

# Impact of food availability and light on *S. purpuratus* larval growth - data analysis

```
library('dplyr')
library('readr')
library('ggplot2')
library('ggdist')
library('knitr')
library('tidyr')
library('emmeans')
library('rstan')
rstan::rstan_options(auto_write = TRUE)
library('brms')
options(mc.cores = parallel::detectCores()) # run all cores
library('bayesplot')
library('marginaleffects')
library('ggdist')

nchain = 4
niter = 2500
moment_match = TRUE
```

## 1. Data overview

Making a data set containing only the data on *S. purpuratus* larvae.

```
Sp_df <- read_delim("larval_morphology.csv", delim = ",",
  col_types = "fffnfifffiniif")
Sp_df = drop_na(Sp_df, length)
# make Pl_df$larva by concatenating Pl_df$species with Pl_df$larva
Sp_df$larva <- as.factor(paste0(Sp_df$species, Sp_df$larva))
Sp_df <- Sp_df[Sp_df$species == "Sp",]
Sp_df <- Sp_df[Sp_df$length > 0,]
Sp_df <- Sp_df[! is.na(Sp_df$length),]
#ensure correct order for levels
Sp_df<-Sp_df %>% mutate(lit = factor(lit, levels = c("DD", "LD", "LL")))
Sp_df<-Sp_df %>% mutate(rod = factor(rod, levels = c("BR", "PO", "ALA")))

print(paste0('There are ', dim(Sp_df)[1], ' measures from ', length(unique(Sp_df$larva)), ' individual larvae.'))

## [1] "There are 573 measures from 111 individual larvae."

head(Sp_df)

## # A tibble: 6 x 15
##   larva side rod   length ate Food_conc Food_species fed lit condition
##   <fct> <fct> <fct>   <dbl> <fct>      <int> <fct>      <fct> <fct> <fct>
## 1 Sp1   R     PO    105. NO         5 D_tertiolecta Fed LD DMSO
## 2 Sp1   R     ALA    169. NO         5 D_tertiolecta Fed LD DMSO
```

```
## 3 Sp1 L BR 170 NO 5 D_tertiolecta Fed LD DMSO
## 4 Sp1 L PO 92.7 NO 5 D_tertiolecta Fed LD DMSO
## 5 Sp2 R BR 184 NO 5 D_tertiolecta Fed LD DMSO
## 6 Sp2 R PO 80.9 NO 5 D_tertiolecta Fed LD DMSO
## # i 5 more variables: larvae_per_well <int>, lar_ml <dbl>, hpf <int>,
## # dpf <int>, species <fct>
```

For the statistical analysis length needs to be scaled to L.

```
meanL <- mean(Sp_df$length)
sdL <- sd(Sp_df$length)

Sp_df$L <- as.numeric(scale(Sp_df$length))
Sp_df <- droplevels(Sp_df) # drop factor levels which are absent
head(Sp_df)
```

```
## # A tibble: 6 x 16
## larva side rod length ate Food_conc Food_species fed lit condition
## <fct> <fct> <fct> <dbl> <fct> <int> <fct> <fct> <fct> <fct>
## 1 Sp1 R PO 105. NO 5 D_tertiolecta Fed LD DMSO
## 2 Sp1 R ALA 169. NO 5 D_tertiolecta Fed LD DMSO
## 3 Sp1 L BR 170 NO 5 D_tertiolecta Fed LD DMSO
## 4 Sp1 L PO 92.7 NO 5 D_tertiolecta Fed LD DMSO
## 5 Sp2 R BR 184 NO 5 D_tertiolecta Fed LD DMSO
## 6 Sp2 R PO 80.9 NO 5 D_tertiolecta Fed LD DMSO
## # i 6 more variables: larvae_per_well <int>, lar_ml <dbl>, hpf <int>,
## # dpf <int>, species <fct>, L <dbl>
```

The chunk below produces a data summary for each condition. In column n we calculated also the number of observations.

```
Sp_df %>% group_by(species, dpf, lar_ml, lit, condition, fed) %>%
  summarise(mean = mean(length, na.rm = TRUE), stdev = sd(length, na.rm = TRUE),
            n = n())
```

```
## `summarise()` has grouped output by 'species', 'dpf', 'lar_ml', 'lit',
## 'condition'. You can override using the `.groups` argument.
```

```
## # A tibble: 8 x 9
## # Groups: species, dpf, lar_ml, lit, condition [4]
## species dpf lar_ml lit condition fed mean stdev n
## <fct> <int> <dbl> <fct> <fct> <fct> <dbl> <dbl> <int>
## 1 Sp 6 25 DD DMSO Fed 129. 36.2 71
## 2 Sp 6 25 DD DMSO Starved 131. 37.9 81
## 3 Sp 6 25 DD TH_inh_10nM Fed 130. 38.1 40
## 4 Sp 6 25 DD TH_inh_10nM Starved 130. 34.8 54
## 5 Sp 6 25 LD DMSO Fed 139. 34.3 96
## 6 Sp 6 25 LD DMSO Starved 147. 28.8 88
## 7 Sp 6 25 LD TH_inh_10nM Fed 143. 31.1 86
## 8 Sp 6 25 LD TH_inh_10nM Starved 142. 34.3 57
```

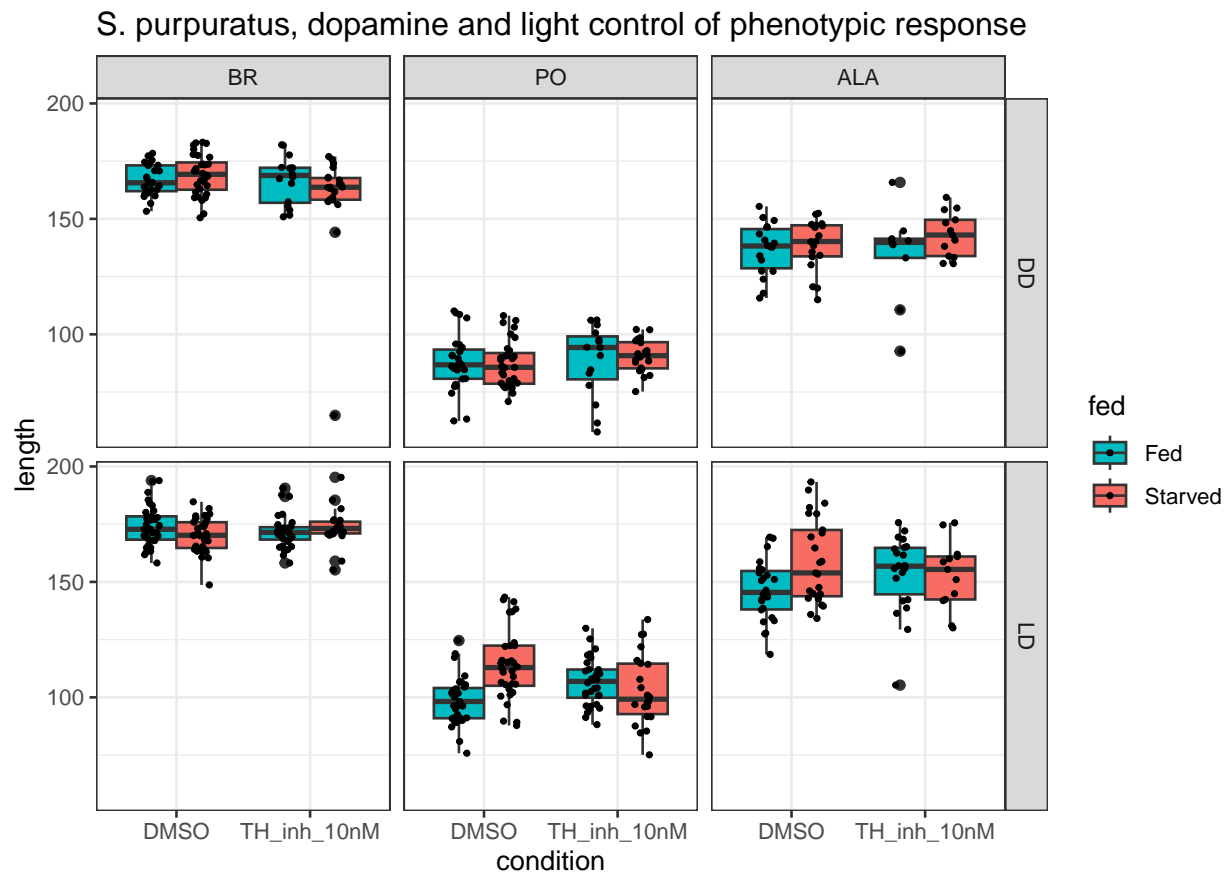
## EXPERIMENTAL SETUP AND AIM

We are interested in investigating how the light-dark cycle (lit) influence the phenotypic response to food availability (fed): larvae grow much shorter arms when food is abundant enough to allow maternal storage; on the contrary, when food is scarce they develop much longer arms to maximize their capability to collect food. This response is controlled by a dopaminergic signalling. To interfere with this signalling we used an in

inhibitor of the TH (one of the enzymes involved in the dopamine synthesis) and DMSO as negative control. Three sets of spicules have been measured: Body Rod (BR), Post Oral (PO), and Anterolateral (ALA) arms.

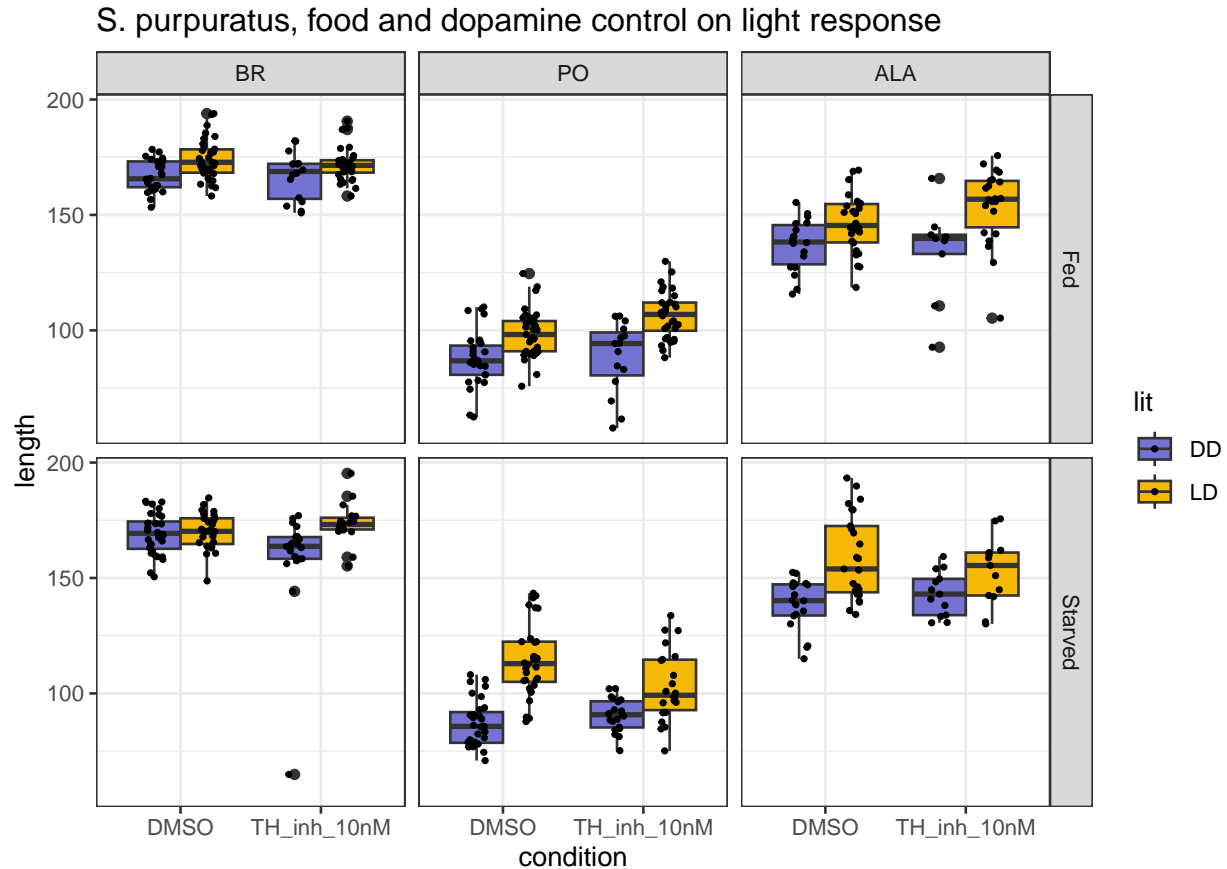
## PLOT DATA OVERVIEW

```
Sp_df %>%
  ggplot(aes(y=length,x=condition, fill=fed)) +
  facet_grid(lit~rod ) +
  geom_boxplot(position = position_dodge(width = 0.75)) +
  geom_jitter(position = position_jitterdodge(jitter.width = 0.25, dodge.width = 0.75), size=0.7)+
  scale_fill_manual(values=c("#00BBC1", "#F86D63"))+
  #geom_violin()+
  theme_bw()+
  theme(axis.text.x = element_text(angle = 0, hjust = 0.5)) +
  ggtitle("S. purpuratus, dopamine and light control of phenotypic response")
```



```
Sp_df %>%
  ggplot(aes(y=length,x=condition, fill=lit, )) +
  facet_grid(fed~ rod) +
  geom_boxplot(position = position_dodge(width = 0.75)) +
  geom_jitter(position = position_jitterdodge(jitter.width = 0.25, dodge.width = 0.75), size=0.7)+
  scale_fill_manual(values=c("#7473d1", "#f5b905", "#d62222"))+
  #geom_violin()+
  theme_bw()+
  theme(axis.text.x = element_text(angle = 0, hjust = 0.5)) +
```

```
ggtitle("S. purpuratus, food and dopamine control on light response")
```



## 2. Statistics

### PRIOR PREDICTIVE TEST

#### M0 Single intercept

Set priors on slope. Weakly informative priors are used to guide the model.

