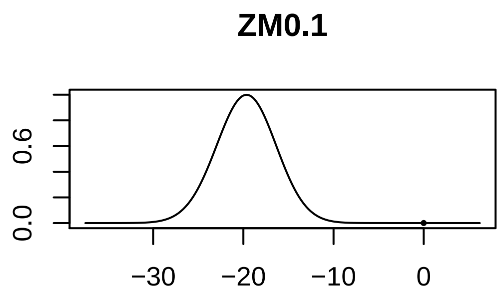


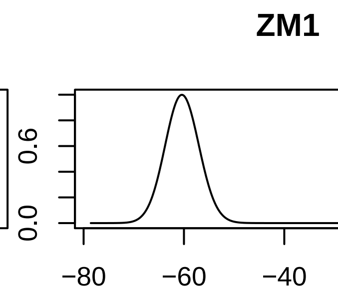

```r
ind.zm=which(a_1("ZM")$ind)
coef(bas.fac.2) %>% plot(.,ask=F,subset=ind.zm)
```











a.2 Concerntrate on `EE:lab_i`, `ZM:lab_i`. Pick out the labs with high inclusive probability but opposite location compared to others. ("Huntingd""Zeneca""TNO""KoreaPar""ChungKor""Poulenc""EnvTox") Simply, the rule is for `EE`, if `EE:lab_i` is at the left side of the verticle black line and the verticle black line is short, we may consider the lab fail to detect. Similar for `ZM`.

a.3 Concerntrate on `EE`,`ZM`, see which dose level the inclusive probability significantly change. EE1. And concerntrate on `EE:lab_i`,`ZM:lab_i` to see which dose level the inclusive probability significantly change. They vary.

b. The dose response vary across labs, because there exist `EE:lab_i`,`ZM:lab_i` with high inclusive probability. There are certain labs ("Huntingd""Zeneca""TNO""KoreaPar""ChungKor""Poulenc""EnvTox") stand out as being different.

c.Protocols differ in the sensitivity to detect effects. Protocol B would be recommended because the length of CI for `protocolB:EE` and `protocolB:ZM` are small compared to others.

```
coefs=rownames(confint(coef(bas.fac.2)))
ci.length=apply(confint(coef(bas.fac.2)),1,function(x) as.numeric(x[2])-as.numeric(x[1]))

bas.coef=confint(coef(bas.fac.2)) %>%
  cbind(coef=coefs,.) %>%
  as.tibble() %>% #get the coefficients matrix
  mutate(ci.length=ci.length)

bas.coef %>% filter(str_detect(coef,"EE.*protocol")) %>% arrange(sort(ci.length)) %>% slice(1:10)
```

```
## # A tibble: 10 x 5
##                coef          `2.5%`          `97.5%`                 beta
##               <chr>           <chr>            <chr>                <chr>
##  1 EE0.01:protocolB               0                0  -0.0484834439277467
##  2 EE0.03:protocolB               0                0 -0.00374225574012542
##  3  EE0.1:protocolB               0 5.80940650865182    0.638071968708935
##  4  EE0.3:protocolB 27.3243696086945 40.8301050511793     34.3450027375794
```

```
## 5    EE1:protocolB 55.0606758083594 68.7850425910737     61.6850608926798
## 6    EE3:protocolB 30.4309555314408 43.5972876086278     36.9792777440934
## 7   EE10:protocolB 8.95360301721218 22.3585365222887     15.4922689713518
## 8 EE0.01:protocolC                0                0  -0.0418508956721509
## 9 EE0.03:protocolC                0                0  -0.0372337439129658
## 10  EE0.1:protocolC 6.40160304041151 22.1403552467264      13.981821135302
## # ... with 1 more variables: ci.length <dbl>
```

```
bas.coef %>% filter(str_detect(coef,"ZM.*protocol")) %>% arrange(sort(ci.length)) %>% slice(1:10)
```

```
## # A tibble: 6 x 5
##              coef             `2.5%`            `97.5%`               beta
##             <chr>              <chr>              <chr>              <chr>
## 1 ZM0.1:protocolB -73.2979747319827 -55.3105391323187   -64.11552608077
## 2   ZM1:protocolB -64.5950185791796 -46.3977700698058  -55.271252867729
## 3 ZM0.1:protocolC -172.933144141374 -152.147357191573 -162.502695556552
## 4   ZM1:protocolC -185.383177143198 -164.195990548043 -174.710735952554
## 5 ZM0.1:protocolD  -203.72229480075  -177.08376868335 -190.406566544859
## 6   ZM1:protocolD -234.651923967539 -208.034474117185 -221.890183747974
## # ... with 1 more variables: ci.length <dbl>
```

Part III

Because I set iteration=30000, and include many predictors. So the jags would be slow. So I load the data I got. An improvement for this is to adjust the distribution for σ_L^2/λ_l behave like double exponential distribution. The hyperparameter a here is important for adjusting whether we want our model more robust. I chose a=2 for I want to let my model get less sensitive to labs "outliers". I use credible interval to answer these questions.

Prepare the data

```
# Create a data list with inputs for JAGS

X.fac=model.matrix(data=bioassay,object =~EE+ZM+lab+protocol+weight+EE:protocol+ZM:protocol+EE:lab+ZM:la
n=nrow(bioassay)
## scale X such that X^TX has ones on the diagonal;
## scale divides by the standard deviation so we need
## to divide by the sqrt(n-1)
scaled.X = scale(X.fac)/sqrt(n-1)
# are diagonal elements 1?
# check
#t(scaled.X) %*% scaled.X
data = list(Y = bioassay$uterus,
            X=scaled.X,
            p=ncol(scaled.X),
            n = n)

#extract the scales from the scaled object and fix--add to attr
data$scales = attr(scaled.X, "scaled:scale")*sqrt(n-1) # fix scale
data$Xbar = attr(scaled.X, "scaled:center")
```

Jags code

```
##For jags: need to use <-; use precision instead of sigma_sq
rr.model = function() {
  a <- 2
```

```
  shape<-a/2

  for (i in 1:n) {
    mu[i] <- alpha0 + inprod(X[i,], alpha)
    prec[i] <- phi
    Y[i] ~ dnorm(mu[i], prec[i])
  }
  phi ~ dgamma(1.0E-6, 1.0E-6)  ##jags do not allow improper prior
  alpha0 ~ dnorm(0, 1.0E-6)

  for (j in 1:p) {
    phi.l[j] <- pow(i.phi.l[j], -2)
    prec.beta[j] <- lambda.l[j]*phi*phi.l[j]
    alpha[j] ~ dnorm(0, prec.beta[j])
    # transform back to original coefficients
    beta[j] <- alpha[j]/scales[j]
    lambda.l[j] ~ dgamma(shape, shape)
    i.phi.l[j] ~ dt(0,1,1)%_%T(0,)

  }

  # transform intercept to usual parameterization
  beta0 <- alpha0 - inprod(beta[1:p], Xbar)

  sigma <- pow(phi, -.5)
}

# parameters to monitor
parameters = c("beta0", "beta", "sigma","lambda.l", "phi.l")

# run jags from R  (see Resources to install)
stack.sim.hfac = jags(data,
                 inits=NULL,
                 par=parameters,
                 model=rr.model,
                 n.iter=30000)
saveRDS(stack.sim.hfac, "stack.sim.rds")
stack.sim=readRDS("stack.sim.rds")
```

Load the data I stored.

```
stack.sim=readRDS("stack.sim.rds")
```

Analysis on simulation result.

```
# create an MCMC object with the results for the MCMC draws
stack.mcmc = as.mcmc(stack.sim$BUGSoutput$sims.matrix)  #get the simulation points

quan=function(x){
  qu=quantile(x,c(.025, .975))
  avg=mean(x)
  res=c(qu,avg=avg)
  return(res)}
ci.all=apply(stack.mcmc,2,quan) %>% t(.)
mcmc.df=stack.mcmc %>% as.tibble()
```

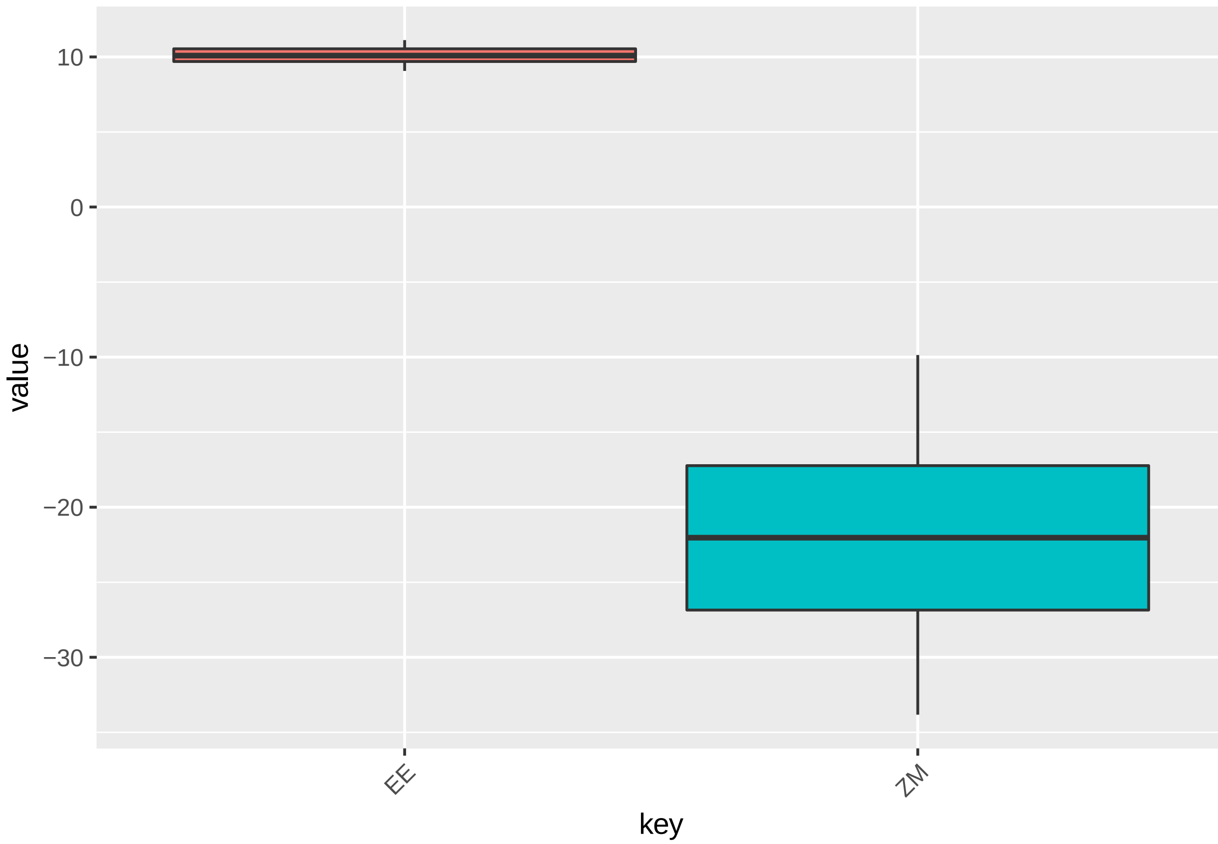
a.1 The method is successful overall at identifying effects because the credible interval for `EE` is above 0, the credible interval for `ZM` is below 0.

```
##code from https://stackoverflow.com/questions/21310609/ggplot2-box-whisker-plot-show-95-confidence-in

X.fac.jags=model.matrix(data=bioassay,object =~EE+ZM+lab+protocol+weight+EE:protocol+ZM:protocol+EE:lab

quantiles_95 <- function(x) {
  r <- quantile(x, probs=c(0.05, 0.25, 0.5, 0.75, 0.95))
  names(r) <- c("ymin", "lower", "middle", "upper", "ymax")
  r
}

mcmc.df.beta=mcmc.df %>% select(`beta[1]`:`beta[2]`)
names(mcmc.df.beta)=c("EE","ZM")
mcmc.df.beta = mcmc.df.beta %>% gather(.)
ggplot(data = mcmc.df.beta,mapping = aes(x = key,y = value,fill=as.factor(key)))+
  theme(axis.text.x = element_text(angle = 45, hjust = 1))+ guides(fill=FALSE)+stat_summary(fun.data = q
```

