# Did Complex Song and Dance Co-Evolve With Brain Size in the Birds of Paradise (Aves: Paradisaeidae)?

2024-08-08

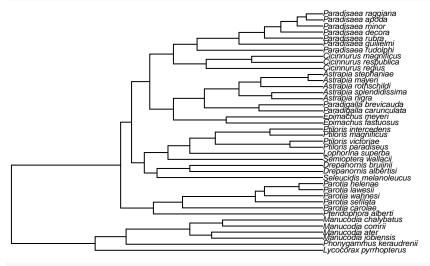
## Code used to analyse the relationship between courtship display complexity and brain size in the birds of paradise

```
# First, load all the required packges and set the working directory
library(phytools) # Comparative methods
library(ggplot2) # Plotting
library(dplyr) # Data wrangling
library(caper) # PGLS
library(patchwork) # Combining plots
library(sensiPhy) # Model stability
library(ggrepel) # Annotating plots more flexibly
```

## Part 1: Associations between complexity scores

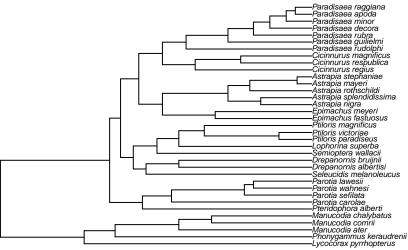
#### 1.1. Prepare the dataframe and tree

```
# First, we'll import the bird of paradise phylogeny from Ligon et al. (2018)
tree <- read.nexus("Ligon.et.al._UltrametricTree") # Import the tree as .nexus
# Quick look at the tree; this includes all species recognized by Irestedt et al. (2009)
plot(tree, cex = .5)
```



# We'll also load the full dataframe that includes complexity scores for all species
data <- read.csv("Paradisaeidae\_Brain.Data.Full.csv")
str(data)</pre>

```
# Some descriptive stats of brain size in the BoPs
data2 <- filter(data, ECV != "NA")</pre>
mean(data2$ECV)
(mean(data2\$ECV)*1.036)/1000 # Conversion to mass (in g)
sd(data2$ECV)
(sd(data2\secv)*1.036)/1000
max(data2$ECV)
(\max(\text{data2\$ECV})*1.036)/1000
min(data2$ECV)
(\min(\text{data2\$ECV})*1.036)/1000
# For behavioral complexity (Miles & Fuxjager, 2018),
# we don't have data for the following species;
missing.fuxjager <- c("Manucodia_jobiensis",</pre>
                       "Paradigalla_brevicauda",
                       "Paradigalla_carunculata",
                       "Parotia_helenae",
                       "Ptiloris intercedens")
# We can drop these species from the tree used for analyses
# incorporating data from Miles & Fuxjager (2018)
tree.fuxjager <- drop.tip(tree, missing.fuxjager)</pre>
sum(table(tree.fuxjager$tip.label)) # this tree has 35 species
plot(tree.fuxjager, cex = .5) # Let's take a look
```



```
# We can also drop these from the data frame
data.fuxjager <- filter(data, complexity.fuxjager != "NA")

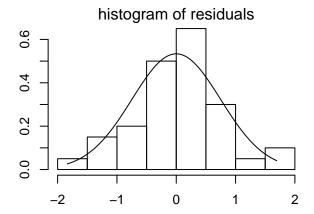
# Let's first take a look at the distribution of all complexity scores
par(mfrow = c(2, 3))
hist(data$behavioral.diversity.ligon, cex.main = .75)
hist(data$behavioral.richness.ligon, cex.main = .75)
hist(data$complexity.fuxjager, cex.main = .75)
hist(data$acoustic.diversity, cex.main = .75)
hist(data$acoustic.diversity, cex.main = .75)
hist(data$acoustic.richness, cex.main = .75)
# Acoustic complexity scores appear skewed, so may need to be transformed later on...

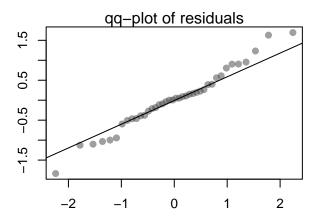
# Create comparative data set for caper for all species with</pre>
```

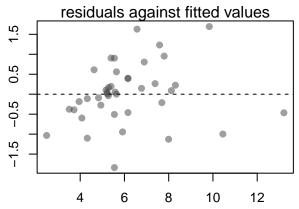
```
# complexity scores from Ligon et al. 2018
complexity_scores_1 <- comparative.data(phy = tree,</pre>
                                                 data = data,
                                                 names.col = species,
                                                 vcv = TRUE,
                                                 na.omit = FALSE,
                                                 warn.dropped = TRUE)
# Create another comparative data set for caper for all species
# with complexity scores from Miles & Fuxjager 2018
complexity_scores_2 <- comparative.data(phy = tree.fuxjager,</pre>
                                                 data = data.fuxjager,
                                                 names.col = species,
                                                 vcv = TRUE,
                                                 na.omit = FALSE,
                                                 warn.dropped = TRUE)
     Histogram of data$behavioral.diversity.ligon
                                            Histogram of data$behavioral.richness.ligon
                                                                                     Histogram of data$complexity.fuxjager
     15
                                           15
-requency
                                       Frequency
                                                                             Frequency
     10
                                           10
     S
                                           2
                                                                                  0
                                           0
           2 4
                  6 8
                            12
                                                 5
                                                       10
                                                             15
                                                                   20
                                                                                           5
                                                                                               10
                                                                                                    15
                                                                                                        20
                                              data$behavioral.richness.ligon
        data$behavioral.diversity.ligon
                                                                                        data$complexity.fuxjager
        Histogram of data$acoustic.diversity
                                               Histogram of data$acoustic.richness
                                           25
Frequency
                                       Frequency
                                           15
                                           2
              2
                   3
                                                         6
                                                                  10
         1
                        4
                                                2
                                                     4
                                                              8
                                                                      12
                                                  data$acoustic.richness
           data$acoustic.diversity
```

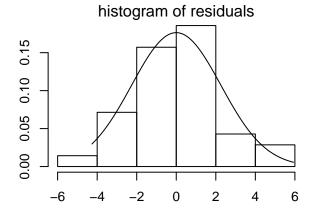
Now that we have all our complexity score data in the same place, we can see how they relate to one another.