Each treatment should be replicated sufficiently within each larva to capture the treatment effect accurately. Typically, having at least 3-5 measurements per treatment per larva can provide a reasonable balance between model complexity and data sufficiency.

Ideally, we would represent the data as a nested structure, with larvae nested within species. This would allow us to estimate the variance components for the species and larva levels. However, given the low number of measures per larva, it might be challenging to estimate these variance components reliably. Therefore, we will start with a simpler model that includes only the larva level as a random effect.

```
get_prior(bf(L ~ 1, sigma ~1), data=Sp_df)
```

```
##           prior      class coef group resp  dpar nlpar lb ub  source
## student_t(3, 0.2, 2.5) Intercept                                     default
## student_t(3, 0, 2.5) Intercept                                     sigma  default
```

```
si_priors <- c(
  set_prior("normal(0, 0.5)", class = "Intercept"), # prior for intercept
```

```

    set_prior("student_t(3, 0, 0.5)", class = "sd", group = "larva"), # Student's t prior for group-level
    set_prior("student_t(3, 0, 0.5)", dpar = "sigma", class = "Intercept") # Student's t prior for resid
  )

```

The zeroth model is built to check the effect of the group level and see how the data is distributed overall. The nesting structure explicitly acknowledges the hierarchical nature of the data. This helps to avoid pseudoreplication and ensures that the estimates of variance components are not biased.

```

Sp_intercept_mod <- brm(
  bf(L ~ 1 + (1|larva), sigma ~ 1),
  family = gaussian,
  data=Sp_df, prior = si_priors,
  chains = nchain,
  iter = niter, warmup = niter/2,
  save_pars = save_pars(all = TRUE)
)
Sp_intercept_mod

```

```

## Family: gaussian
## Links: mu = identity; sigma = log
## Formula: L ~ 1 + (1 | larva)
##          sigma ~ 1
## Data: Sp_df (Number of observations: 573)
## Draws: 4 chains, each with iter = 2500; warmup = 1250; thin = 1;
##        total post-warmup draws = 5000
##
## Multilevel Hyperparameters:
## ~larva (Number of levels: 111)
##          Estimate Est.Error 1-95% CI u-95% CI Rhat Bulk_ESS Tail_ESS
## sd(Intercept)    0.05      0.04    0.00    0.13 1.00    3742    2780
##
## Regression Coefficients:
##          Estimate Est.Error 1-95% CI u-95% CI Rhat Bulk_ESS Tail_ESS
## Intercept      -0.00      0.04   -0.08    0.08 1.00    10618    3351
## sigma_Intercept  0.00      0.03   -0.06    0.06 1.00    12612    3364
##
## Draws were sampled using sampling(NUTS). For each parameter, Bulk_ESS
## and Tail_ESS are effective sample size measures, and Rhat is the potential
## scale reduction factor on split chains (at convergence, Rhat = 1).

```

```

get_prior(bf(L ~ rod, sigma ~ rod), data=Sp_df)

```

```

##          prior      class  coef group resp  dpar nlpar lb ub
##          (flat)         b
##          (flat)         b rodALA
##          (flat)         b rodPO
## student_t(3, 0.2, 2.5) Intercept
##          (flat)         b          sigma
##          (flat)         b rodALA      sigma
##          (flat)         b rodPO      sigma
## student_t(3, 0, 2.5) Intercept          sigma
## source
## default
## (vectorized)
## (vectorized)

```

```
##      default
##      default
## (vectorized)
## (vectorized)
##      default

priors <- c(
  set_prior("normal(0, 1)", class = "Intercept"), # prior for intercept
  set_prior("normal(0, 2)", class = "b"),
  set_prior("student_t(3, 0, 1)", class = "sd", group = "larva"), # Student's t prior for group-level
  set_prior("student_t(3, 0, 1)", dpar = "sigma", class = "Intercept"), # Student's t prior for residual

  set_prior("normal(0, 2)", class = "b", dpar = "sigma")
)
```

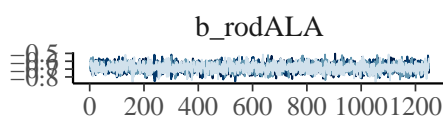
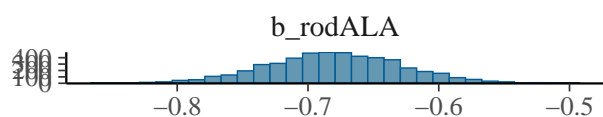
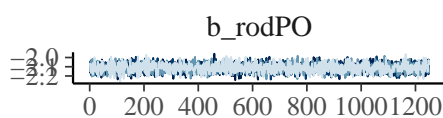
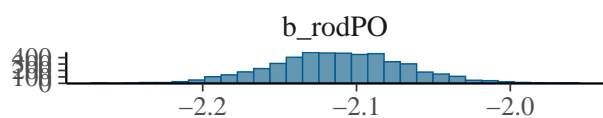
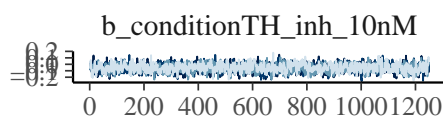
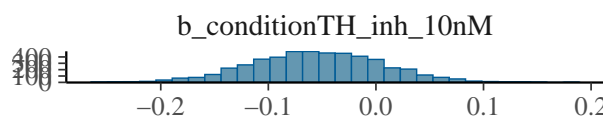
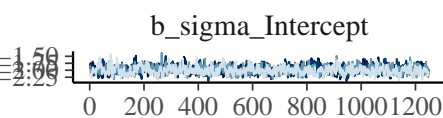
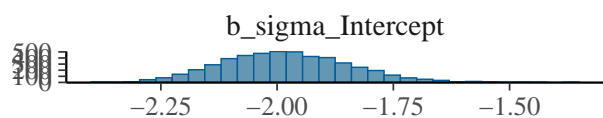
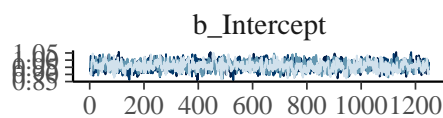
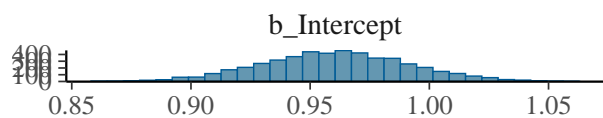
## M1 Rod model

```
Sp_rod_mod <- brm(
  bf(L ~ condition*rod + (1|larva), sigma ~ condition*rod),
  family = gaussian,
  data=Sp_df, prior = priors,
  chains = nchain,
  iter = niter, warmup = niter/2,
  save_pars = save_pars(all = TRUE)
)
Sp_rod_mod
```

```
## Family: gaussian
## Links: mu = identity; sigma = log
## Formula: L ~ condition * rod + (1 | larva)
##          sigma ~ condition * rod
## Data: Sp_df (Number of observations: 573)
## Draws: 4 chains, each with iter = 2500; warmup = 1250; thin = 1;
##          total post-warmup draws = 5000
##
## Multilevel Hyperparameters:
## ~larva (Number of levels: 111)
##          Estimate Est.Error l-95% CI u-95% CI Rhat Bulk_ESS Tail_ESS
## sd(Intercept)    0.22      0.02    0.18    0.27 1.01    1118    1792
##
## Regression Coefficients:
##          Estimate Est.Error l-95% CI u-95% CI Rhat
## Intercept          0.96      0.03    0.90    1.02 1.00
## sigma_Intercept    -1.98      0.14   -2.23   -1.70 1.01
## conditionTH_inh_10nM -0.06      0.06   -0.18    0.06 1.00
## rodPO              -2.11      0.04   -2.20   -2.03 1.00
## rodALA              -0.68      0.05   -0.78   -0.58 1.00
## conditionTH_inh_10nM:rodPO  0.10      0.07   -0.04    0.23 1.00
## conditionTH_inh_10nM:rodALA  0.08      0.08   -0.09    0.24 1.00
## sigma_conditionTH_inh_10nM  1.02      0.16    0.69    1.32 1.01
## sigma_rodPO         1.23      0.18    0.86    1.55 1.01
## sigma_rodALA         1.22      0.18    0.83    1.55 1.01
## sigma_conditionTH_inh_10nM:rodPO -1.50      0.24   -1.95   -1.03 1.01
## sigma_conditionTH_inh_10nM:rodALA -1.30      0.24   -1.76   -0.82 1.01
```

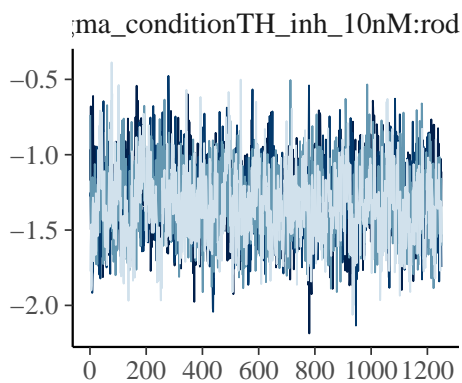
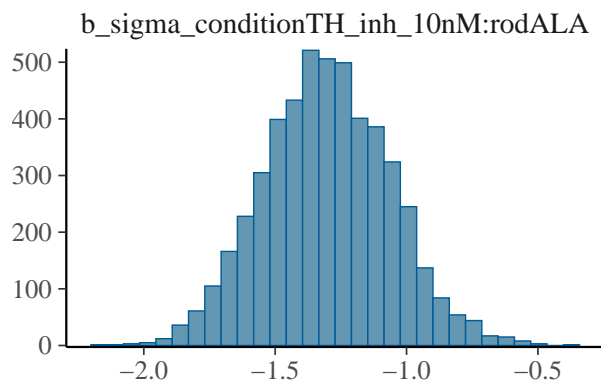
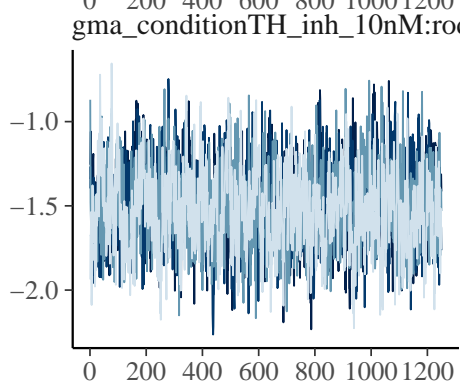
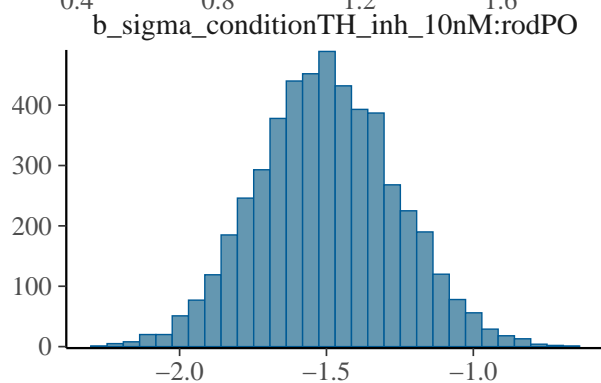
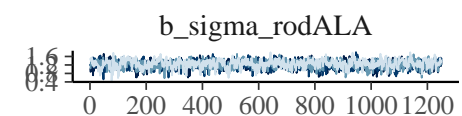
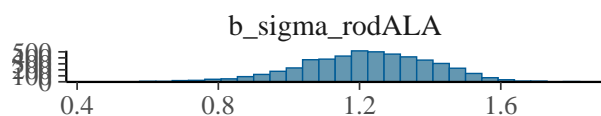
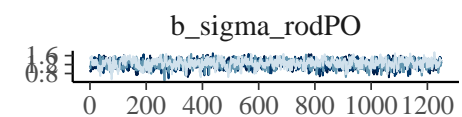
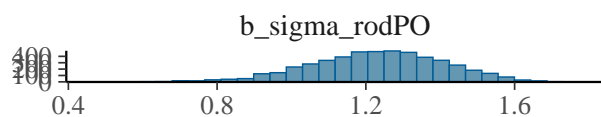
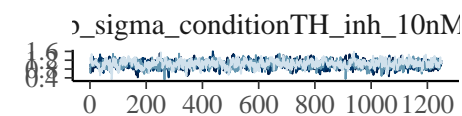
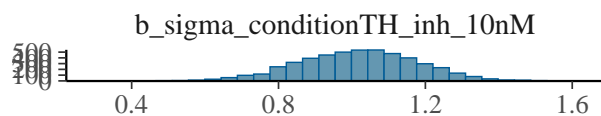
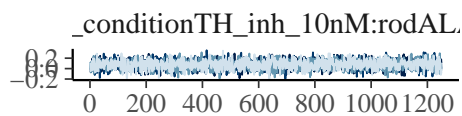
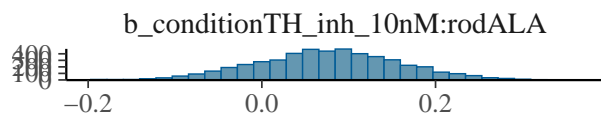
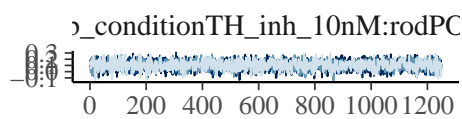
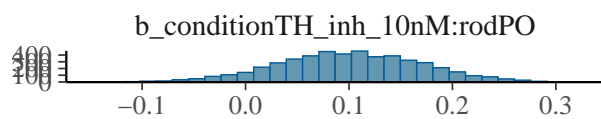
```
##                               Bulk_ESS Tail_ESS
## Intercept                     1301    2050
## sigma_Intercept                739    1619
## conditionTH_inh_10nM          2020    2890
## rodPO                          4768    3790
## rodALA                        4490    3514
## conditionTH_inh_10nM:rodPO     4103    3349
## conditionTH_inh_10nM:rodALA    4027    3530
## sigma_conditionTH_inh_10nM     774    1934
## sigma_rodPO                    810    1722
## sigma_rodALA                   809    1703
## sigma_conditionTH_inh_10nM:rodPO 891    1943
## sigma_conditionTH_inh_10nM:rodALA 927    2102
##
## Draws were sampled using sampling(NUTS). For each parameter, Bulk_ESS
## and Tail_ESS are effective sample size measures, and Rhat is the potential
## scale reduction factor on split chains (at convergence, Rhat = 1).
```

```
plot(Sp_rod_mod, ask=FALSE, variable = "~b_", regex = TRUE)
```