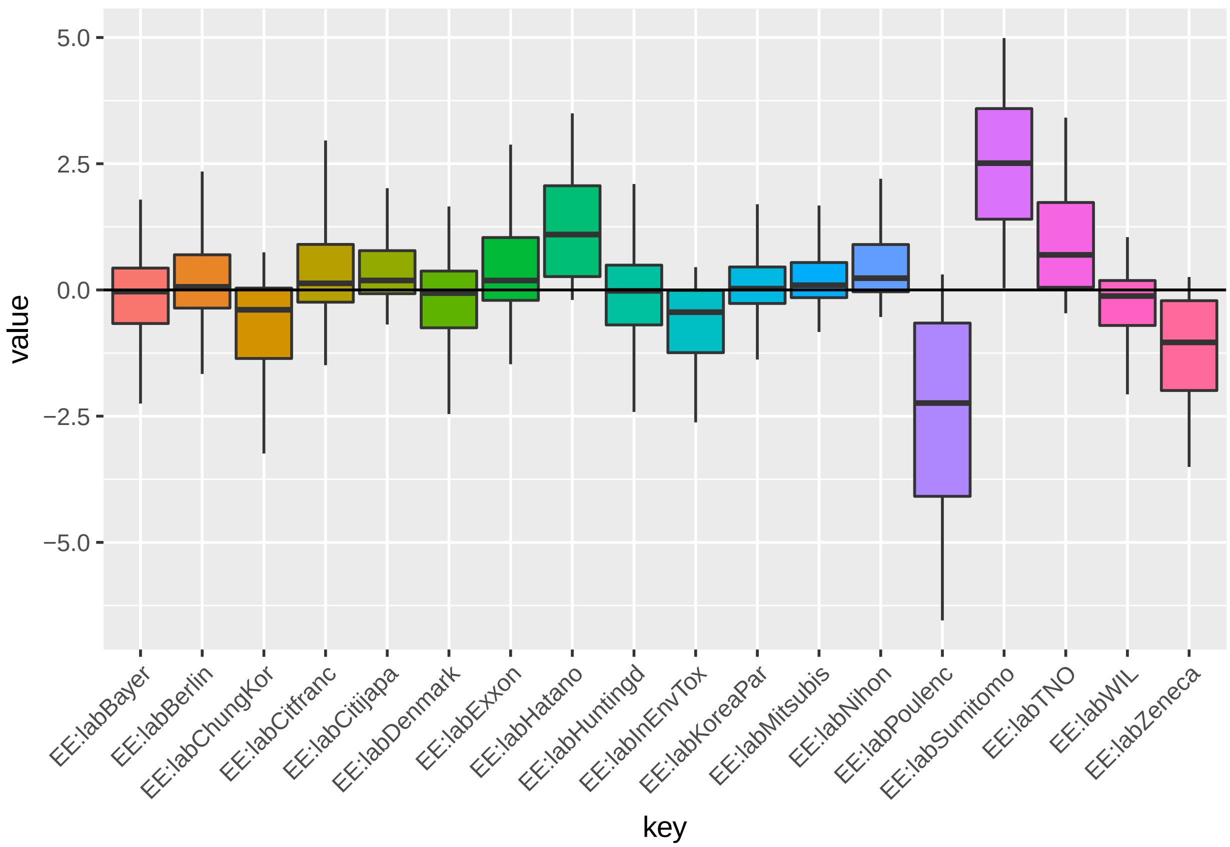


a.2 There are labs Poulenc,ChungKor,EnvTox,Zeneca,KoreaPar,Hungtingd fail to detect such effects.(below the 0)

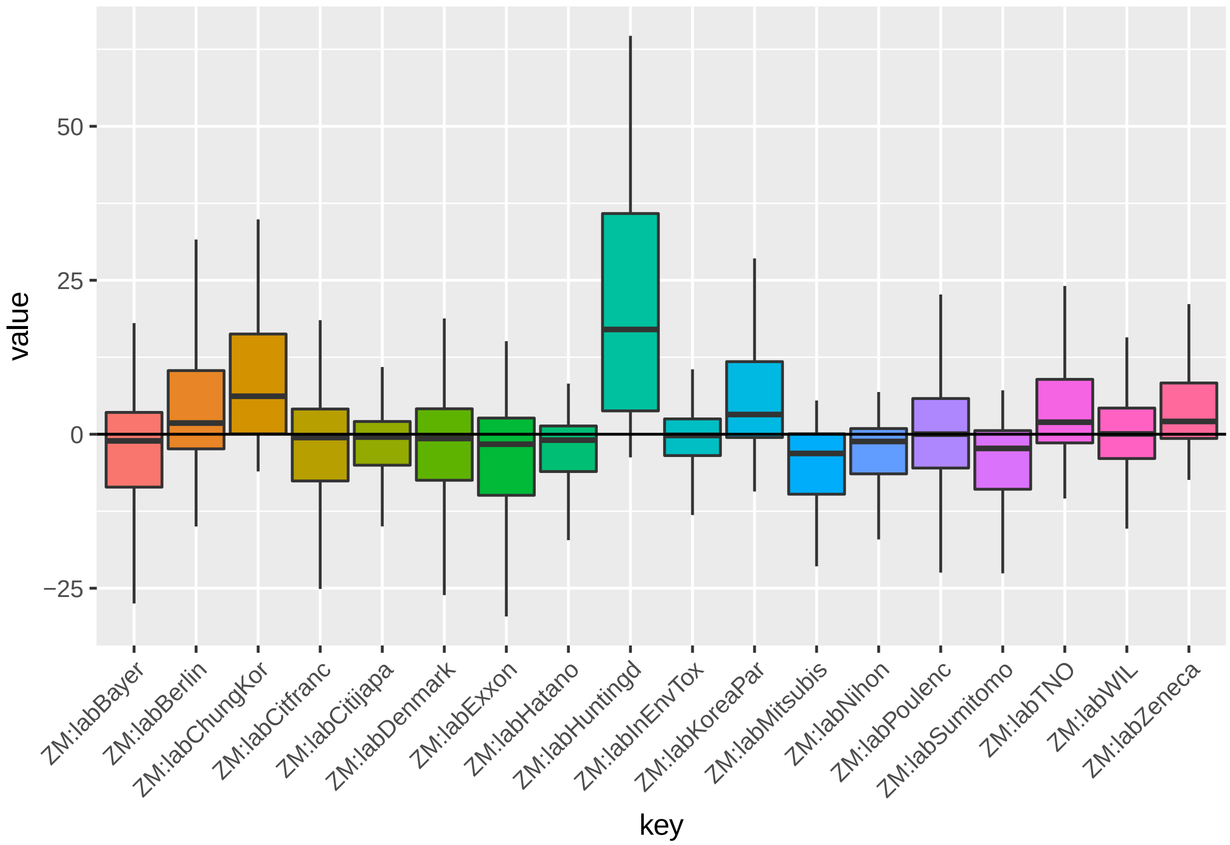
```
realname=X.fac.jags %>% colnames()
jagsname=mcmc.df %>% names()

temp.ee.lab=jagsname[str_detect(realname,"EE.*lab")]
real.tag=realname[str_detect(realname,"EE.*lab")]
mcmc.df.beta=mcmc.df %>% select(temp.ee.lab[1:18])
```

```
colnames(mcmc.df.beta)=real.tag
mcmc.df.beta = mcmc.df.beta %>% gather(.)
ggplot(data = mcmc.df.beta,mapping = aes(x = key,y = value,fill=as.factor(key)))+
  theme(axis.text.x = element_text(angle = 45, hjust = 1))+ guides(fill=FALSE)+stat_summary(fun.data = c
```



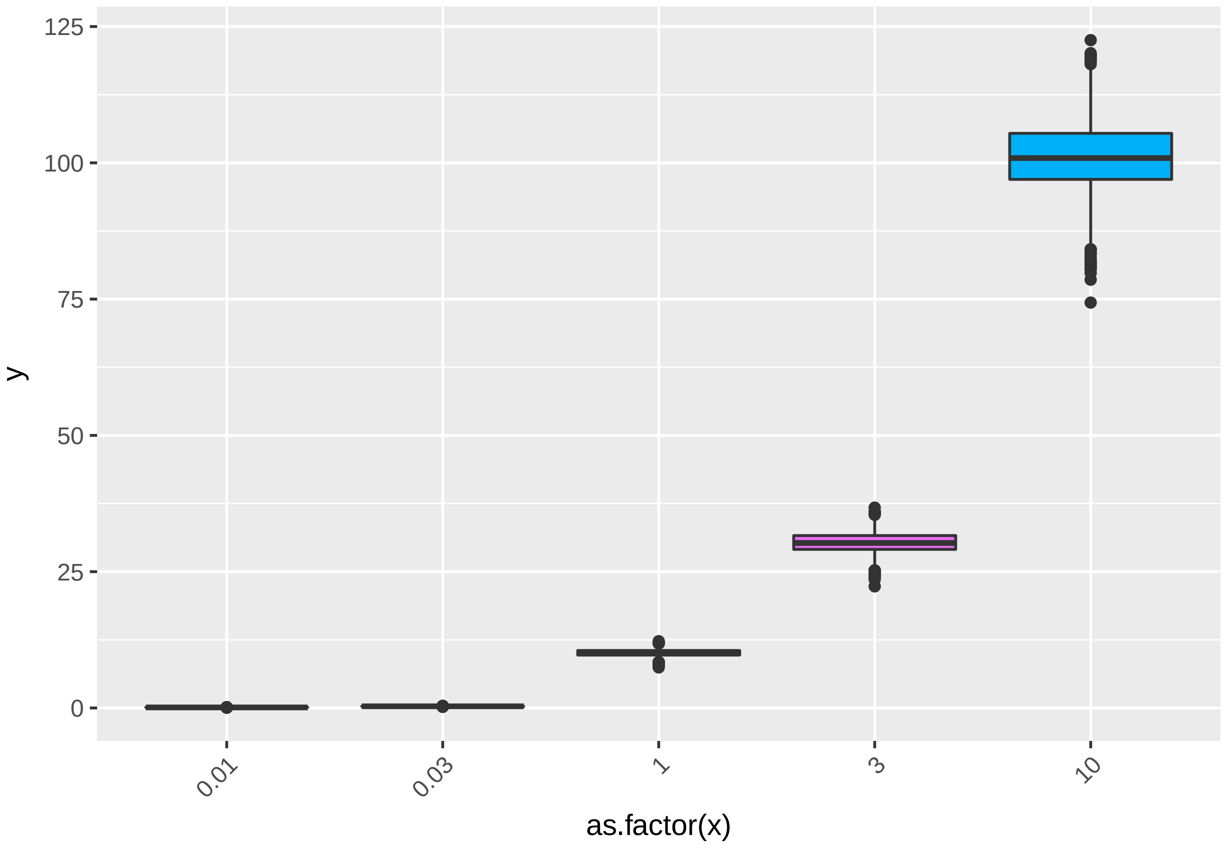

```
temp.zm.lab=jagsname[str_detect(realname,"ZM.*lab")]
real.tag=realname[str_detect(realname,"ZM.*lab")]
mcmc.df.beta=mcmc.df %>% select(temp.zm.lab[1:18])
colnames(mcmc.df.beta)=real.tag
mcmc.df.beta = mcmc.df.beta %>% gather(.)
ggplot(data = mcmc.df.beta,mapping = aes(x = key,y = value,fill=as.factor(key)))+
  theme(axis.text.x = element_text(angle = 45, hjust = 1))+ guides(fill=FALSE)+stat_summary(fun.data = c
```