Chain

— 1  
— 2  
— 3  
— 4



Chain

- 1
- 2
- 3
- 4

Chain

- 1
- 2
- 3
- 4



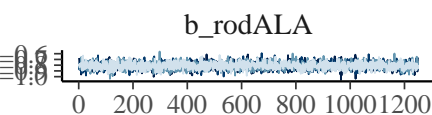
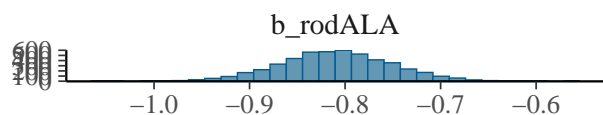
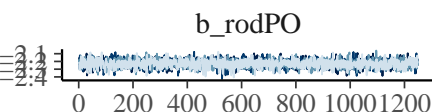
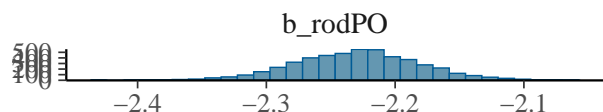
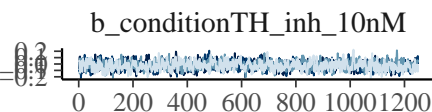
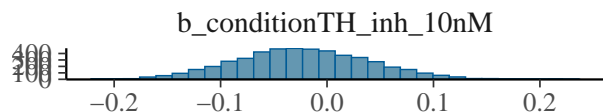
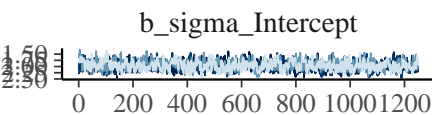
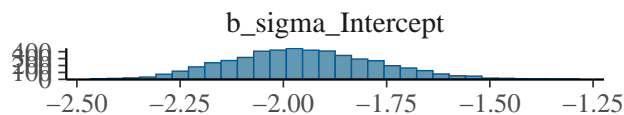
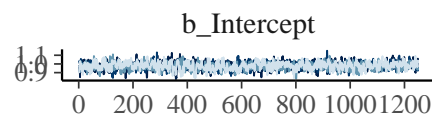
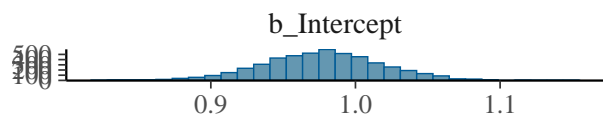
## M2 Rod Fed model

```
Sp_rod_fed_mod <- brm(
  bf(L ~ condition*rod*fed + (1|larva), sigma ~ condition*rod*fed),
  family = gaussian,
  data=Sp_df, prior = priors,
  chains = nchain,
  iter = niter, warmup = niter/2,
  save_pars = save_pars(all = TRUE)
)
Sp_rod_fed_mod
```

```
## Family: gaussian
## Links: mu = identity; sigma = log
## Formula: L ~ condition * rod * fed + (1 | larva)
##          sigma ~ condition * rod * fed
## Data: Sp_df (Number of observations: 573)
## Draws: 4 chains, each with iter = 2500; warmup = 1250; thin = 1;
##        total post-warmup draws = 5000
##
## Multilevel Hyperparameters:
## ~larva (Number of levels: 111)
##           Estimate Est.Error 1-95% CI u-95% CI Rhat Bulk_ESS Tail_ESS
## sd(Intercept)      0.21      0.02    0.17    0.25 1.00     1399     2562
##
## Regression Coefficients:
##                                     Estimate Est.Error 1-95% CI
## Intercept                          0.98      0.04    0.89
## sigma_Intercept                     -1.95     0.18   -2.28
## conditionTH_inh_10nM                 -0.02     0.06   -0.14
## rodPO                                -2.23     0.05   -2.33
## rodALA                               -0.81     0.06   -0.92
## fedStarved                           -0.04     0.06   -0.15
## conditionTH_inh_10nM:rodPO             0.22     0.08    0.07
## conditionTH_inh_10nM:rodALA             0.14     0.11   -0.07
## conditionTH_inh_10nM:fedStarved        -0.07     0.12   -0.31
## rodPO:fedStarved                       0.23     0.09    0.07
## rodALA:fedStarved                       0.26     0.10    0.06
## conditionTH_inh_10nM:rodPO:fedStarved   -0.24     0.14   -0.51
## conditionTH_inh_10nM:rodALA:fedStarved  -0.14     0.17   -0.46
## sigma_conditionTH_inh_10nM              0.08     0.25   -0.40
## sigma_rodPO                             0.87     0.24    0.40
## sigma_rodALA                             0.91     0.25    0.41
## sigma_fedStarved                       -0.02     0.24   -0.50
## sigma_conditionTH_inh_10nM:rodPO        -0.00     0.33   -0.67
## sigma_conditionTH_inh_10nM:rodALA        0.26     0.34   -0.40
## sigma_conditionTH_inh_10nM:fedStarved    1.20     0.31    0.58
## sigma_rodPO:fedStarved                  0.52     0.31   -0.10
## sigma_rodALA:fedStarved                 0.45     0.33   -0.20
## sigma_conditionTH_inh_10nM:rodPO:fedStarved -1.94     0.43   -2.77
## sigma_conditionTH_inh_10nM:rodALA:fedStarved -2.24     0.45   -3.11
##                                     u-95% CI Rhat Bulk_ESS Tail_ESS
## Intercept                          1.06 1.00     1321     2262
## sigma_Intercept                     -1.58 1.01      891     2055
```

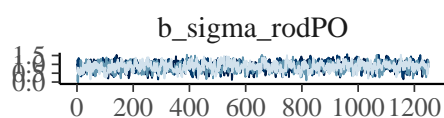
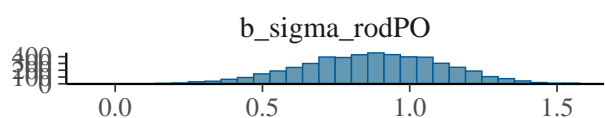
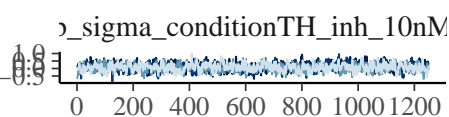
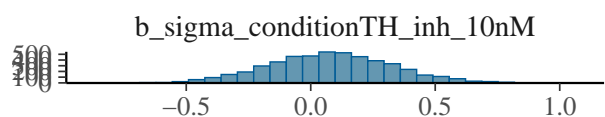
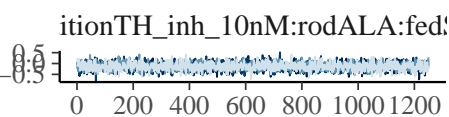
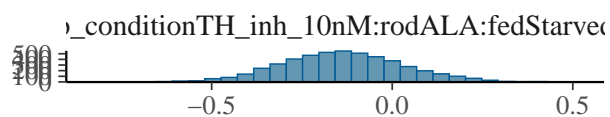
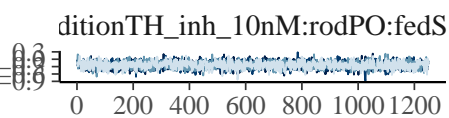
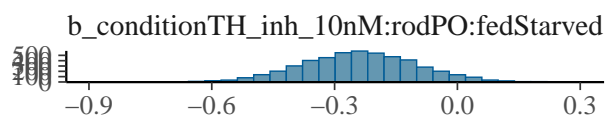
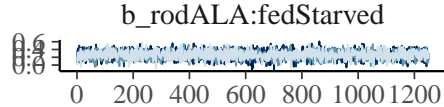
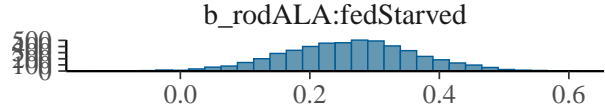
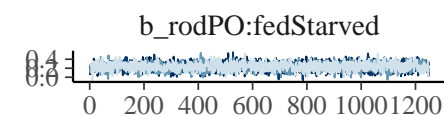
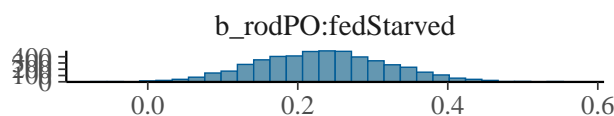
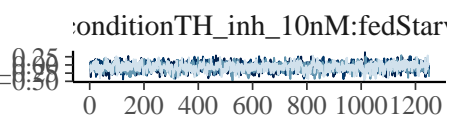
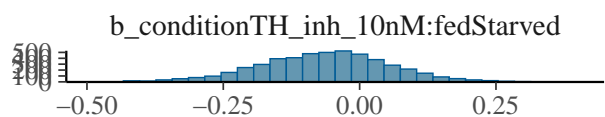
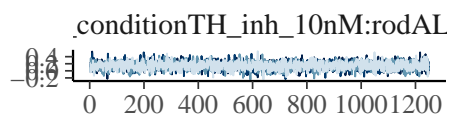
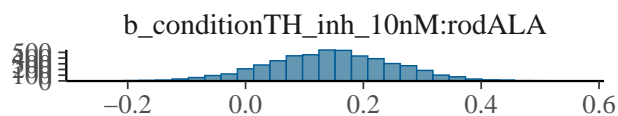
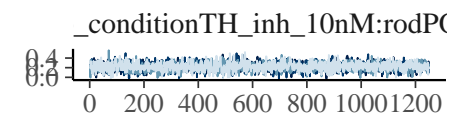
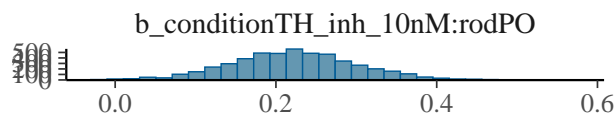
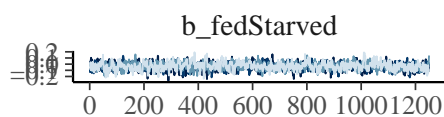
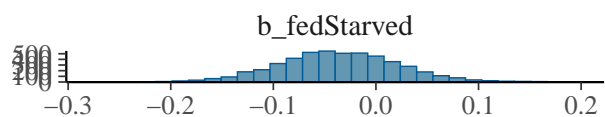
```
## conditionTH_inh_10nM      0.10 1.00      1166      2236
## rodPO                     -2.13 1.00      3674      3297
## rodALA                    -0.69 1.00      3630      3646
## fedStarved                0.08 1.00      1238      1851
## conditionTH_inh_10nM:rodPO 0.38 1.00      3816      3503
## conditionTH_inh_10nM:rodALA 0.35 1.00      3407      3633
## conditionTH_inh_10nM:fedStarved 0.16 1.00      1578      2437
## rodPO:fedStarved          0.40 1.00      3789      3618
## rodALA:fedStarved         0.46 1.00      3787      3703
## conditionTH_inh_10nM:rodPO:fedStarved 0.03 1.00      3083      3657
## conditionTH_inh_10nM:rodALA:fedStarved 0.20 1.00      2868      3680
## sigma_conditionTH_inh_10nM 0.57 1.01       893      1653
## sigma_rodPO               1.31 1.00       984      2179
## sigma_rodALA              1.37 1.00       932      2207
## sigma_fedStarved          0.45 1.01       870      1525
## sigma_conditionTH_inh_10nM:rodPO 0.64 1.01       965      1884
## sigma_conditionTH_inh_10nM:rodALA 0.93 1.01       943      1655
## sigma_conditionTH_inh_10nM:fedStarved 1.83 1.01       818      1839
## sigma_rodPO:fedStarved     1.12 1.00       943      1669
## sigma_rodALA:fedStarved    1.11 1.00       942      1699
## sigma_conditionTH_inh_10nM:rodPO:fedStarved -1.09 1.00       926      2018
## sigma_conditionTH_inh_10nM:rodALA:fedStarved -1.38 1.01       995      1742
##
## Draws were sampled using sampling(NUTS). For each parameter, Bulk_ESS
## and Tail_ESS are effective sample size measures, and Rhat is the potential
## scale reduction factor on split chains (at convergence, Rhat = 1).
```

```
plot(Sp_rod_fed_mod, ask=FALSE, variable = "^b_", regex = TRUE)
```



Chain

— 1  
— 2  
— 3  
— 4

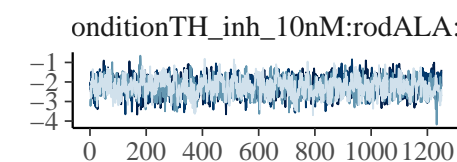
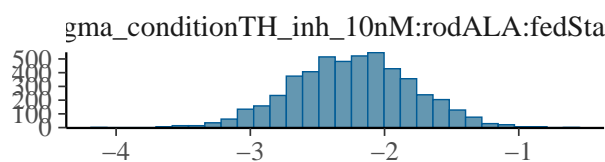
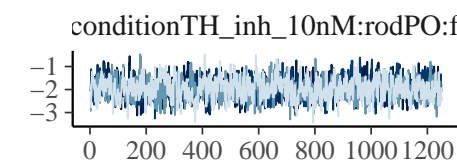
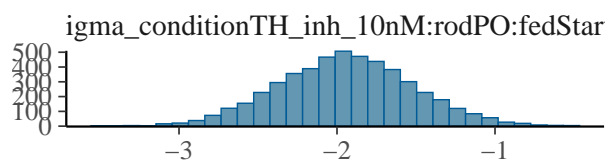
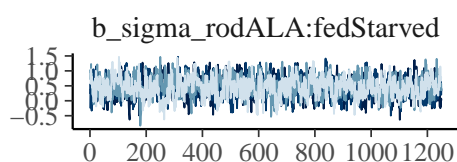
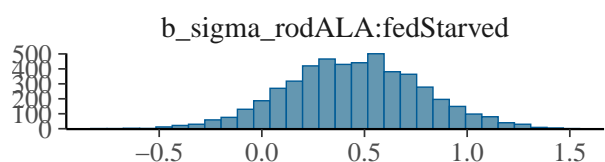
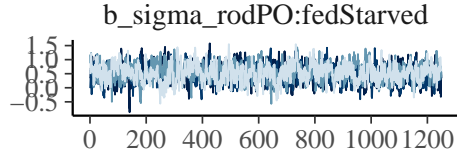
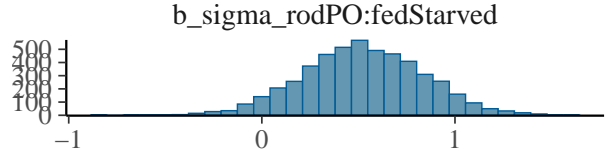
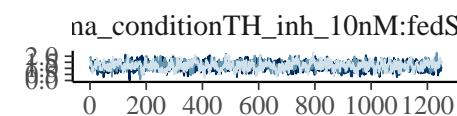
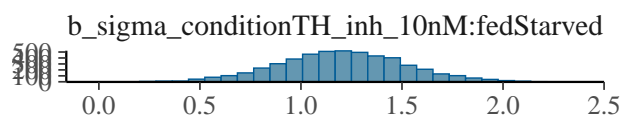
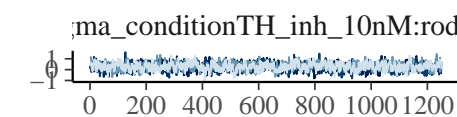
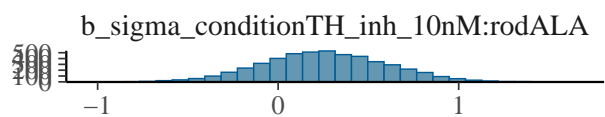
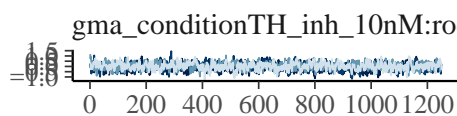
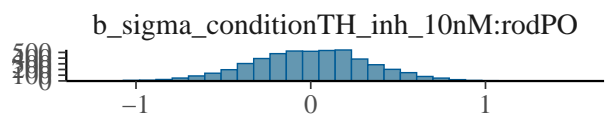
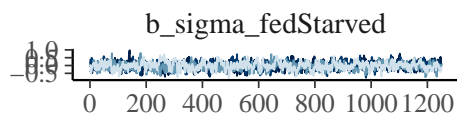
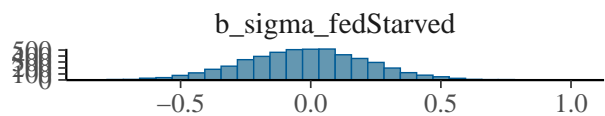
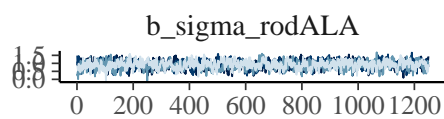
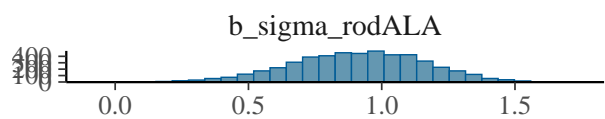