a.3 what the change point for the dose for `EE`. Under the model that `EE` and `ZM` are continuous, based on the linear regression assumption, we may think 1 is the change point. However, it is not rigorous. This changing point may vary across labs but it is hard to get the conclusion directly.

```
mcmc.df.beta=mcmc.df %>% pull(`beta[1]`)
a=0.01*mcmc.df.beta
b=0.03*mcmc.df.beta
c=mcmc.df.beta
d=3*mcmc.df.beta
e=10*mcmc.df.beta
mcmc.df.beta=cbind(y=c(a,b,c,d,e),x=rep(c("0.01","0.03","1","3","10"),each=nrow(mcmc.df))) %>% as.tibbl
  mutate(y=as.numeric(y))

ggplot(data = mcmc.df.beta,mapping = aes(x = as.factor(x),y=y,fill=factor(x)))+
  theme(axis.text.x = element_text(angle = 45, hjust = 1))+ guides(fill=FALSE)+geom_boxplot()+
  scale_x_discrete(limits=c("0.01","0.03","1","3","10"))
```

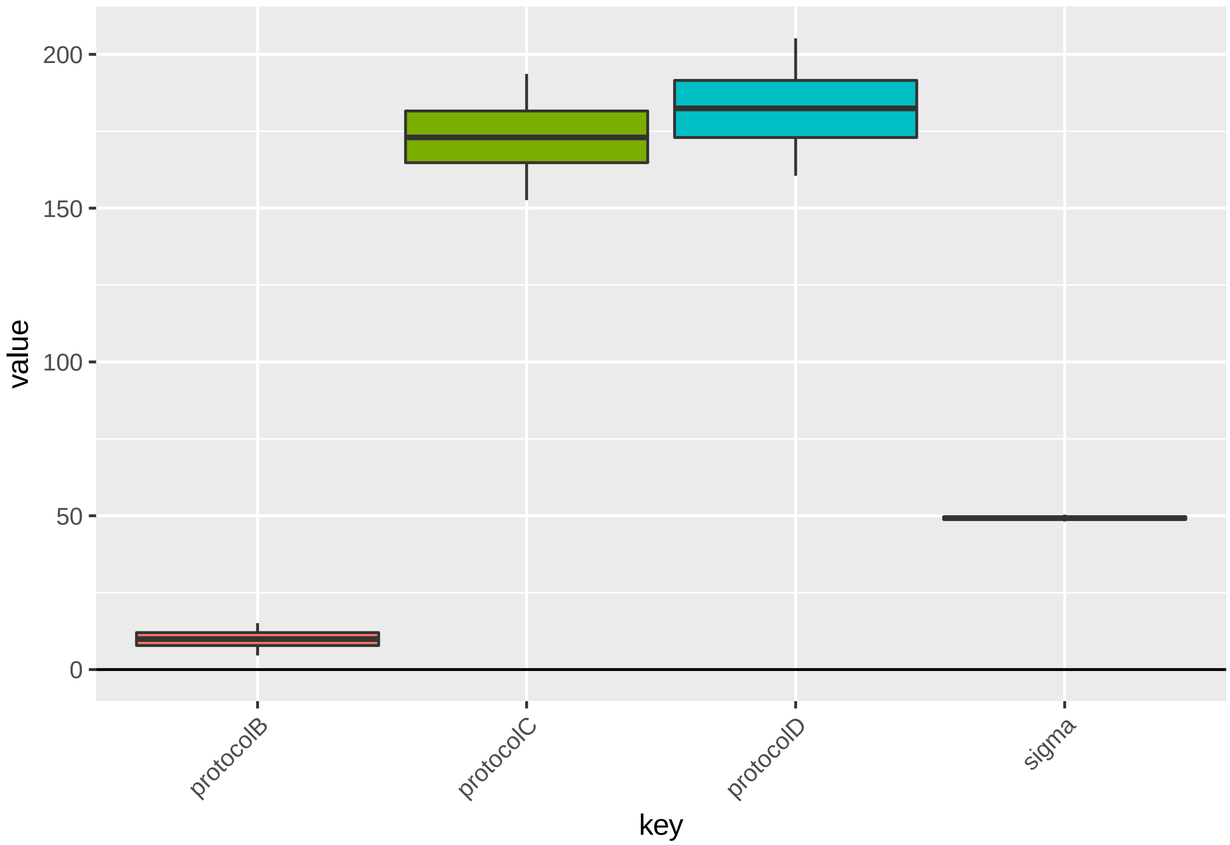


b.The dose response vary across labs. See from the credible interval "boxplot" for a.2. The position and length(with color– 95% credible interval) for each lab is different. Lab Poulenc,Huntingd stands out as being different. However, there are still some overlap between the "outliers" and other labs. So we may say they are not too different from others.