Chain

— 1  
— 2  
— 3  
— 4

Chain

— 1  
— 2  
— 3  
— 4



Chain

- 1
- 2
- 3
- 4

Chain

- 1
- 2
- 3
- 4

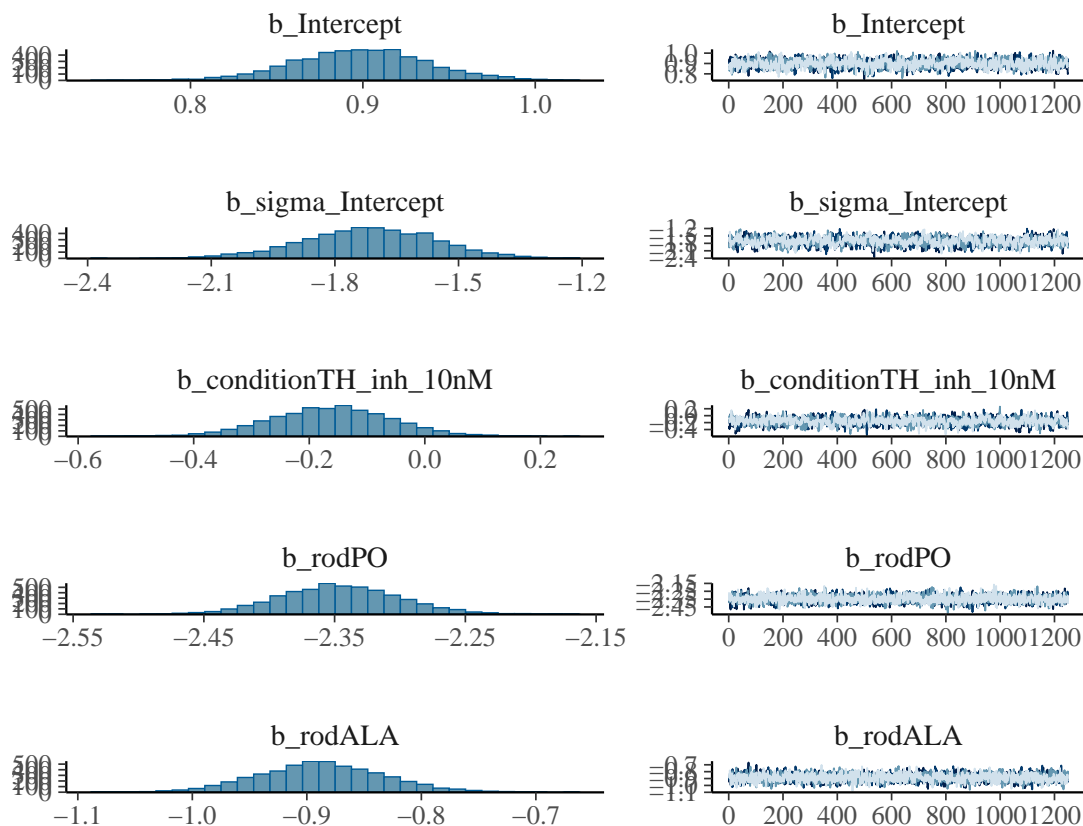
## M3 Rod Lit model

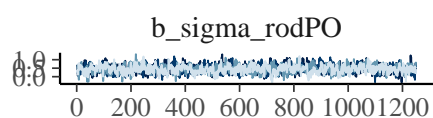
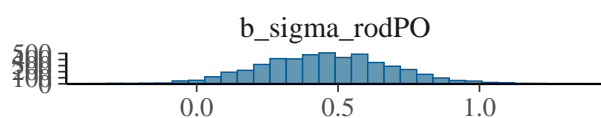
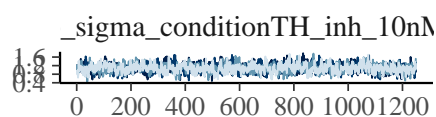
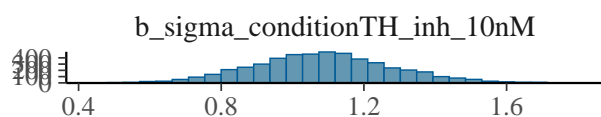
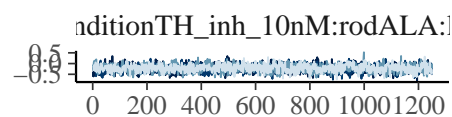
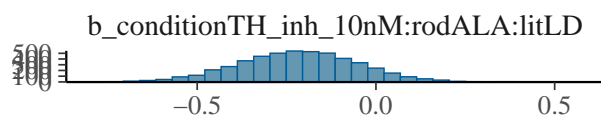
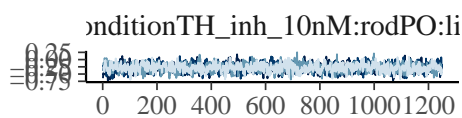
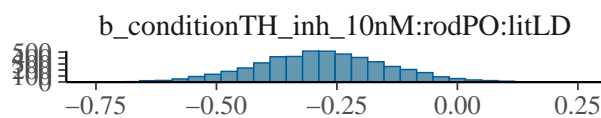
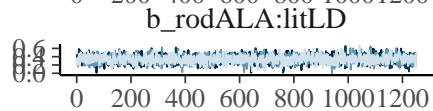
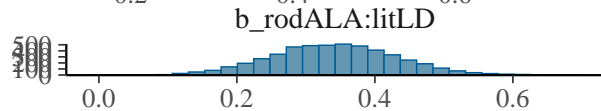
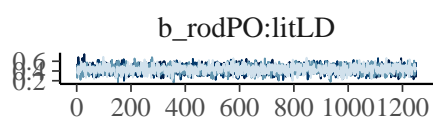
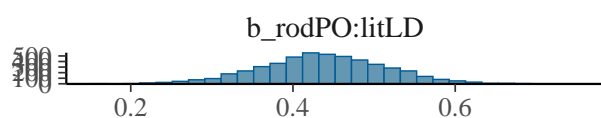
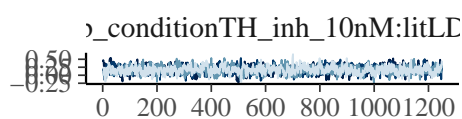
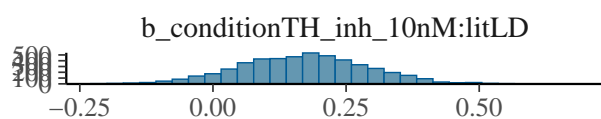
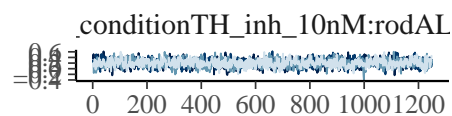
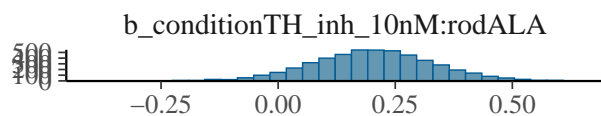
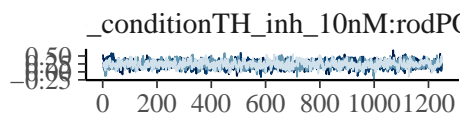
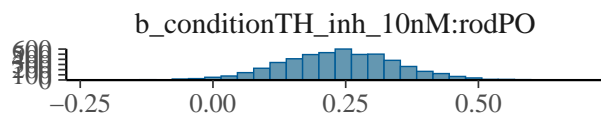
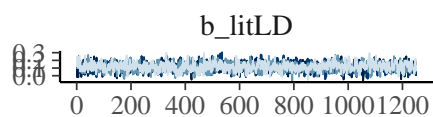
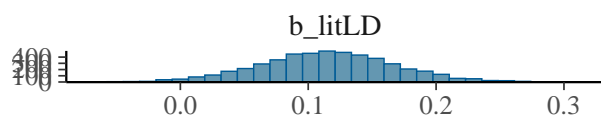
```
Sp_rod_lit_mod <- brm(
  bf(L ~ condition*rod*lit + (1|larva), sigma ~ condition*rod*lit),
  family = gaussian,
  data=Sp_df, prior = priors,
  chains = nchain,
  iter = niter, warmup = niter/2,
  save_pars = save_pars(all = TRUE)
)
Sp_rod_lit_mod
```

```
## Family: gaussian
## Links: mu = identity; sigma = log
## Formula: L ~ condition * rod * lit + (1 | larva)
##          sigma ~ condition * rod * lit
## Data: Sp_df (Number of observations: 573)
## Draws: 4 chains, each with iter = 2500; warmup = 1250; thin = 1;
##        total post-warmup draws = 5000
##
## Multilevel Hyperparameters:
## ~larva (Number of levels: 111)
##           Estimate Est.Error 1-95% CI u-95% CI Rhat Bulk_ESS Tail_ESS
## sd(Intercept)      0.16      0.02   0.13    0.20 1.00      918    2145
##
## Regression Coefficients:
##                                     Estimate Est.Error 1-95% CI u-95% CI
## Intercept                        0.90      0.04   0.82    0.98
## sigma_Intercept                  -1.72     0.16  -2.04   -1.40
## conditionTH_inh_10nM             -0.16     0.11  -0.37    0.04
## rodPO                           -2.35     0.05  -2.43   -2.25
## rodALA                          -0.89     0.05  -0.99   -0.78
## litLD                           0.11     0.05   0.01    0.22
## conditionTH_inh_10nM:rodPO        0.24     0.11   0.02    0.45
## conditionTH_inh_10nM:rodALA       0.20     0.13  -0.05    0.46
## conditionTH_inh_10nM:litLD       0.17     0.12  -0.06    0.40
## rodPO:litLD                     0.44     0.08   0.28    0.59
## rodALA:litLD                    0.34     0.09   0.16    0.52
## conditionTH_inh_10nM:rodPO:litLD -0.28     0.14  -0.55   -0.01
## conditionTH_inh_10nM:rodALA:litLD -0.22     0.17  -0.55    0.10
## sigma_conditionTH_inh_10nM       1.08     0.20   0.71    1.48
## sigma_rodPO                      0.46     0.23   0.02    0.91
## sigma_rodALA                     0.46     0.24   0.00    0.94
## sigma_litLD                     -0.02     0.24  -0.51    0.42
## sigma_conditionTH_inh_10nM:rodPO -1.25     0.31  -1.89   -0.65
## sigma_conditionTH_inh_10nM:rodALA -0.92     0.33  -1.57   -0.27
## sigma_conditionTH_inh_10nM:litLD -1.10     0.30  -1.68   -0.52
## sigma_rodPO:litLD                0.50     0.34  -0.12    1.19
## sigma_rodALA:litLD               0.55     0.34  -0.09    1.25
## sigma_conditionTH_inh_10nM:rodPO:litLD 1.02     0.43   0.16    1.85
## sigma_conditionTH_inh_10nM:rodALA:litLD 0.79     0.44  -0.09    1.63
##                                     Rhat Bulk_ESS Tail_ESS
## Intercept                        1.00    1553    2534
## sigma_Intercept                  1.00     712    1602
```

```
## conditionTH_inh_10nM      1.00      1080      1816
## rodPO                     1.00      2522      2699
## rodALA                    1.00      2812      3356
## litLD                     1.00      1374      2270
## conditionTH_inh_10nM:rodPO 1.00      1215      2121
## conditionTH_inh_10nM:rodALA 1.00      1668      2397
## conditionTH_inh_10nM:litLD 1.00      1106      1826
## rodPO:litLD               1.00      2329      2994
## rodALA:litLD              1.00      2779      3541
## conditionTH_inh_10nM:rodPO:litLD 1.00      1294      2196
## conditionTH_inh_10nM:rodALA:litLD 1.00      1536      2762
## sigma_conditionTH_inh_10nM 1.00       802      1510
## sigma_rodPO               1.00       746      1611
## sigma_rodALA              1.00       802      1814
## sigma_litLD               1.00       596      1289
## sigma_conditionTH_inh_10nM:rodPO 1.00       898      1501
## sigma_conditionTH_inh_10nM:rodALA 1.00       946      1762
## sigma_conditionTH_inh_10nM:litLD 1.00       760      1453
## sigma_rodPO:litLD         1.00       616      1157
## sigma_rodALA:litLD        1.00       688      1394
## sigma_conditionTH_inh_10nM:rodPO:litLD 1.00       859      1635
## sigma_conditionTH_inh_10nM:rodALA:litLD 1.00       906      1707
##
## Draws were sampled using sampling(NUTS). For each parameter, Bulk_ESS
## and Tail_ESS are effective sample size measures, and Rhat is the potential
## scale reduction factor on split chains (at convergence, Rhat = 1).
```

```
plot(Sp_rod_lit_mod, ask=FALSE, variable = "^b_", regex = TRUE)
```



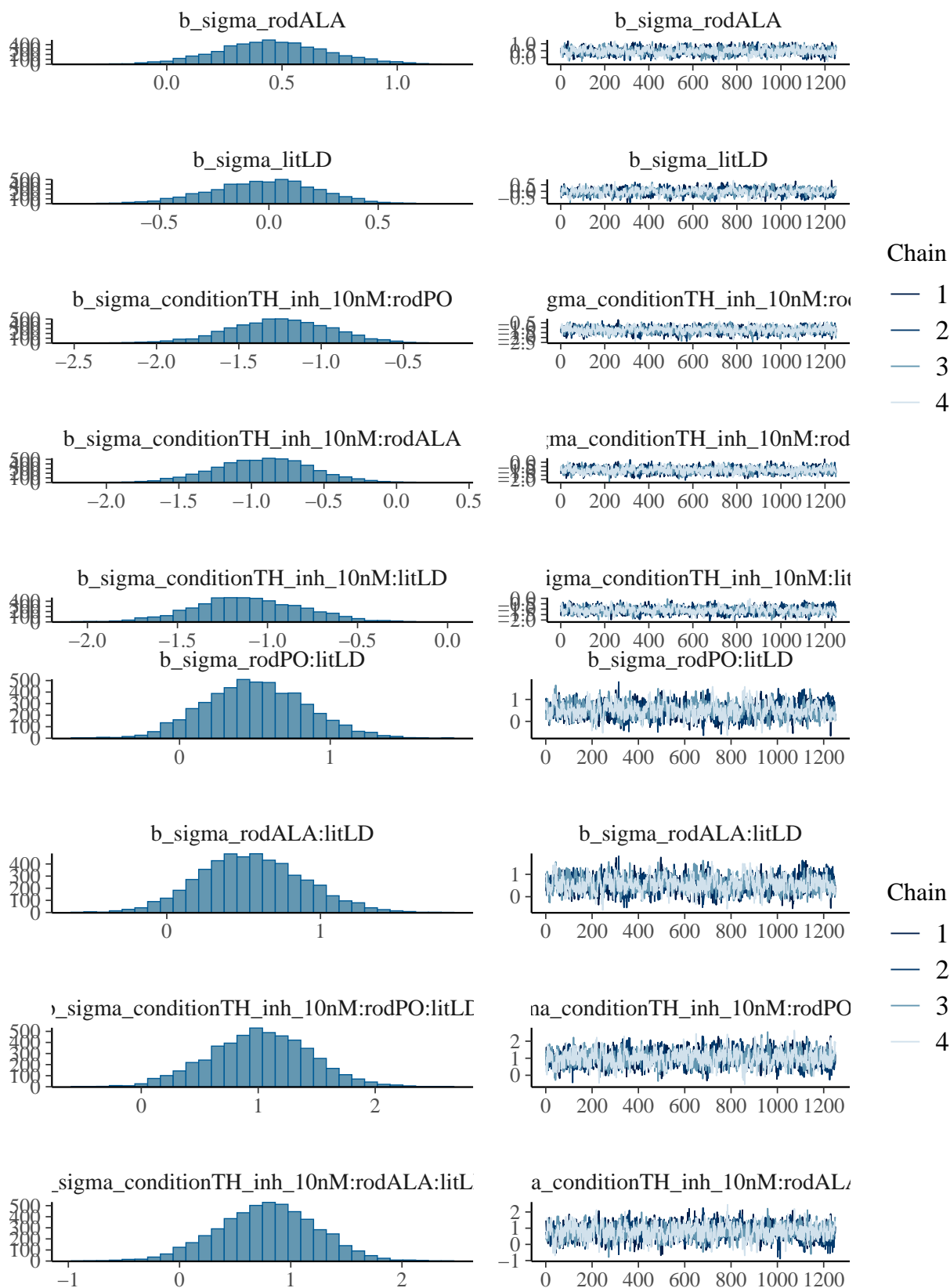


Chain

— 1  
— 2  
— 3  
— 4

Chain

— 1  
— 2  
— 3  
— 4





## M4 condition Rod Fed Lit model

```
Sp_rod_fed_lit_mod <- brm(
  bf(L ~ condition*rod*fed*lit + (1|larva), sigma ~ condition*rod*fed*lit),
  family = gaussian,
  data=Sp_df, prior = priors,
  chains = nchain,
  iter = niter, warmup = niter/2,
  save_pars = save_pars(all = TRUE)
)
Sp_rod_fed_lit_mod
```

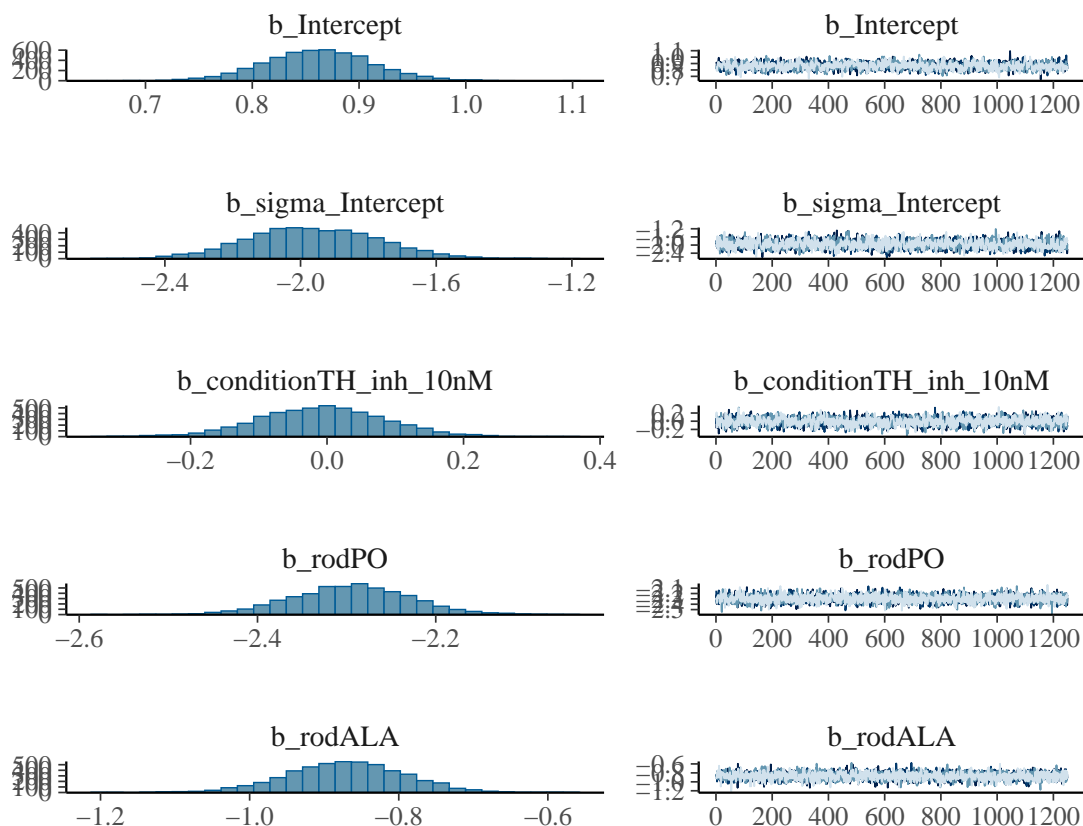
```
## Family: gaussian
## Links: mu = identity; sigma = log
## Formula: L ~ condition * rod * fed * lit + (1 | larva)
##          sigma ~ condition * rod * fed * lit
## Data: Sp_df (Number of observations: 573)
## Draws: 4 chains, each with iter = 2500; warmup = 1250; thin = 1;
##          total post-warmup draws = 5000
##
## Multilevel Hyperparameters:
## ~larva (Number of levels: 111)
##          Estimate Est.Error 1-95% CI u-95% CI Rhat Bulk_ESS Tail_ESS
## sd(Intercept)      0.15      0.02    0.12    0.19 1.00    1430    2983
##
## Regression Coefficients:
##                                     Estimate Est.Error 1-95% CI
## Intercept                        0.86      0.05    0.76
## sigma_Intercept                  -1.96      0.19   -2.33
## conditionTH_inh_10nM             -0.01      0.09   -0.19
## rodPO                           -2.29      0.07   -2.43
## rodALA                          -0.87      0.08   -1.03
## fedStarved                       0.07      0.07   -0.07
## litLD                            0.20      0.07    0.06
## conditionTH_inh_10nM:rodPO        0.04      0.13   -0.22
## conditionTH_inh_10nM:rodALA      -0.05      0.21   -0.45
## conditionTH_inh_10nM:fedStarved  -0.26      0.19   -0.64
## rodPO:fedStarved                 -0.09      0.09   -0.27
## rodALA:fedStarved                -0.04      0.11   -0.27
## conditionTH_inh_10nM:litLD       -0.05      0.12   -0.28
## rodPO:litLD                      0.12      0.09   -0.06
## rodALA:litLD                     0.09      0.11   -0.14
## fedStarved:litLD                 -0.18      0.10   -0.38
## conditionTH_inh_10nM:rodPO:fedStarved 0.33      0.21   -0.08
## conditionTH_inh_10nM:rodALA:fedStarved 0.46      0.27   -0.09
## conditionTH_inh_10nM:rodPO:litLD      0.24      0.16   -0.07
## conditionTH_inh_10nM:rodALA:litLD     0.28      0.24   -0.19
## conditionTH_inh_10nM:fedStarved:litLD 0.42      0.22   -0.01
## rodPO:fedStarved:litLD              0.65      0.14    0.38
## rodALA:fedStarved:litLD             0.52      0.18    0.17
## conditionTH_inh_10nM:rodPO:fedStarved:litLD -1.04      0.26   -1.55
## conditionTH_inh_10nM:rodALA:fedStarved:litLD -0.97      0.34   -1.65
## sigma_conditionTH_inh_10nM         0.36      0.31   -0.26
## sigma_rodPO                       0.78      0.26    0.28
```

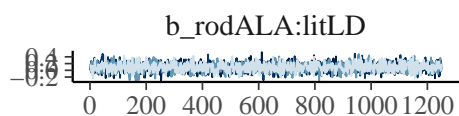
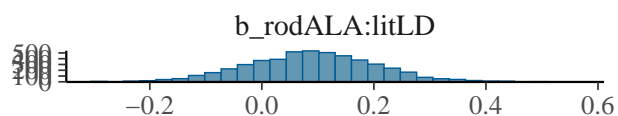
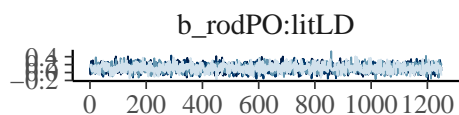
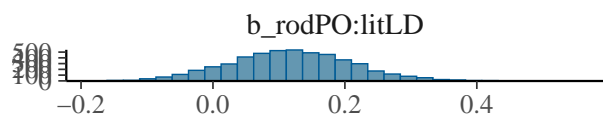
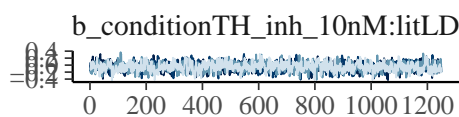
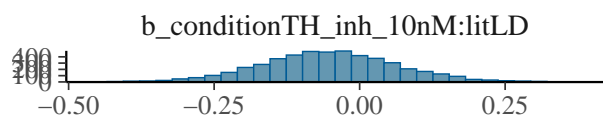
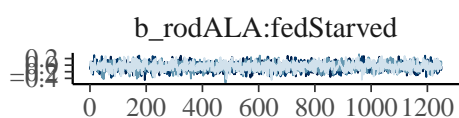
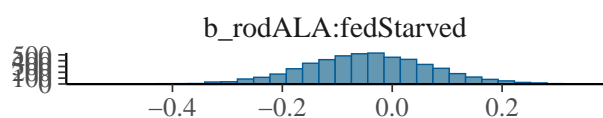
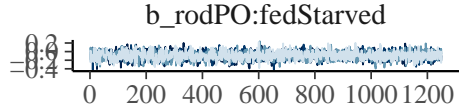
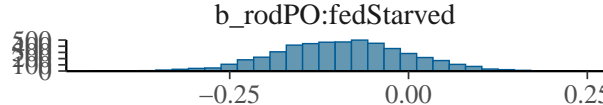
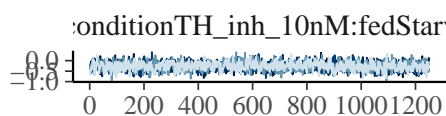
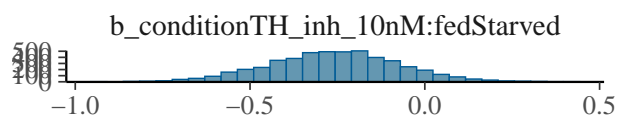
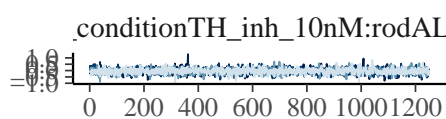
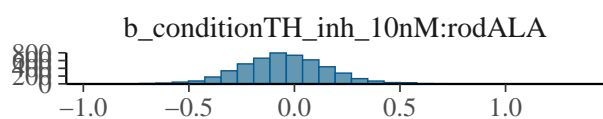
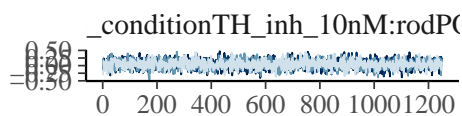
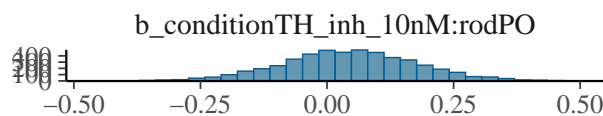
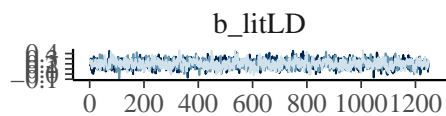
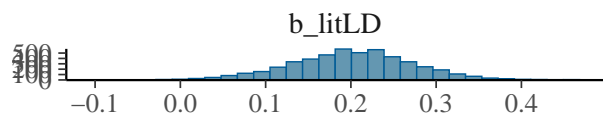
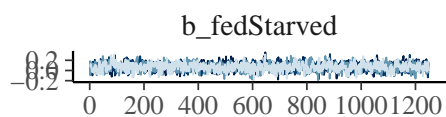
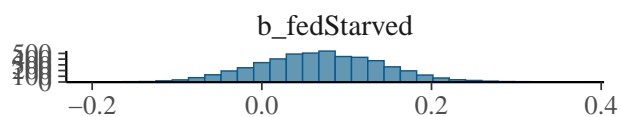
## sigma_rodALA	0.76	0.28	0.21
## sigma_fedStarved	0.45	0.26	-0.09
## sigma_litLD	0.32	0.27	-0.23
## sigma_conditionTH_inh_10nM:rodPO	-0.14	0.42	-0.96
## sigma_conditionTH_inh_10nM:rodALA	0.18	0.45	-0.68
## sigma_conditionTH_inh_10nM:fedStarved	0.75	0.37	0.02
## sigma_rodPO:fedStarved	-0.61	0.38	-1.34
## sigma_rodALA:fedStarved	-0.51	0.40	-1.27
## sigma_conditionTH_inh_10nM:litLD	-0.52	0.40	-1.29
## sigma_rodPO:litLD	-0.28	0.38	-1.00
## sigma_rodALA:litLD	-0.15	0.39	-0.89
## sigma_fedStarved:litLD	-0.61	0.37	-1.33
## sigma_conditionTH_inh_10nM:rodPO:fedStarved	-1.41	0.54	-2.46
## sigma_conditionTH_inh_10nM:rodALA:fedStarved	-1.46	0.58	-2.60
## sigma_conditionTH_inh_10nM:rodPO:litLD	0.21	0.55	-0.89
## sigma_conditionTH_inh_10nM:rodALA:litLD	0.22	0.56	-0.87
## sigma_conditionTH_inh_10nM:fedStarved:litLD	-0.47	0.50	-1.46
## sigma_rodPO:fedStarved:litLD	1.13	0.53	0.07
## sigma_rodALA:fedStarved:litLD	1.04	0.53	-0.02
## sigma_conditionTH_inh_10nM:rodPO:fedStarved:litLD	1.19	0.73	-0.21
## sigma_conditionTH_inh_10nM:rodALA:fedStarved:litLD	0.62	0.74	-0.81
##	u-95% CI	Rhat	Bulk_ESS
## Intercept	0.96	1.00	1706
## sigma_Intercept	-1.59	1.00	1581
## conditionTH_inh_10nM	0.17	1.00	1807
## rodPO	-2.16	1.00	2675
## rodALA	-0.72	1.00	2825
## fedStarved	0.21	1.00	1587
## litLD	0.34	1.00	1634
## conditionTH_inh_10nM:rodPO	0.31	1.00	2584
## conditionTH_inh_10nM:rodALA	0.36	1.00	2709
## conditionTH_inh_10nM:fedStarved	0.11	1.00	1748
## rodPO:fedStarved	0.08	1.00	2684
## rodALA:fedStarved	0.19	1.00	2624
## conditionTH_inh_10nM:litLD	0.18	1.00	1590
## rodPO:litLD	0.30	1.00	2489
## rodALA:litLD	0.32	1.00	2640
## fedStarved:litLD	0.02	1.00	1674
## conditionTH_inh_10nM:rodPO:fedStarved	0.74	1.00	1913
## conditionTH_inh_10nM:rodALA:fedStarved	1.00	1.00	2076
## conditionTH_inh_10nM:rodPO:litLD	0.56	1.00	2359
## conditionTH_inh_10nM:rodALA:litLD	0.76	1.00	2624
## conditionTH_inh_10nM:fedStarved:litLD	0.83	1.00	1597
## rodPO:fedStarved:litLD	0.93	1.00	2703
## rodALA:fedStarved:litLD	0.87	1.00	2798
## conditionTH_inh_10nM:rodPO:fedStarved:litLD	-0.52	1.00	2109
## conditionTH_inh_10nM:rodALA:fedStarved:litLD	-0.30	1.00	2296
## sigma_conditionTH_inh_10nM	0.96	1.01	1085
## sigma_rodPO	1.27	1.00	1697
## sigma_rodALA	1.30	1.00	1788
## sigma_fedStarved	0.95	1.00	1382
## sigma_litLD	0.83	1.00	1074
## sigma_conditionTH_inh_10nM:rodPO	0.68	1.00	1128
## sigma_conditionTH_inh_10nM:rodALA	1.07	1.00	1437