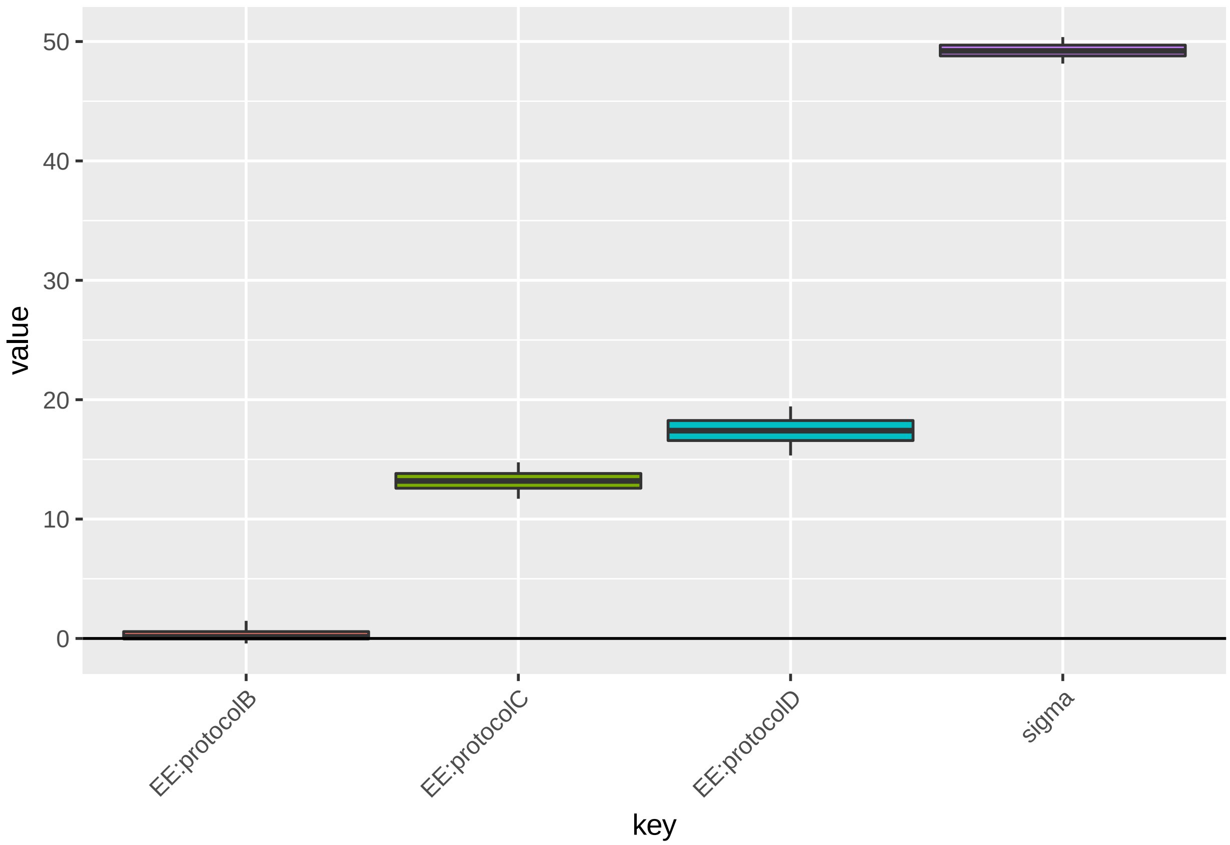
c.The protocol differ in the sensitivity to detecting the effects especially for `EE`. Protocol B is recommended for its lower variance compared to others.

```
#consider sigma as measuring error

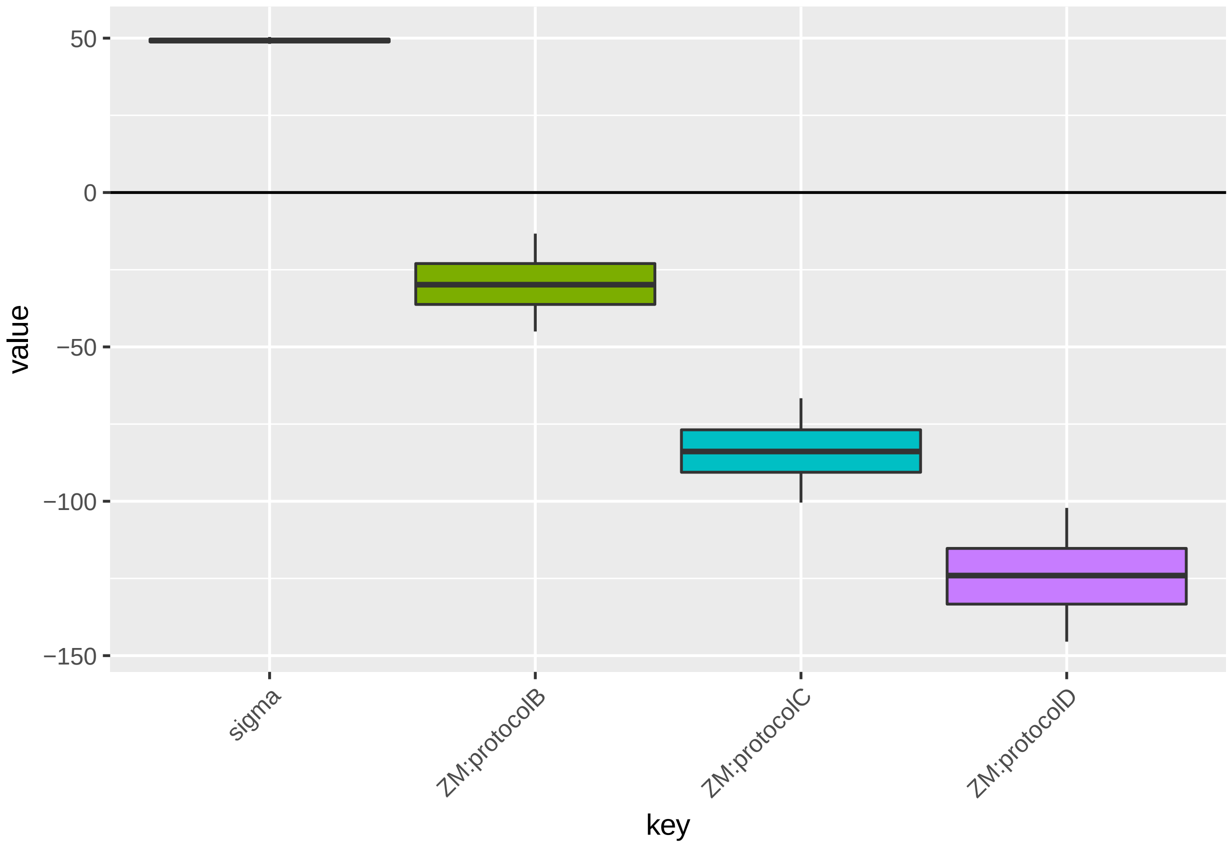
temp.ee.lab=jagsname[str_detect(realname,"^protocol")]
real.tag=realname[str_detect(realname,"^protocol")]
mcmc.df.beta=mcmc.df %>% select(temp.ee.lab[1:3],sigma)
colnames(mcmc.df.beta)=c(real.tag,"sigma")
mcmc.df.beta = mcmc.df.beta %>% gather(.)
ggplot(data = mcmc.df.beta,mapping = aes(x = key,y = value,fill=as.factor(key)))+
  theme(axis.text.x = element_text(angle = 45, hjust = 1))+ guides(fill=FALSE)+stat_summary(fun.data = 
```




```
temp.ee.lab=jagsname[str_detect(realname,"EE.*protocol")]
real.tag=realname[str_detect(realname,"EE.*protocol")]
mcmc.df.beta=mcmc.df %>% select(temp.ee.lab[1:3],sigma)
colnames(mcmc.df.beta)=c(real.tag,"sigma")
mcmc.df.beta = mcmc.df.beta %>% gather(.)
ggplot(data = mcmc.df.beta,mapping = aes(x = key,y = value,fill=as.factor(key)))+
  theme(axis.text.x = element_text(angle = 45, hjust = 1))+ guides(fill=FALSE)+stat_summary(fun.data = 
```




```
temp.zm.lab=jagsname[str_detect(realname,"ZM.*protocol")]
real.tag=realname[str_detect(realname,"ZM.*protocol")]
mcmc.df.beta=mcmc.df %>% select(temp.zm.lab[1:3],sigma)
colnames(mcmc.df.beta)=c(real.tag,"sigma")
mcmc.df.beta = mcmc.df.beta %>% gather(.)
ggplot(data = mcmc.df.beta,mapping = aes(x = key,y = value,fill=as.factor(key)))+
  theme(axis.text.x = element_text(angle = 45, hjust = 1))+ guides(fill=FALSE)+stat_summary(fun.data = c
```




```
mcmc.df.lambda=mcmc.df %>% select(`lambda.l[1]`:`lambda.l[66]`) %>% gather(.)
mcmc.df.phi.l=mcmc.df %>% select(`phi.l[1]`:`phi.l[66]`) %>% gather(.)
beta.levels=paste0("beta[",1:66,"]","beta0")
lambda.levels=paste0("lambda.l[",1:66,"]")
phi.l.levels=paste0("phi.l[",1:66,"]")
```

Table for the whole model

```
kable(summary(lm.full.fac)$coefficients, format = "markdown")
```

	Estimate	Std. Error	t value	Pr(>|t|)
(Intercept)	17.5174726	6.0832664	2.8796162	0.0040160
EE0.01	1.7634590	6.2225208	0.2833995	0.7768945
EE0.03	1.0348581	9.8997869	0.1045334	0.9167546
EE0.1	2.7516396	9.9000339	0.2779424	0.7810799
EE0.3	-1.2258396	9.8997530	-0.1238253	0.9014637
EE1	4.9137998	9.8997612	0.4963554	0.6196881
EE3	69.3169544	9.8998665	7.0018070	0.0000000
EE10	85.6474733	9.9001737	8.6511082	0.0000000
ZM0.1	-44.2697078	11.2619189	-3.9309205	0.0000870
ZM1	-68.4662160	11.2618892	-6.0794610	0.0000000
labBayer	13.6089109	8.1539860	1.6689888	0.0952470
labBerlin	5.2019905	8.1706700	0.6366663	0.5244015
labChungKor	17.0236675	7.2154001	2.3593518	0.0183847
labCitfranc	19.9168751	8.1423844	2.4460740	0.0145118

	Estimate	Std. Error	t value	Pr(>|t|)
labCitijapa	13.4596775	6.8936320	1.9524798	0.0509947
labDenmark	9.6122452	8.5189868	1.1283320	0.2592899
labExxon	15.6678556	9.8999699	1.5826165	0.1136376
labHatano	11.9391885	6.7473960	1.7694513	0.0769426
labHuntingd	-8.3391169	8.8013746	-0.9474789	0.3434880
labInEnvTox	4.8104074	6.7951943	0.7079131	0.4790663
labKoreaPar	-2.3948281	7.4778542	-0.3202561	0.7488015
labMitsubis	11.9407498	6.7484149	1.7694155	0.0769486
labNihon	5.9191632	6.7487889	0.8770704	0.3805341
labPoulenc	-3.8337704	8.1513040	-0.4703260	0.6381639
labSumitomo	10.7213694	6.8927463	1.5554568	0.1199661
labTNO	5.1741985	7.2817950	0.7105663	0.4774204
labWIL	6.7631678	7.2179124	0.9369978	0.3488518
labZeneca	-4.0680776	6.9129760	-0.5884698	0.5562711
protocolB	-2.1607713	2.4955878	-0.8658366	0.3866643
protocolC	56.9794121	5.4037785	10.5443649	0.0000000
protocolD	47.3180475	6.1563031	7.6861140	0.0000000
weight	0.1013519	0.0269476	3.7610787	0.0001731
EE0.01:protocolB	1.1910814	4.3163572	0.2759460	0.7826128
EE0.03:protocolB	3.5413070	4.3163543	0.8204394	0.4120453
EE0.1:protocolB	7.4548817	4.3164162	1.7270999	0.0842754
EE0.3:protocolB	35.0983219	4.3163533	8.1314756	0.0000000
EE1:protocolB	58.2145221	4.3163905	13.4868524	0.0000000
EE3:protocolB	34.4029535	4.3163793	7.9703268	0.0000000
EE10:protocolB	17.5749522	4.3279683	4.0607858	0.0000504
EE0.01:protocolC	-0.3230727	4.9003837	-0.0659280	0.9474405
EE0.03:protocolC	2.7225504	4.9003811	0.5555793	0.5785491
EE0.1:protocolC	14.0429743	4.9212596	2.8535325	0.0043598
EE0.3:protocolC	100.2001531	4.9010674	20.4445572	0.0000000
EE1:protocolC	186.2957590	4.9056058	37.9760965	0.0000000
EE3:protocolC	170.0100300	4.9148171	34.5913240	0.0000000
EE10:protocolC	157.5564078	4.9217713	32.0121353	0.0000000
EE0.01:protocolD	6.4547359	6.2222407	1.0373652	0.2996678
EE0.03:protocolD	4.8409616	6.2794259	0.7709242	0.4408260
EE0.1:protocolD	24.4881903	6.2874449	3.8947761	0.0001009
EE0.3:protocolD	140.9911182	6.2315658	22.6253118	0.0000000
EE1:protocolD	230.5357409	6.2588387	36.8336284	0.0000000
EE3:protocolD	208.1653132	6.2771622	33.1623280	0.0000000
EE10:protocolD	216.9748633	6.2947772	34.4690300	0.0000000
ZM0.1:protocolB	-61.0379638	4.9806146	-12.2551068	0.0000000
ZM1:protocolB	-53.8667551	4.9805753	-10.8153681	0.0000000
ZM0.1:protocolC	-158.4145809	5.6799781	-27.8899987	0.0000000
ZM1:protocolC	-171.3240393	5.6613955	-30.2618037	0.0000000
ZM0.1:protocolD	-183.6447648	7.2074293	-25.4799259	0.0000000
ZM1:protocolD	-217.2506012	7.2037058	-30.1581723	0.0000000
EE0.1:labBayer	-1.9456140	13.8970874	-0.1400016	0.8886702
EE0.3:labBayer	-1.0689227	13.8971751	-0.0769165	0.9386962
EE1:labBayer	2.4451549	13.8974734	0.1759424	0.8603537
EE3:labBayer	-28.2023694	13.8970615	-2.0293765	0.0425276
EE10:labBayer	13.3618173	13.8973214	0.9614671	0.3364120
EE0.01:labBerlin	-0.8711178	11.5688730	-0.0752984	0.9399834
EE0.03:labBerlin	2.9075964	13.8970389	0.2092242	0.8342906

	Estimate	Std. Error	t value	Pr(>|t|)
EE0.1:labBerlin	-2.8133528	13.8977646	-0.2024320	0.8395957
EE0.3:labBerlin	15.6240363	13.8971717	1.1242601	0.2610125
EE1:labBerlin	49.4837223	13.8970358	3.5607394	0.0003768
EE3:labBerlin	36.1854101	13.8971988	2.6037916	0.0092754
EE10:labBerlin	5.9294383	13.8987704	0.4266160	0.6696964
EE0.01:labChungKor	-4.4112228	9.0183089	-0.4891408	0.6247857
EE0.03:labChungKor	3.6572980	12.2566224	0.2983936	0.7654280
EE0.1:labChungKor	25.1157672	12.2569386	2.0491061	0.0405577
EE0.3:labChungKor	29.9697260	12.2567299	2.4451649	0.0145484
EE1:labChungKor	33.4910175	12.2566535	2.7324765	0.0063310
EE3:labChungKor	5.8710111	12.2568226	0.4789994	0.6319817
EE10:labChungKor	-13.1352580	12.2576968	-1.0715927	0.2840083
EE0.01:labCitfranc	-5.4581770	11.5691596	-0.4717868	0.6371209
EE0.03:labCitfranc	2.1032608	13.8970370	0.1513460	0.8797152
EE0.1:labCitfranc	-4.7742861	13.8972539	-0.3435417	0.7312204
EE0.3:labCitfranc	4.4922701	13.8970495	0.3232535	0.7465308
EE1:labCitfranc	15.3991170	13.8970550	1.1080849	0.2679336
EE3:labCitfranc	-11.4493741	13.8970501	-0.8238708	0.4100929
EE10:labCitfranc	12.3162322	13.8971999	0.8862384	0.3755758
EE0.01:labCitijapa	-3.0151260	7.9637089	-0.3786083	0.7050115
EE0.03:labCitijapa	-4.5806369	11.6928831	-0.3917457	0.6952801
EE0.1:labCitijapa	-6.1052594	11.6939503	-0.5220870	0.6016568
EE0.3:labCitijapa	-3.2741206	11.6927905	-0.2800119	0.7794919
EE1:labCitijapa	35.0675543	11.6929228	2.9990410	0.0027355
EE3:labCitijapa	5.0502495	11.6927877	0.4319115	0.6658436
EE10:labCitijapa	10.5650698	11.6931765	0.9035244	0.3663362
EE0.01:labDenmark	-2.1078621	11.5430753	-0.1826084	0.8551204
EE0.03:labDenmark	-3.8631575	14.5521183	-0.2654705	0.7906693
EE0.1:labDenmark	-5.2945269	14.5519685	-0.3638358	0.7160119
EE0.3:labDenmark	27.6921013	14.5519290	1.9029849	0.0571593
EE1:labDenmark	40.2593492	14.5522648	2.7665350	0.0057080
EE3:labDenmark	8.8664099	14.5520236	0.6092905	0.5423882
EE10:labDenmark	-2.3109937	14.5553893	-0.1587724	0.8738613
EE0.01:labExxon	5.2457749	12.8665555	0.4077062	0.6835249
EE0.03:labExxon	0.6607488	14.9945279	0.0440660	0.9648554
EE0.1:labExxon	-0.3802441	14.9949332	-0.0253582	0.9797713
EE0.3:labExxon	9.4611994	14.9945142	0.6309774	0.5281140
EE1:labExxon	11.9059065	14.9945225	0.7940171	0.4272622
EE3:labExxon	5.4743729	14.9949929	0.3650801	0.7150831
EE10:labExxon	14.6708826	14.9947799	0.9783993	0.3279732
EE0.01:labHatano	-3.1285617	7.5814767	-0.4126586	0.6798928
EE0.03:labHatano	-3.6387506	11.4378435	-0.3181326	0.7504114
EE0.1:labHatano	-3.0319622	11.4536376	-0.2647161	0.7912504
EE0.3:labHatano	2.9262057	11.4357534	0.2558822	0.7980632
EE1:labHatano	25.9831604	11.4358435	2.2720808	0.0231677
EE3:labHatano	14.2633513	11.4358590	1.2472479	0.2124255
EE10:labHatano	23.8446654	11.4651242	2.0797564	0.0376513
EE0.01:labHuntingd	7.8757716	11.6203523	0.6777567	0.4979898
EE0.03:labHuntingd	-5.1484581	14.7358705	-0.3493827	0.7268320
EE0.1:labHuntingd	-30.0494023	14.7449823	-2.0379409	0.0416627
EE0.3:labHuntingd	-91.0483605	14.7382196	-6.1777042	0.0000000
EE1:labHuntingd	-151.3072461	14.7357224	-10.2680576	0.0000000

	Estimate	Std. Error	t value	Pr(>|t|)
EE3:labHuntingd	-101.1729866	14.7419254	-6.8629425	0.0000000
EE10:labHuntingd	-5.3201467	14.7374840	-0.3609942	0.7181348
EE0.01:labInEnvTox	-5.5008881	7.5810410	-0.7256112	0.4681463
EE0.03:labInEnvTox	-2.4986614	11.4377038	-0.2184583	0.8270902
EE0.1:labInEnvTox	2.0522573	11.4391119	0.1794070	0.8576329
EE0.3:labInEnvTox	8.1025280	11.4357597	0.7085256	0.4786862
EE1:labInEnvTox	35.7901398	11.4359495	3.1296168	0.0017709
EE3:labInEnvTox	5.7978376	11.4362920	0.5069683	0.6122226
EE10:labInEnvTox	-5.1590307	11.4364117	-0.4511057	0.6519532
EE0.01:labKoreaPar	-4.5600764	9.0012641	-0.5066040	0.6124782
EE0.03:labKoreaPar	-9.0474745	12.7018088	-0.7122981	0.4763478
EE0.1:labKoreaPar	-12.0801279	12.7043258	-0.9508673	0.3417653
EE0.3:labKoreaPar	-8.2114601	12.7018086	-0.6464796	0.5180292
EE1:labKoreaPar	32.4911955	12.7020103	2.5579569	0.0105884
EE3:labKoreaPar	-5.7024976	12.7024277	-0.4489297	0.6535219
EE10:labKoreaPar	10.6688331	12.7031098	0.8398599	0.4010686
EE0.01:labMitsubis	-6.9589534	7.5812514	-0.9179162	0.3587528
EE0.03:labMitsubis	-3.6469335	11.4534126	-0.3184146	0.7501975
EE0.1:labMitsubis	-5.4309427	11.4626114	-0.4737963	0.6356873
EE0.3:labMitsubis	10.1528255	11.4359123	0.8878020	0.3747342
EE1:labMitsubis	24.0054736	11.4365053	2.0990218	0.0359168
EE3:labMitsubis	12.0242638	11.4361293	1.0514278	0.2931656
EE10:labMitsubis	10.1999962	11.4358854	0.8919289	0.3725184
EE0.01:labNihon	1.1443408	7.5814228	0.1509401	0.8800353
EE0.03:labNihon	-6.8516033	11.4377109	-0.5990362	0.5492039
EE0.1:labNihon	-8.6410539	11.4380866	-0.7554632	0.4500435
EE0.3:labNihon	-4.3106596	11.4359951	-0.3769379	0.7062523
EE1:labNihon	22.3213216	11.4357866	1.9518834	0.0510655
EE3:labNihon	16.6933209	11.4357639	1.4597469	0.1444875
EE10:labNihon	16.7073132	11.4360027	1.4609399	0.1441598
EE0.01:labPoulenc	-2.6746648	11.5688865	-0.2311947	0.8171828
EE0.03:labPoulenc	-1.0820997	13.8970357	-0.0778655	0.9379414
EE0.1:labPoulenc	-2.1316505	13.8971591	-0.1533875	0.8781053
EE0.3:labPoulenc	15.6353563	13.8971182	1.1250790	0.2606654
EE1:labPoulenc	31.5495444	13.8970358	2.2702355	0.0232795
EE3:labPoulenc	-17.8699366	13.8970993	-1.2858753	0.1986078
EE10:labPoulenc	-25.6412231	13.8972852	-1.8450527	0.0651501
EE0.01:labSumitomo	-0.7738165	7.9635207	-0.0971701	0.9225992
EE0.03:labSumitomo	-1.5638764	11.6928688	-0.1337462	0.8936142
EE0.1:labSumitomo	-5.9424405	11.6939738	-0.5081626	0.6113849
EE0.3:labSumitomo	11.7129107	11.6928318	1.0017172	0.3165788
EE1:labSumitomo	42.0319864	11.6927892	3.5946929	0.0003312
EE3:labSumitomo	24.4487282	11.6928765	2.0909079	0.0366388
EE10:labSumitomo	35.6613733	11.6931561	3.0497646	0.0023147
EE0.01:labTNO	0.1459632	9.0558909	0.0161180	0.9871415
EE0.03:labTNO	-0.9345580	12.2903092	-0.0760402	0.9393933
EE0.1:labTNO	-5.5301417	12.2904691	-0.4499537	0.6527835
EE0.3:labTNO	2.7554038	12.2903618	0.2241922	0.8226264
EE1:labTNO	32.7429120	12.2903774	2.6641096	0.0077697
EE3:labTNO	10.9566903	12.2903462	0.8914875	0.3727550
EE10:labTNO	20.5077951	12.2917541	1.6684189	0.0953600
EE0.01:labWIL	2.3868885	9.0177255	0.2646885	0.7912716