## sigma_conditionTH_inh_10nM:fedStarved	1.47 1.01	1064
## sigma_rodPO:fedStarved	0.14 1.00	1488
## sigma_rodALA:fedStarved	0.30 1.00	1671
## sigma_conditionTH_inh_10nM:litLD	0.26 1.00	959
## sigma_rodPO:litLD	0.48 1.00	1111
## sigma_rodALA:litLD	0.63 1.00	1255
## sigma_fedStarved:litLD	0.12 1.00	1267
## sigma_conditionTH_inh_10nM:rodPO:fedStarved	-0.34 1.01	1255
## sigma_conditionTH_inh_10nM:rodALA:fedStarved	-0.35 1.00	1460
## sigma_conditionTH_inh_10nM:rodPO:litLD	1.27 1.00	1037
## sigma_conditionTH_inh_10nM:rodALA:litLD	1.31 1.00	1356
## sigma_conditionTH_inh_10nM:fedStarved:litLD	0.51 1.00	1174
## sigma_rodPO:fedStarved:litLD	2.16 1.00	1377
## sigma_rodALA:fedStarved:litLD	2.08 1.00	1440
## sigma_conditionTH_inh_10nM:rodPO:fedStarved:litLD	2.59 1.00	1396
## sigma_conditionTH_inh_10nM:rodALA:fedStarved:litLD	2.07 1.00	1596
##	Tail_ESS	
## Intercept	2705	
## sigma_Intercept	3270	
## conditionTH_inh_10nM	2965	
## rodPO	3457	
## rodALA	3077	
## fedStarved	2756	
## litLD	2604	
## conditionTH_inh_10nM:rodPO	3175	
## conditionTH_inh_10nM:rodALA	2856	
## conditionTH_inh_10nM:fedStarved	2678	
## rodPO:fedStarved	3514	
## rodALA:fedStarved	3402	
## conditionTH_inh_10nM:litLD	2884	
## rodPO:litLD	3659	
## rodALA:litLD	3570	
## fedStarved:litLD	2551	
## conditionTH_inh_10nM:rodPO:fedStarved	2864	
## conditionTH_inh_10nM:rodALA:fedStarved	2900	
## conditionTH_inh_10nM:rodPO:litLD	3243	
## conditionTH_inh_10nM:rodALA:litLD	3118	
## conditionTH_inh_10nM:fedStarved:litLD	2612	
## rodPO:fedStarved:litLD	3399	
## rodALA:fedStarved:litLD	3128	
## conditionTH_inh_10nM:rodPO:fedStarved:litLD	3069	
## conditionTH_inh_10nM:rodALA:fedStarved:litLD	3184	
## sigma_conditionTH_inh_10nM	2243	
## sigma_rodPO	3187	
## sigma_rodALA	3269	
## sigma_fedStarved	2521	
## sigma_litLD	2323	
## sigma_conditionTH_inh_10nM:rodPO	2305	
## sigma_conditionTH_inh_10nM:rodALA	2587	
## sigma_conditionTH_inh_10nM:fedStarved	2322	
## sigma_rodPO:fedStarved	2704	
## sigma_rodALA:fedStarved	2917	
## sigma_conditionTH_inh_10nM:litLD	1785	
## sigma_rodPO:litLD	2046	

```
## sigma_rodALA:litLD 2432
## sigma_fedStarved:litLD 2294
## sigma_conditionTH_inh_10nM:rodPO:fedStarved 2651
## sigma_conditionTH_inh_10nM:rodALA:fedStarved 2750
## sigma_conditionTH_inh_10nM:rodPO:litLD 2212
## sigma_conditionTH_inh_10nM:rodALA:litLD 2573
## sigma_conditionTH_inh_10nM:fedStarved:litLD 2257
## sigma_rodPO:fedStarved:litLD 2668
## sigma_rodALA:fedStarved:litLD 2783
## sigma_conditionTH_inh_10nM:rodPO:fedStarved:litLD 2613
## sigma_conditionTH_inh_10nM:rodALA:fedStarved:litLD 2745
##
## Draws were sampled using sampling(NUTS). For each parameter, Bulk_ESS
## and Tail_ESS are effective sample size measures, and Rhat is the potential
## scale reduction factor on split chains (at convergence, Rhat = 1).
```

```
plot(Sp_rod_fed_lit_mod, ask=FALSE, variable = "~b_", regex = TRUE)
```



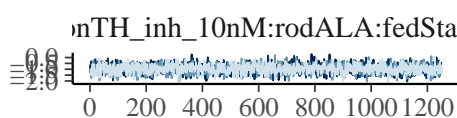
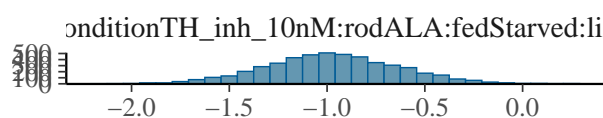
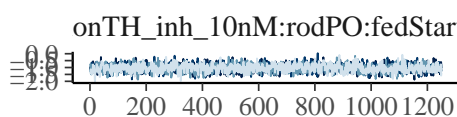
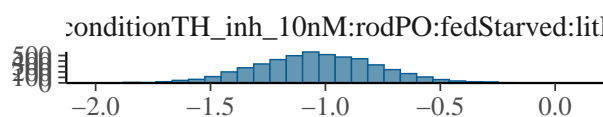
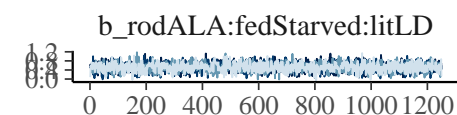
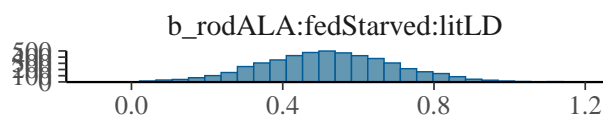
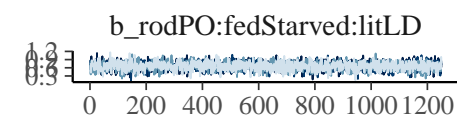
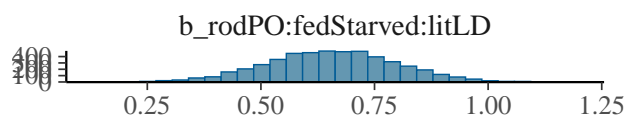
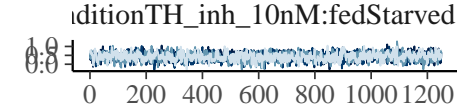
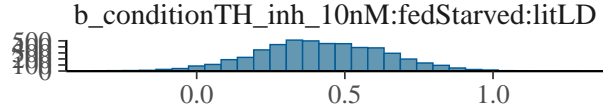
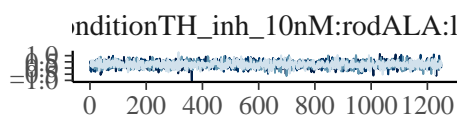
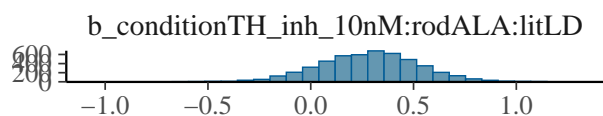
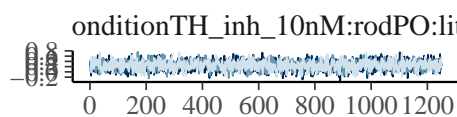
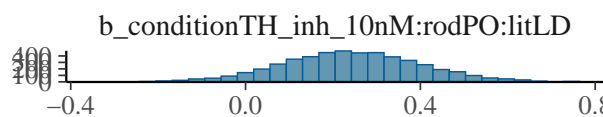
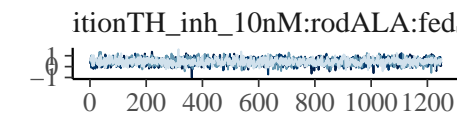
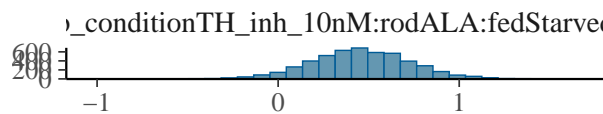
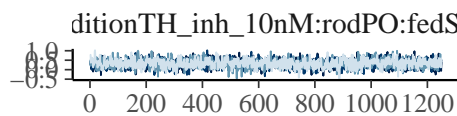
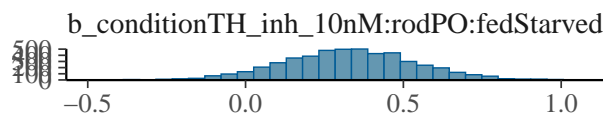
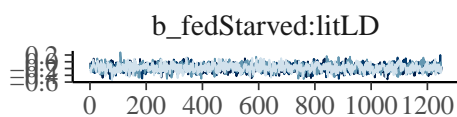
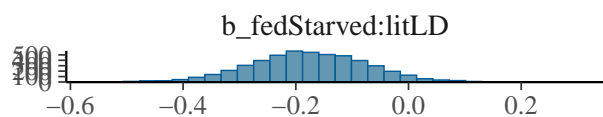


Chain

— 1  
— 2  
— 3  
— 4

Chain

— 1  
— 2  
— 3  
— 4

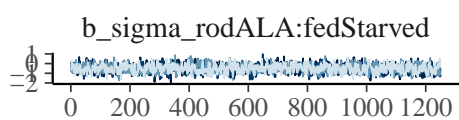
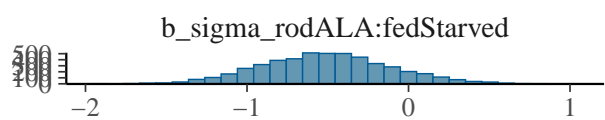
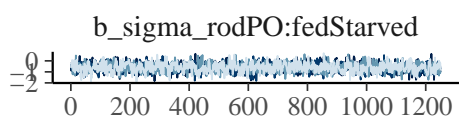
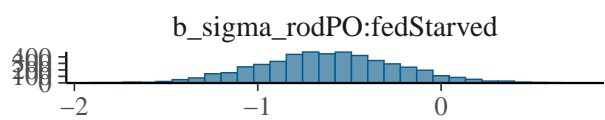
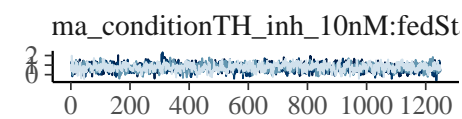
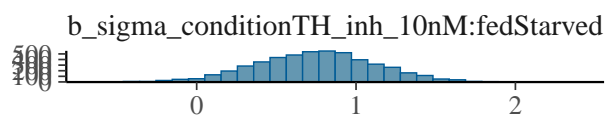
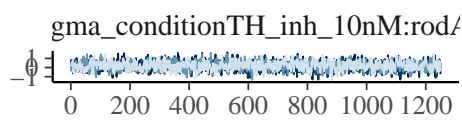
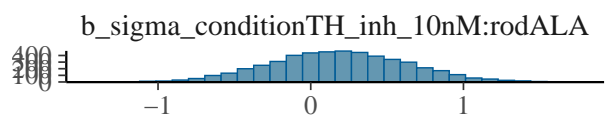
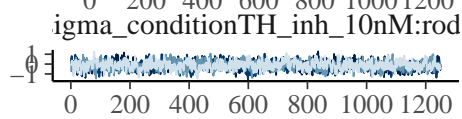
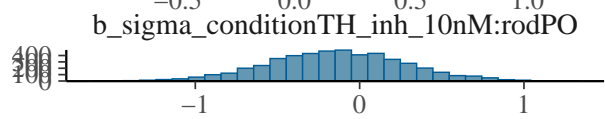
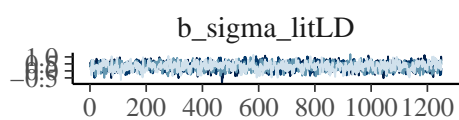
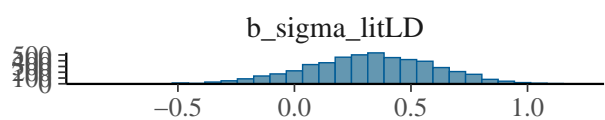
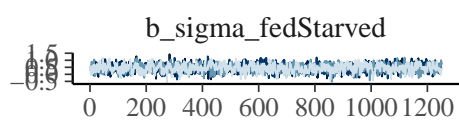
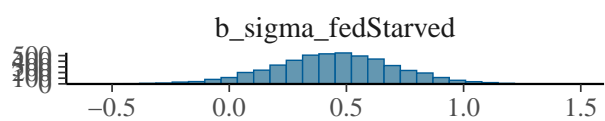
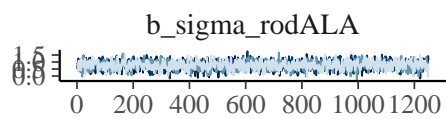
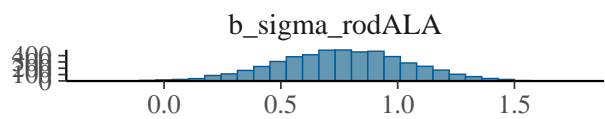
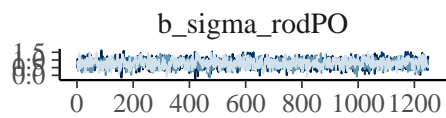
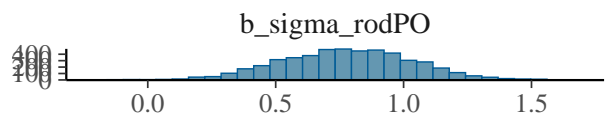
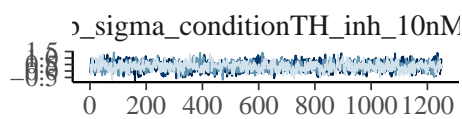
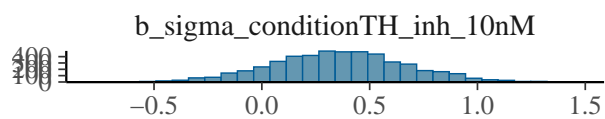