	Estimate	Std. Error	t value	Pr(>|t|)
EE0.03:labWIL	-0.9974044	12.2565949	-0.0813770	0.9351488
EE0.1:labWIL	1.6262677	12.2572149	0.1326784	0.8944586
EE0.3:labWIL	-0.5899327	12.2566676	-0.0481316	0.9616153
EE1:labWIL	13.0420573	12.2566878	1.0640768	0.2873985
EE3:labWIL	-12.0139275	12.2569909	-0.9801694	0.3270990
EE10:labWIL	4.3028315	12.2582459	0.3510153	0.7256070
EE0.03:labZeneca	0.2504818	11.6928837	0.0214217	0.9829110
EE0.1:labZeneca	1.1680882	11.6941543	0.0998865	0.9204426
EE0.3:labZeneca	13.2661190	11.6928050	1.1345540	0.2566729
EE1:labZeneca	21.7877479	11.6928006	1.8633473	0.0625326
EE3:labZeneca	-23.5618392	11.6930187	-2.0150348	0.0440097
EE10:labZeneca	-16.9092188	11.6936855	-1.4460128	0.1483012
ZM0.1:labBayer	50.8727461	15.9269030	3.1941392	0.0014202
ZM1:labBayer	32.7792790	15.9267178	2.0581315	0.0396828
ZM0.1:labBerlin	27.7253380	15.9267127	1.7408073	0.0818425
ZM1:labBerlin	-2.2226356	15.9267230	-0.1395539	0.8890239
ZM0.1:labChungKor	57.6940393	14.0160636	4.1162798	0.0000398
ZM1:labChungKor	33.0262842	14.0160945	2.3563115	0.0185356
ZM0.1:labCitfranc	30.2045937	15.9267649	1.8964676	0.0580154
ZM1:labCitfranc	12.7354950	15.9267284	0.7996303	0.4240023
ZM0.1:labCitijapa	31.8017854	13.3591547	2.3805238	0.0173639
ZM1:labCitijapa	7.7386338	13.3582359	0.5793155	0.5624294
ZM0.1:labDenmark	23.1410049	16.6873655	1.3867381	0.1656474
ZM1:labDenmark	8.2176564	16.6873351	0.4924487	0.6224462
ZM0.1:labExxon	23.0663308	15.9269827	1.4482549	0.1476734
ZM1:labExxon	-5.2036023	15.9268284	-0.3267193	0.7439080
ZM0.1:labHatano	9.0102103	13.0802294	0.6888419	0.4909878
ZM1:labHatano	0.3096981	13.0582014	0.0237167	0.9810805
ZM0.1:labHuntingd	72.4342844	16.9076766	4.2841063	0.0000191
ZM1:labHuntingd	114.0571430	16.9017085	6.7482612	0.0000000
ZM0.1:labInEnvTox	23.3265752	13.0584338	1.7863226	0.0741703
ZM1:labInEnvTox	10.2372871	13.0581623	0.7839761	0.4331297
ZM0.1:labKoreaPar	16.1498041	14.5364690	1.1109854	0.2666834
ZM1:labKoreaPar	40.0390337	14.5346073	2.7547379	0.0059172
ZM0.1:labMitsubis	13.2492104	13.0584341	1.0146094	0.3103919
ZM1:labMitsubis	-5.9918796	13.0581623	-0.4588609	0.6463747
ZM0.1:labNihon	12.5949318	13.0584778	0.9645023	0.3348891
ZM1:labNihon	-4.3232424	13.0581774	-0.3310755	0.7406157
ZM0.1:labPoulenc	49.0113737	15.9267124	3.0773064	0.0021118
ZM1:labPoulenc	29.6003373	15.9267334	1.8585316	0.0632131
ZM0.1:labSumitomo	30.8781749	13.3592364	2.3113727	0.0208946
ZM1:labSumitomo	-7.6949612	13.3582819	-0.5760442	0.5646380
ZM0.1:labTNO	77.4798497	14.0160034	5.5279560	0.0000000
ZM1:labTNO	22.6405850	14.0159523	1.6153440	0.1063646
ZM0.1:labWIL	38.1873945	14.0159664	2.7245638	0.0064843
ZM1:labWIL	29.8072517	14.0159523	2.1266662	0.0335472
ZM0.1:labZeneca	77.9602706	13.3595517	5.8355454	0.0000000
ZM1:labZeneca	44.7841288	13.3582788	3.3525374	0.0008129

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bas.coef.need=bas.coef[,-5]
kable((bas.coef.need), format = "markdown")
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coef	2.5%	97.5%	beta
Intercept	100.055044462133	101.596736582621	100.828516996638
EE0.01	0	0	-0.0185387426737127
EE0.03	0	0	-0.0275088514937671
EE0.1	0	2.48795539720713	0.189311946202372
EE0.3	0	6.96681299760768	1.11073445885781
EE1	22.3934899770032	33.4979889689778	28.003109420928
EE3	65.2310235728102	75.8219266602307	70.413914630952
EE10	92.9134103684365	103.899297831118	98.1973432100308
ZM0.1	-26.359203748441	-13.2829350947192	-19.6798511510181
ZM1	-66.9229877533104	-53.555658915096	-60.3056742525893
labBayer	0	2.52688815382711	0.220800441474336
labBerlin	-0.0297587258253578	1.38938626456493	0.209550665083875
labChungKor	9.37733866762145	21.1429166148873	15.0780642288339
labCitfranc	7.82819922217412	19.6588396099078	13.8110238932413
labCitijapa	6.10405900451737	14.3093786345217	9.97798647076344
labDenmark	0	12.1943833732338	3.45176188059285
labExxon	7.3225600473368	19.7280820905143	13.4342169367462
labHatano	7.40334158368509	14.6942050707092	11.0262962495423
labHuntingd	-13.1557952346906	0	-1.40888520966668
labInEnvTox	0	2.25786614321194	0.160454143848624
labKoreaPar	-16.8559527625728	-5.93966950401491	-11.3142372819277
labMitsubis	5.42182990896181	12.7243110654696	8.93092165456198
labNihon	0	2.15924383565917	0.165148896403275
labPoulenc	-11.0126972356564	0	-2.79269851434394
labSumitomo	4.3077943997536	16.9747912508505	10.5806272400484
labTNO	0	4.7270241203087	0.447113932286084
labWIL	0	0	0.0184266536855071
labZeneca	-4.83714536179102	0	-0.497802428696683
protocolB	-0.134242945004499	0	-0.0508615175612661
protocolC	63.549638754069	78.0111757649244	72.3903834247473
protocolD	56.7960956271419	73.213986816297	66.4004111656585
weight	-3.04848398673292e-05	0.0562708841164303	0.00564174454860273
EE0.01:protocolB	0	0	-0.0484834439277467
EE0.03:protocolB	0	0	-0.00374225574012542
EE0.1:protocolB	0	5.80940650865182	0.638071968708935
EE0.3:protocolB	27.3243696086945	40.8301050511793	34.3450027375794
EE1:protocolB	55.0606758083594	68.7850425910737	61.6850608926798
EE3:protocolB	30.4309555314408	43.5972876086278	36.9792777440934
EE10:protocolB	8.95360301721218	22.3585365222887	15.4922689713518
EE0.01:protocolC	0	0	-0.0418508956721509
EE0.03:protocolC	0	0	-0.0372337439129658
EE0.1:protocolC	6.40160304041151	22.1403552467264	13.981821135302
EE0.3:protocolC	92.6326923991964	108.858102808275	100.948337570761
EE1:protocolC	182.028890232746	198.78081566387	190.406252465165
EE3:protocolC	167.223493089784	184.022556494145	174.990429384391
EE10:protocolC	147.3881625556	164.566613656041	155.913850151031
EE0.01:protocolD	-0.0561508992998876	2.00753396917747	0.248096917898323
EE0.03:protocolD	0	0	0.00277534356778904
EE0.1:protocolD	18.0864954532965	37.2686057558763	27.8652318613424
EE0.3:protocolD	127.96604208147	149.069576453157	139.059476650572
EE1:protocolD	218.523282911513	239.726423918936	228.700019222896
EE3:protocolD	201.297317108481	222.51051315143	211.884372937883

coef	2.5%	97.5%	beta
EE10:protocolD	202.381848903618	224.294508229596	213.348662486525
ZM0.1:protocolB	-73.2979747319827	-55.3105391323187	-64.11552608077
ZM1:protocolB	-64.5950185791796	-46.3977700698058	-55.271252867729
ZM0.1:protocolC	-172.933144141374	-152.147357191573	-162.502695556552
ZM1:protocolC	-185.383177143198	-164.195990548043	-174.710735952554
ZM0.1:protocolD	-203.72229480075	-177.08376868335	-190.406566544859
ZM1:protocolD	-234.651923967539	-208.034474117185	-221.890183747974
EE0.01:labBayer	0	0	0
EE0.03:labBayer	0	0	0
EE0.1:labBayer	0	6.98222226675029	0.664354599330979
EE0.3:labBayer	0	0	0.233288184483956
EE1:labBayer	-14.6861142164707	0	-1.26987758053313
EE3:labBayer	-1.39011447636814	0.00250530331685761	-0.310238841966281
EE10:labBayer	-0.167775551829681	8.70290713581227	0.756059181743361
EE0.01:labBerlin	0	0	0.0328915241542893
EE0.03:labBerlin	0	0	0.188650430509136
EE0.1:labBerlin	0	0	-0.0046621172776184
EE0.3:labBerlin	0	16.7813719529561	1.68346041757266
EE1:labBerlin	0	40.0681543755993	19.7637177727677
EE3:labBerlin	21.3796783612084	43.6361382608409	32.3828066855934
EE10:labBerlin	-1.08278763935899	0.300376150251354	-0.347611454147453
EE0.01:labChungKor	-3.2003714879822	0.0967514439623152	-0.330234504361566
EE0.03:labChungKor	-0.328578420787251	0.291277504460988	0.235949231306266
EE0.1:labChungKor	14.8852365438112	41.8344248591544	28.0123630936599
EE0.3:labChungKor	0	36.2648214827171	24.0182020795729
EE1:labChungKor	0	1.82050500208793	0.42045616027402
EE3:labChungKor	0	4.06921500106467	0.375413312490984
EE10:labChungKor	-41.6292031628101	-13.2232110074277	-27.9070077206815
EE0.01:labCitfranc	0	0	-0.020742726892048
EE0.03:labCitfranc	0	0	0.325718052677833
EE0.1:labCitfranc	0	0	0.0524716666609937
EE0.3:labCitfranc	0	0	0.258154763093812
EE1:labCitfranc	0	0	-0.221817527178989
EE3:labCitfranc	-10.352660146984	0	-0.966863557689107
EE10:labCitfranc	0	0	0.169000261859233
EE0.01:labCitijapa	0	0	-0.0686280985012496
EE0.03:labCitijapa	0	0	-0.0718178868406088
EE0.1:labCitijapa	0	0	-0.0855924435617015
EE0.3:labCitijapa	-7.41644927480898	0	-0.68328429484802
EE1:labCitijapa	0	13.9392676306171	1.66073293639647
EE3:labCitijapa	-0.00228895235153637	6.09126552415674	0.536535244730492
EE10:labCitijapa	0	0	-0.113070203172257
EE0.01:labDenmark	0	0	0.0463715212290357
EE0.03:labDenmark	0	0	0.0453278579269114
EE0.1:labDenmark	0	0	0.213146512874544
EE0.3:labDenmark	-0.0286826802441098	42.8422533118709	20.255390216775
EE1:labDenmark	0	21.9142884296369	2.58318515754546
EE3:labDenmark	0	13.0077235344585	1.40208302767441
EE10:labDenmark	-23.8970527597477	0	-2.52771160187223
EE0.01:labExxon	-0.820265701851967	0.805082031752182	0.40698948245146
EE0.03:labExxon	0	0	0.0369496641113636
EE0.1:labExxon	0	0	0.0488421501686859

coef	2.5%	97.5%	beta
EE0.3:labExxon	0	0	0.29006240015626
EE1:labExxon	-16.0752625339963	0	-1.46286354304054
EE3:labExxon	0	0	-0.0812431171094426
EE10:labExxon	0	0	0.090801418411952
EE0.01:labHatano	0	0	-0.0875500242959871
EE0.03:labHatano	0	0	-0.0942272058149964
EE0.1:labHatano	-0.0040176516493311	6.05739385677857	0.554268298218406
EE0.3:labHatano	-0.869393969793513	0.00449935119966804	-0.145835001241427
EE1:labHatano	0	0	-0.182527638599073
EE3:labHatano	0	2.16563508776784	0.193848057597366
EE10:labHatano	0	15.545022119219	2.72378393228172
EE0.01:labHuntingd	-0.269398281052665	1.85922867010245	0.552799256571524
EE0.03:labHuntingd	0	0	-0.127917959081275
EE0.1:labHuntingd	-45.4105636075782	0	-26.8641691982711
EE0.3:labHuntingd	-114.846832752547	-76.7964129723193	-96.2318369357506
EE1:labHuntingd	-201.587608428543	-162.937396005455	-182.105999368377
EE3:labHuntingd	-131.084717130115	-91.5139341487413	-110.513556323155
EE10:labHuntingd	-36.2421835254143	0	-11.6122973154115
EE0.01:labInEnvTox	0	0	-0.200095355826062
EE0.03:labInEnvTox	0	0	-0.0161104850102804
EE0.1:labInEnvTox	0	0	0.172653163302355
EE0.3:labInEnvTox	-0.0039874053426181	1.43216758223949	0.257984747160931
EE1:labInEnvTox	0	13.8384056910689	2.25663006321677
EE3:labInEnvTox	-0.363354782919505	1.33372976732317	0.173492497754692
EE10:labInEnvTox	-30.170164922196	-9.4527185632498	-19.5098253415702
EE0.01:labKoreaPar	0	0	0.0714250483582735
EE0.03:labKoreaPar	0	0	-0.0458743027779919
EE0.1:labKoreaPar	0	0	-0.140548508816847
EE0.3:labKoreaPar	-9.6714725898472	0	-0.859890270825166
EE1:labKoreaPar	0	13.1276900476046	1.34869837061141
EE3:labKoreaPar	-18.2530186320855	0	-4.10937270485454
EE10:labKoreaPar	0	0	0.158904724955371
EE0.01:labMitsubis	-0.650496994804272	0.00888140495494216	-0.208603707491529
EE0.03:labMitsubis	0	0	-0.000602843278671269
EE0.1:labMitsubis	0	0	0.126058795292167
EE0.3:labMitsubis	-0.0155851978460575	12.6704360725369	1.69100509066866
EE1:labMitsubis	0	0	-0.126972627041779
EE3:labMitsubis	0	0	0.0401203000898646
EE10:labMitsubis	-1.25626964246478	0.330989820634723	-0.253991003500099
EE0.01:labNihon	0	6.25202257650698	0.570220894245634
EE0.03:labNihon	0	0	-0.0538181174197236
EE0.1:labNihon	-2.26618828640252	0	-0.296887977700119
EE0.3:labNihon	-7.39772633035771	0.00867031651665062	-0.657412347098441
EE1:labNihon	-0.600688595384389	0.0723300685509169	-0.125067910800698
EE3:labNihon	0	12.6264929750716	4.98015818213604
EE10:labNihon	0	8.8262361834466	0.728116193613814
EE0.01:labPoulenc	0	0	-0.280739868542243
EE0.03:labPoulenc	-0.816742824911627	0.15250566330298	-0.286073674573711
EE0.1:labPoulenc	0	0	-0.241131351671458
EE0.3:labPoulenc	0	4.05795199020997	0.630288677561376
EE1:labPoulenc	0	0	0.158899696650978
EE3:labPoulenc	-19.245192956313	0	-3.86652314535332

coef	2.5%	97.5%	beta
EE10:labPoulenc	-62.7626336513895	-24.7149139094657	-43.5295203217091
EE0.01:labSumitomo	0	0	-0.107038907283634
EE0.03:labSumitomo	0	0.007037898288975	-0.0968423536005913
EE0.1:labSumitomo	-5.99682759639787	0	-0.467359735018106
EE0.3:labSumitomo	0	9.57104000909294	0.802060296537872
EE1:labSumitomo	0	22.0970956888042	6.27387086651717
EE3:labSumitomo	0	27.7056485865378	12.9340710743932
EE10:labSumitomo	0	29.6007414034816	17.0067381943043
EE0.01:labTNO	0	0	0.0606903543541841
EE0.03:labTNO	0	0	0.0523394456161165
EE0.1:labTNO	0	0	-0.0299344840498434
EE0.3:labTNO	0	0	-0.0330058494042813
EE1:labTNO	0	4.17420487515085	0.520736349287754
EE3:labTNO	0	20.6893312087819	4.74488033227444
EE10:labTNO	0	10.9339307732857	0.897343408937183
EE0.01:labWIL	-0.0993296662091545	3.83061588114357	0.457338497589537
EE0.03:labWIL	0	0	0.17458701495044
EE0.1:labWIL	0	12.3483006842774	1.21467577663379
EE0.3:labWIL	0	0	-0.0319506299289634
EE1:labWIL	-14.0999607793154	0	-1.46836423293617
EE3:labWIL	0	0	-0.0966645500686589
EE10:labWIL	-2.36441912164557	0.400220389159569	-0.354297432541307
EE0.01:labZeneca	0	0	-0.109154738976368
EE0.03:labZeneca	0	0	-0.0504491929178649
EE0.1:labZeneca	0	0	0.0256461655033761
EE0.3:labZeneca	-0.00340250013743493	6.14373181479124	0.568144213344154
EE1:labZeneca	-15.7840644434845	0	-2.45523851681031
EE3:labZeneca	-43.6335781986781	-21.7346922493736	-32.977006319426
EE10:labZeneca	-44.8690586554108	-22.7218636283122	-34.2511962645609
ZM0.1:labBayer	-0.251232318992438	1.55664595470979	0.363279889404439
ZM1:labBayer	0	0	0.274834283180745
ZM0.1:labBerlin	-0.294739537412196	1.10052569782366	0.41556858235453
ZM1:labBerlin	-9.21970916360437	0.0117711234808446	-0.857696299951436
ZM0.1:labChungKor	20.42207527752	49.5675044294405	34.502355712754
ZM1:labChungKor	0	37.8302714134603	24.6744987446387
ZM0.1:labCitfranc	0	0	-0.158053122319695
ZM1:labCitfranc	0	0	-0.228008379295375
ZM0.1:labCitijapa	0	17.128061258127	2.92438389712858
ZM1:labCitijapa	0	0	0.0901044552711169
ZM0.1:labDenmark	0	2.31830186083176	0.446744906067789
ZM1:labDenmark	0	0	0.317312963431555
ZM0.1:labExxon	0	0	0.100857964323021
ZM1:labExxon	-8.02509567848456	0	-0.778033765806314
ZM0.1:labHatano	-8.09998923000124	0	-0.679426389111064
ZM1:labHatano	0	0	0.117163251135331
ZM0.1:labHuntingd	28.1008058647553	79.3321976254753	53.0464474609025
ZM1:labHuntingd	85.2492182057782	136.162180022261	110.351550606786
ZM0.1:labInEnvTox	0	0	0.134052082422926
ZM1:labInEnvTox	0	2.64135992753573	0.344626383411986
ZM0.1:labKoreaPar	-14.84118954067	0	-1.42451470553109
ZM1:labKoreaPar	14.0971689523121	49.5608789793022	31.0795139194591
ZM0.1:labMitsubis	0	0	-0.0463160027986592