Chain

— 1  
— 2  
— 3  
— 4

Chain

— 1  
— 2  
— 3  
— 4

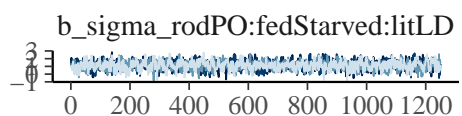
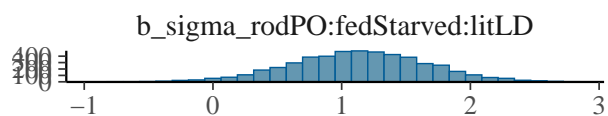
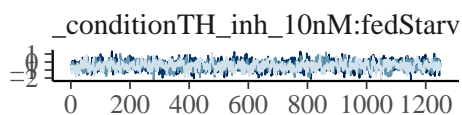
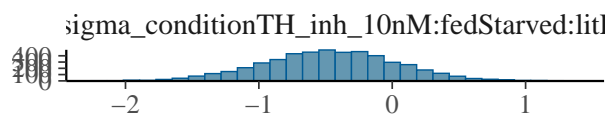
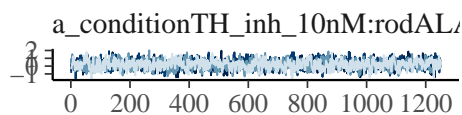
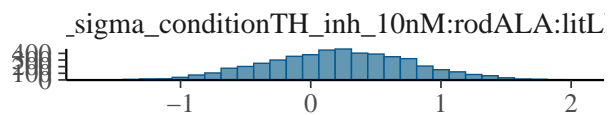
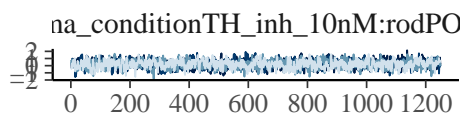
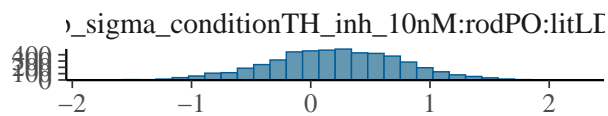
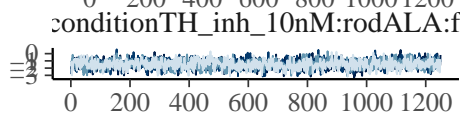
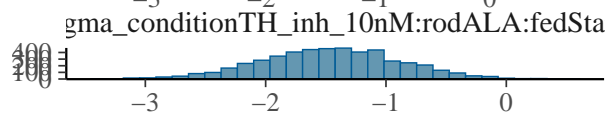
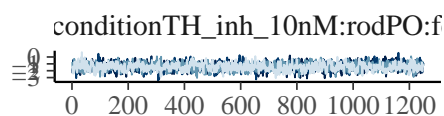
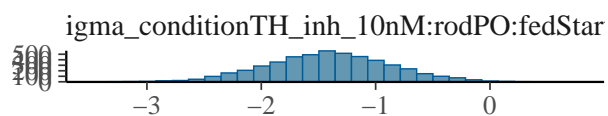
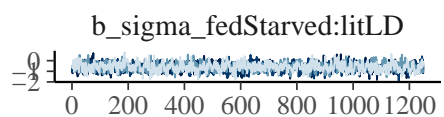
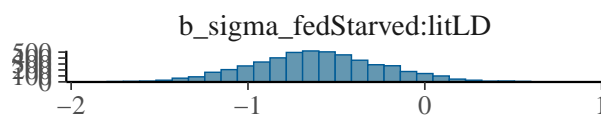
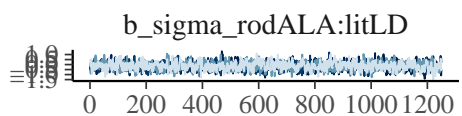
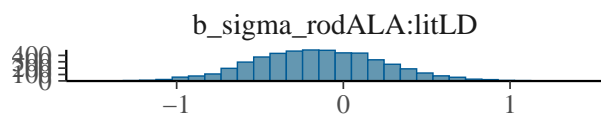
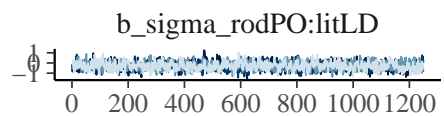
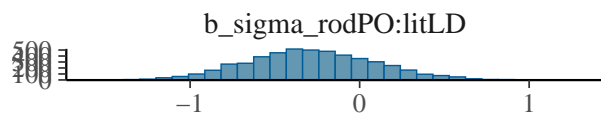
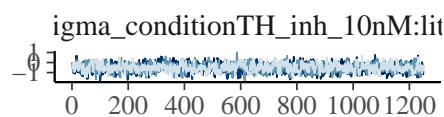
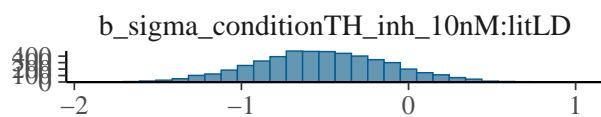


Chain

— 1  
— 2  
— 3  
— 4

Chain

— 1  
— 2  
— 3  
— 4



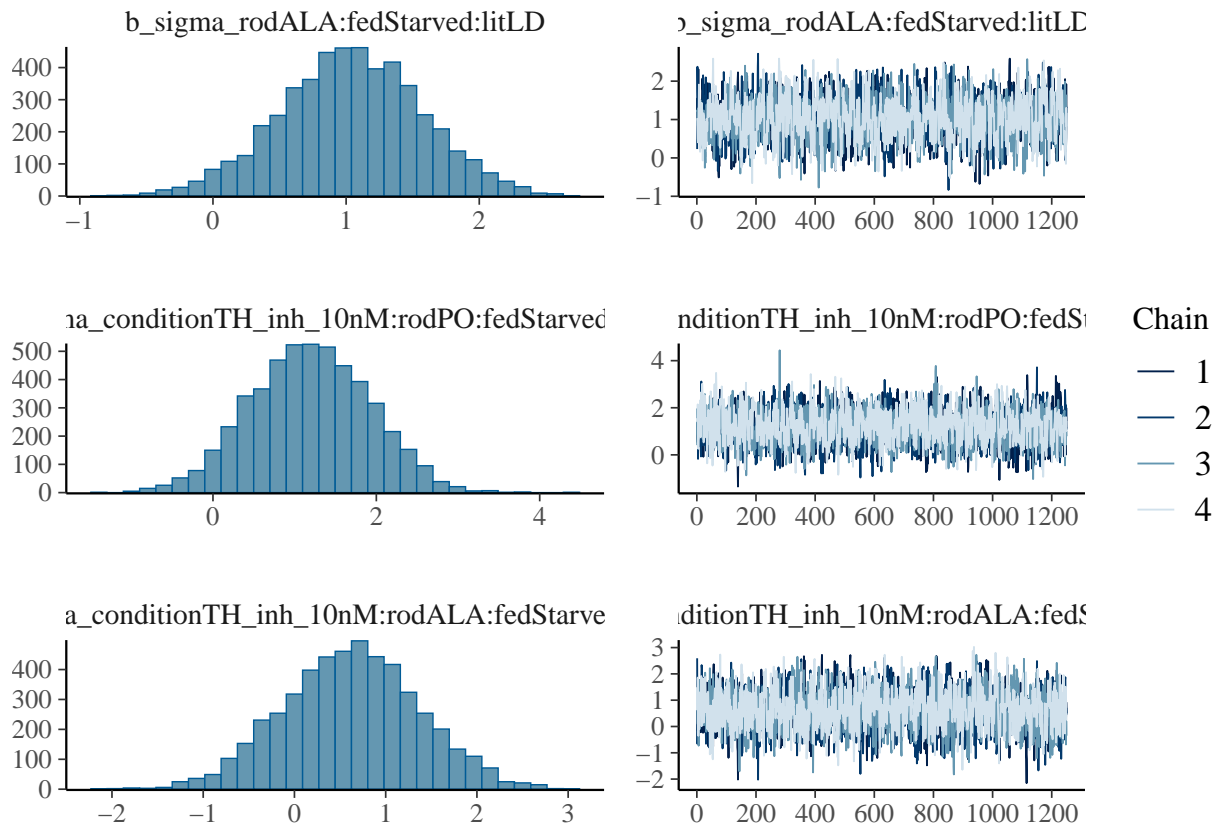
Chain

— 1  
— 2  
— 3  
— 4

Chain

— 1  
— 2  
— 3  
— 4





### 3. Models evaluation using LOO

```
Sp_intercept_mod = add_criterion(Sp_intercept_mod,
                                criterion = "loo", moment_match = moment_match, reloo = TRUE)
```

```
## No problematic observations found. Returning the original 'loo' object.
```

```
Sp_rod_mod = add_criterion(Sp_rod_mod,
                           criterion = "loo", moment_match = moment_match, reloo = TRUE)
```

```
## Warning: Some Pareto k diagnostic values are too high. See help('pareto-k-diagnostic') for details.
```

```
## 1 problematic observation(s) found.
```

```
## The model will be refit 1 times.
```

```
##
```

```
## Fitting model 1 out of 1 (leaving out observation 545)
```

```
## Start sampling
```

```
Sp_rod_lit_mod = add_criterion(Sp_rod_lit_mod,
                               criterion = "loo", moment_match = moment_match, reloo = TRUE)
```

```
## Warning: Some Pareto k diagnostic values are too high. See help('pareto-k-diagnostic') for details.
```

```
## 1 problematic observation(s) found.
```

```
## The model will be refit 1 times.
```

```
##
```

```
## Fitting model 1 out of 1 (leaving out observation 545)
```

```

## Start sampling
Sp_rod_fed_mod = add_criterion(Sp_rod_fed_mod,
                              criterion = "loo", moment_match = moment_match, reloo = TRUE)

## Warning: Some Pareto k diagnostic values are too high. See help('pareto-k-diagnostic') for details.
## 1 problematic observation(s) found.
## The model will be refit 1 times.

##
## Fitting model 1 out of 1 (leaving out observation 545)
## Start sampling
Sp_rod_fed_lit_mod = add_criterion(Sp_rod_fed_lit_mod,
                                   criterion = "loo", moment_match = moment_match, reloo = TRUE)

## Warning: Some Pareto k diagnostic values are too high. See help('pareto-k-diagnostic') for details.
## 3 problematic observation(s) found.
## The model will be refit 3 times.

##
## Fitting model 1 out of 3 (leaving out observation 334)
## Start sampling

##
## Fitting model 2 out of 3 (leaving out observation 359)
## Start sampling

##
## Fitting model 3 out of 3 (leaving out observation 545)
## Start sampling
# Perform LOO comparison
loo_results <- loo_compare(Sp_intercept_mod,
                          Sp_rod_mod,
                          Sp_rod_fed_mod,
                          Sp_rod_lit_mod,
                          Sp_rod_fed_lit_mod)

loo_results

##              elpd_diff se_diff
## Sp_rod_fed_lit_mod    0.0     0.0
## Sp_rod_lit_mod       -22.8    13.4
## Sp_rod_fed_mod       -42.5    20.1
## Sp_rod_mod           -85.9    48.0
## Sp_intercept_mod     -639.7   38.9

best_model_name <- rownames(loo_results)[1]
best_model <- get(best_model_name)

# Save the best model to an RDS file
saveRDS(best_model, file = paste0(
  "./model_objects/", best_model_name, ".rds"))

# Print the name of the best model
print(paste("The best model is:", best_model_name))

```

```
## [1] "The best model is: Sp_rod_fed_lit_mod"
```

## Model Equation

The response variable follows a normal distribution:

$$Y_i \sim \mathcal{N}(\mu_i, \sigma_i)$$

where:

**Linear Predictor for the Mean ( $\mu_i$ ):**

$$\mu_i = \beta_0 + X_i\beta + u_{J_1[i]}Z_{1,i}$$

- $\beta_0$  (Intercept): The population-level intercept.
- $X_i\beta$ : Fixed effects (population-level predictors) with centered design matrix.
- $u_{J_1[i]}$ : Random effect for group-level predictor, where  $J_1[i]$  is the grouping index.
- $Z_{1,i}$ : Group-level predictor values.
- $u_{J_1[i]}$  follows a normal distribution:

$$u_{J_1[i]} \sim \mathcal{N}(0, \sigma_u)$$

where  $\sigma_u$  is the standard deviation of the group-level effect.

**Linear Predictor for the Standard Deviation ( $\sigma_i$ ):**

$$\log(\sigma_i) = \alpha_0 + X_{\sigma,i}\alpha$$

- $\alpha_0$  (Intercept\_sigma): Population-level intercept for the variance structure.
- $X_{\sigma,i}\alpha$ : Fixed effects for the variance model.

**Prior Distributions:**

$$\beta \sim \mathcal{N}(0, 2), \quad \beta_0 \sim t_5(0, 2)$$

$$\alpha \sim \mathcal{N}(0, 1), \quad \alpha_0 \sim t_5(0, 2)$$

$$\sigma_u \sim t_3(0, 0.5)$$

This model estimates both the mean and variance of the response variable ( $Y$ ), incorporating fixed and random effects while allowing for hierarchical structure in the data.

```
#saveRDS(best_model, file = paste0("./model_objects/", best_model_name, ".rds"))
```