coef	2.5%	97.5%	beta
ZM1:labMitsubis	-6.48054063012295	0	-0.534753607488527
ZM0.1:labNihon	0	0	0.00595629858996349
ZM1:labNihon	-1.65190405446594	1.21366311140615	-0.234355918547412
ZM0.1:labPoulenc	0	5.9379168678425	0.600722346926037
ZM1:labPoulenc	0	0	0.177931230367605
ZM0.1:labSumitomo	0	29.2148984828894	9.320695104568
ZM1:labSumitomo	-26.4517569094168	0	-7.4713740744158
ZM0.1:labTNO	36.9508511947017	73.8902716467913	56.9785749113444
ZM1:labTNO	0	33.0224661223427	15.3382562174175
ZM0.1:labWIL	-0.65936808613842	3.2745489419638	0.224389472303372
ZM1:labWIL	0	16.6474744868292	1.92309520818635
ZM0.1:labZeneca	41.3417270375553	70.3127742061609	55.9459513556495
ZM1:labZeneca	25.4454925287635	54.6164026767922	39.0808743065111

```
kable((ci.all), format = "markdown")
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	2.5%	97.5%	avg
beta[1]	8.8365014	11.3157390	1.010393e+01
beta[2]	-35.5481331	-7.2303389	-2.194679e+01
beta[3]	-15.3633936	6.2030236	-2.444652e+00
beta[4]	-10.0607058	9.0074942	-2.403781e-01
beta[5]	1.8639767	27.2705865	1.497987e+01
beta[6]	-4.1845423	18.9069612	4.652796e+00
beta[7]	-2.6668646	11.7070554	2.520891e+00
beta[8]	-6.1158319	13.3485869	1.811556e+00
beta[9]	-3.7520377	19.7476013	4.780068e+00
beta[10]	-1.2758324	16.0327748	5.710292e+00
beta[11]	-42.7132883	-2.3263277	-2.378664e+01
beta[12]	-20.4362790	-0.1418263	-1.054050e+01
beta[13]	-28.7650802	-3.7929756	-1.666659e+01
beta[14]	-0.9748967	15.1518507	5.382818e+00
beta[15]	-10.8134752	2.6238819	-2.184642e+00
beta[16]	-27.6174202	1.8925654	-1.096457e+01
beta[17]	-1.5918537	16.9987647	5.536941e+00
beta[18]	-8.0376887	6.4812404	-3.166028e-01
beta[19]	-12.7628959	3.4434788	-2.617430e+00
beta[20]	-6.1073140	8.0502651	2.797168e-01
beta[21]	3.4192654	15.8485231	9.865203e+00
beta[22]	148.5505553	197.4493047	1.732028e+02
beta[23]	156.7079306	209.3245686	1.824887e+02
beta[24]	-0.4820041	-0.2084486	-3.450777e-01
beta[25]	-0.5957285	1.7850036	3.008687e-01
beta[26]	11.4397456	15.0258903	1.320351e+01
beta[27]	14.9067883	19.8549021	1.740912e+01
beta[28]	-48.0333386	-9.1079543	-2.953165e+01
beta[29]	-103.9855754	-63.0491960	-8.379720e+01
beta[30]	-150.1584332	-97.6835043	-1.241106e+02
beta[31]	-2.9856505	2.3114884	-1.305104e-01
beta[32]	-2.2713833	2.9903560	1.859151e-01
beta[33]	-3.7434507	1.1062846	-7.452749e-01
beta[34]	-2.0321831	3.4970301	3.746349e-01

	2.5%	97.5%	avg
beta[35]	-1.0194131	2.4600349	3.871943e-01
beta[36]	-2.9463864	2.2423009	-2.121780e-01
beta[37]	-1.9510140	3.5155818	4.463132e-01
beta[38]	-0.3819274	3.8938185	1.270870e+00
beta[39]	-3.1878659	2.9103142	-8.444010e-02
beta[40]	-3.1058070	0.7042954	-6.952802e-01
beta[41]	-1.7727653	2.1796425	1.003206e-01
beta[42]	-1.1492605	2.0971465	2.289696e-01
beta[43]	-0.7790169	2.6057144	4.854920e-01
beta[44]	-7.3468828	0.6817587	-2.543417e+00
beta[45]	-0.0937489	5.4192344	2.509969e+00
beta[46]	-0.7213705	3.9108728	9.959124e-01
beta[47]	-2.6193193	1.4260846	-2.929527e-01
beta[48]	-3.9167638	0.4977894	-1.225197e+00
beta[49]	-34.7920548	23.1764572	-2.796734e+00
beta[50]	-19.8943344	37.4853244	4.577191e+00
beta[51]	-9.3500232	40.9550427	9.313243e+00
beta[52]	-32.9137200	25.5981573	-1.890928e+00
beta[53]	-18.8270608	13.9090749	-1.440328e+00
beta[54]	-32.5282429	24.9504446	-2.018041e+00
beta[55]	-36.8170466	20.9541657	-4.055351e+00
beta[56]	-21.2480567	11.0096543	-2.588106e+00
beta[57]	-8.4137759	73.5901816	2.194932e+01
beta[58]	-16.2322733	14.0881307	-5.374156e-01
beta[59]	-13.0663692	33.8230748	6.002765e+00
beta[60]	-25.5476929	8.5578773	-5.282263e+00
beta[61]	-21.0228062	9.3443733	-2.981419e+00
beta[62]	-29.0936462	30.4469497	1.402748e-01
beta[63]	-27.4113816	10.7286188	-4.606928e+00
beta[64]	-13.7362072	29.7183498	4.195145e+00
beta[65]	-20.4704319	20.0447721	8.311150e-02
beta[66]	-10.0683533	26.2389378	4.175395e+00
beta0	47.6508185	65.7375120	5.691318e+01
deviance	28440.2695375	28482.0774121	2.845916e+04
lambda.l[1]	0.0031882	2.3446782	5.105991e-01
lambda.l[2]	0.0101551	2.7390222	6.457556e-01
lambda.l[3]	0.0431421	3.9608306	1.146287e+00
lambda.l[4]	0.0587005	3.8361176	1.193139e+00
lambda.l[5]	0.0215315	3.0631228	7.728083e-01
lambda.l[6]	0.0405556	3.8961244	1.096224e+00
lambda.l[7]	0.0477371	3.9363378	1.108687e+00
lambda.l[8]	0.0513177	3.9837403	1.166479e+00
lambda.l[9]	0.0487740	3.9798069	1.079830e+00
lambda.l[10]	0.0291561	3.6682041	9.979569e-01
lambda.l[11]	0.0154245	3.0290944	7.303916e-01
lambda.l[12]	0.0192503	3.2488954	7.862111e-01
lambda.l[13]	0.0171977	3.0697937	7.524282e-01
lambda.l[14]	0.0308350	3.3008325	9.317961e-01
lambda.l[15]	0.0434057	3.7380499	1.068904e+00
lambda.l[16]	0.0308423	3.4736655	9.360505e-01
lambda.l[17]	0.0316535	3.5901378	9.854693e-01
lambda.l[18]	0.0532298	4.0897691	1.170507e+00

	2.5%	97.5%	avg
lambda.l[19]	0.0480695	3.7414024	1.109800e+00
lambda.l[20]	0.0541571	4.0251378	1.157940e+00
lambda.l[21]	0.0157709	2.7868826	6.890049e-01
lambda.l[22]	0.0016490	2.5279695	5.050090e-01
lambda.l[23]	0.0016353	2.3848564	4.976127e-01
lambda.l[24]	0.0030498	2.6038984	5.328624e-01
lambda.l[25]	0.0488746	3.8373979	1.108734e+00
lambda.l[26]	0.0037399	2.5452039	5.480747e-01
lambda.l[27]	0.0044487	2.6285197	5.595168e-01
lambda.l[28]	0.0169323	2.9798364	7.058398e-01
lambda.l[29]	0.0063239	2.6948191	5.880865e-01
lambda.l[30]	0.0063801	2.4701565	5.597687e-01
lambda.l[31]	0.0577059	4.0198951	1.131808e+00
lambda.l[32]	0.0484858	4.0138294	1.152321e+00
lambda.l[33]	0.0448972	3.9895523	1.103072e+00
lambda.l[34]	0.0551721	4.0831373	1.170724e+00
lambda.l[35]	0.0564754	4.0943049	1.156631e+00
lambda.l[36]	0.0473066	4.0688921	1.172528e+00
lambda.l[37]	0.0483418	4.1778554	1.170805e+00
lambda.l[38]	0.0337724	3.5870260	9.853317e-01
lambda.l[39]	0.0622667	4.0493989	1.152929e+00
lambda.l[40]	0.0422016	4.0479546	1.104503e+00
lambda.l[41]	0.0517579	3.5826133	1.120556e+00
lambda.l[42]	0.0553602	3.8964854	1.145804e+00
lambda.l[43]	0.0434383	3.6793352	1.082284e+00
lambda.l[44]	0.0322688	3.3768723	9.522361e-01
lambda.l[45]	0.0245242	3.1545299	8.396896e-01
lambda.l[46]	0.0404574	3.6502095	1.074084e+00
lambda.l[47]	0.0467243	4.1091030	1.160815e+00
lambda.l[48]	0.0449567	3.6406617	9.965603e-01
lambda.l[49]	0.0537043	3.8452006	1.163394e+00
lambda.l[50]	0.0526893	4.0465729	1.141596e+00
lambda.l[51]	0.0428696	3.9683189	1.111151e+00
lambda.l[52]	0.0527862	3.8839950	1.159493e+00
lambda.l[53]	0.0545172	3.9389200	1.194681e+00
lambda.l[54]	0.0535716	4.1943350	1.177619e+00
lambda.l[55]	0.0632276	3.9625311	1.179642e+00
lambda.l[56]	0.0595880	3.7703189	1.127434e+00
lambda.l[57]	0.0401704	3.7402610	1.043949e+00
lambda.l[58]	0.0509127	3.8799609	1.157144e+00
lambda.l[59]	0.0503856	3.8722314	1.145341e+00
lambda.l[60]	0.0499328	3.6672722	1.121327e+00
lambda.l[61]	0.0581146	3.8858736	1.126073e+00
lambda.l[62]	0.0549518	3.6704406	1.161368e+00
lambda.l[63]	0.0473105	4.0724429	1.152643e+00
lambda.l[64]	0.0541267	4.1052285	1.162788e+00
lambda.l[65]	0.0570178	3.8350682	1.149015e+00
lambda.l[66]	0.0500898	3.9531481	1.144425e+00
phi.l[1]	0.0001381	0.4103465	1.931195e-01
phi.l[2]	0.0019335	2.6300644	5.846634e-01
phi.l[3]	0.0470746	1273.4405237	1.435267e+03
phi.l[4]	0.0367869	1495.3680483	1.062121e+04

	2.5%	97.5%	avg
phi.l[5]	0.0038941	7.6883265	4.984731e+01
phi.l[6]	0.0282721	566.4235951	1.012865e+04
phi.l[7]	0.0212342	765.5806686	2.541725e+05
phi.l[8]	0.0363941	1701.1246255	1.862788e+06
phi.l[9]	0.0289427	651.9251126	3.055818e+03
phi.l[10]	0.0000218	194.5860072	2.809590e+02
phi.l[11]	0.0046140	8.0265599	4.076660e+01
phi.l[12]	0.0022147	18.4789977	2.444695e+03
phi.l[13]	0.0035392	5.8721953	3.113231e+00
phi.l[14]	0.0117195	186.5831164	3.635489e+03
phi.l[15]	0.0364760	644.5272140	3.803349e+02
phi.l[16]	0.0093039	140.5030970	8.509154e+02
phi.l[17]	0.0140974	212.7067943	5.047895e+02
phi.l[18]	0.0535304	1474.9979819	6.267587e+04
phi.l[19]	0.0318647	873.1017896	8.021387e+03
phi.l[20]	0.0424449	1934.3901089	4.115974e+03
phi.l[21]	0.0021357	4.2027845	1.038074e+00
phi.l[22]	0.0000213	0.1464476	2.490330e-02
phi.l[23]	0.0000285	0.2553721	5.495620e-02
phi.l[24]	0.0000862	0.5281239	6.399010e-02
phi.l[25]	0.0317122	793.1107355	1.272974e+04
phi.l[26]	0.0002526	0.7681272	1.026946e-01
phi.l[27]	0.0002864	0.6170216	1.090302e-01
phi.l[28]	0.0020085	3.4736911	6.634432e-01
phi.l[29]	0.0005309	1.1221278	2.945256e-01
phi.l[30]	0.0005714	1.0962943	1.523273e-01
phi.l[31]	0.0509132	1567.4702930	5.748538e+03
phi.l[32]	0.0437086	1906.8161635	2.594940e+07
phi.l[33]	0.0282398	1009.2114265	8.998192e+03
phi.l[34]	0.0530758	1545.5022542	9.767835e+03
phi.l[35]	0.0063966	1274.0185798	1.754748e+03
phi.l[36]	0.0079204	2992.3252910	2.585482e+03
phi.l[37]	0.0459128	1522.2095664	1.172974e+05
phi.l[38]	0.0160658	312.5298300	1.438986e+04
phi.l[39]	0.0523330	1672.5737607	1.099922e+03
phi.l[40]	0.0175153	718.7931221	1.236629e+04
phi.l[41]	0.0258521	1478.6482319	1.036675e+05
phi.l[42]	0.0166906	1397.6056301	1.719696e+03
phi.l[43]	0.0341116	1673.2034364	5.090324e+03
phi.l[44]	0.0160282	285.3990834	3.581003e+02
phi.l[45]	0.0105659	66.8013562	1.085811e+04
phi.l[46]	0.0125340	912.6103621	3.686919e+03
phi.l[47]	0.0359206	1424.9071140	4.263917e+04
phi.l[48]	0.0176843	495.2081341	4.727162e+04
phi.l[49]	0.0616489	1971.7105622	1.201982e+04
phi.l[50]	0.0543708	1523.9123946	1.476967e+04
phi.l[51]	0.0341761	1706.3530762	2.095626e+03
phi.l[52]	0.0672256	1583.9766130	2.674527e+05
phi.l[53]	0.0632146	2337.5012071	3.044488e+04
phi.l[54]	0.0521276	1821.2970220	4.967040e+04
phi.l[55]	0.0627032	1459.0331835	2.597141e+04
phi.l[56]	0.0584466	1807.7582769	2.116757e+04

	2.5%	97.5%	avg
phi.l[57]	0.0103806	414.6948496	4.747299e+04
phi.l[58]	0.0445868	1827.5956709	2.976761e+04
phi.l[59]	0.0301180	1507.9346464	2.699966e+03
phi.l[60]	0.0326768	1350.6065404	1.540829e+04
phi.l[61]	0.0417732	2217.6793119	9.760032e+03
phi.l[62]	0.0407344	2246.2814382	1.269737e+04
phi.l[63]	0.0328065	1199.4214958	1.967799e+04
phi.l[64]	0.0389523	1119.1234934	5.794659e+03
phi.l[65]	0.0505939	1611.8788315	4.709987e+03
phi.l[66]	0.0413778	1582.7616668	3.417997e+03
sigma	47.9615921	50.6070721	4.923983e+01