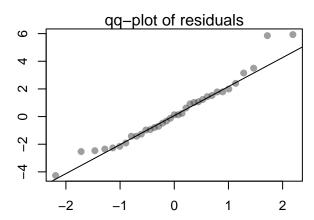
#### 1.2. Running PGLS models

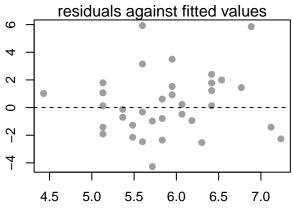


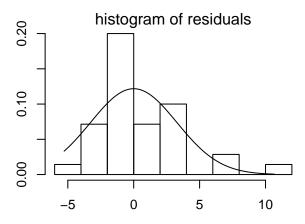


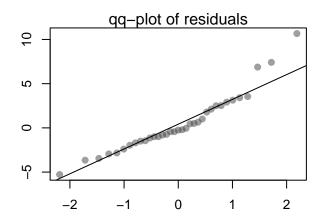


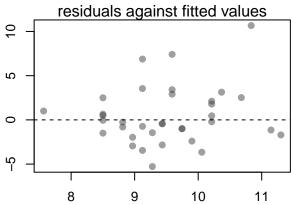


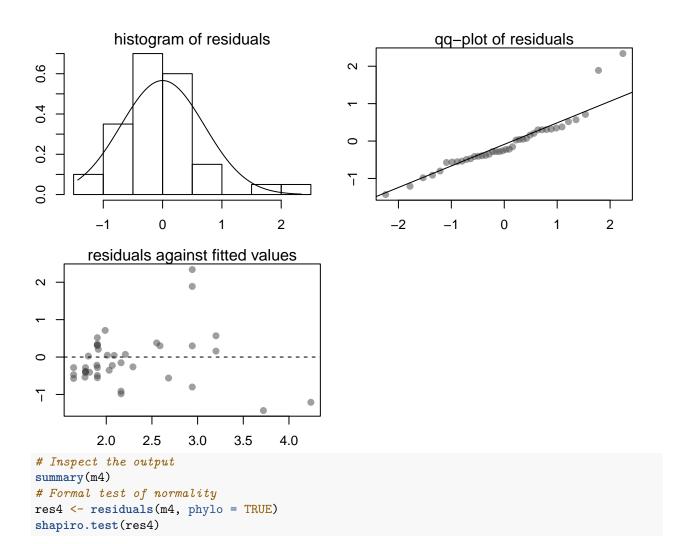






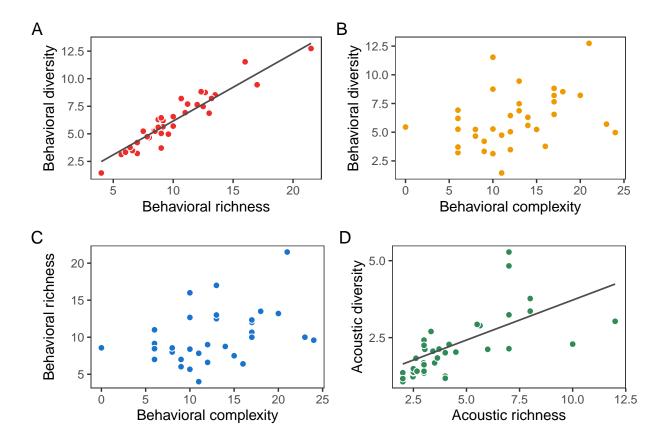






#### 1.3. Plotting associations between complexity scores

```
# Model 2 #
p2 <- ggplot(data.fuxjager, aes(y = behavioral.diversity.ligon, x = complexity.fuxjager)) +
  geom point(data.fuxjager = data, shape = 21, size = 2, alpha = 1,
             col = "white", fill = "orange2") +
  theme_bw() + ylab("Behavioral diversity") + xlab("Behavioral complexity") +
  labs(colour = "Clade") +
  theme(panel.grid.major = element blank(), panel.grid.minor = element blank())
# Model 3 #
p3 <- ggplot(data.fuxjager, aes(y = behavioral.richness.ligon, x = complexity.fuxjager)) +
  geom_point(data.fuxjager = data, shape = 21, size = 2, alpha = 1,
             col = "white", fill = "dodgerblue3") +
  theme_bw() + ylab("Behavioral richness") + xlab("Behavioral complexity") +
  labs(colour = "Clade") +
  theme(panel.grid.major = element_blank(), panel.grid.minor = element_blank())
# Model 4 #
# Predict values
m4.fit<- predict(m4, data)</pre>
# Create data frame for males with predicted values
df predicted.m4 <- mutate(data, predicted = m4.fit)</pre>
p4 <- ggplot(data, aes(y = acoustic.diversity, x = acoustic.richness)) +
  geom_point(data = data, shape = 21, size = 2, alpha = 1,
             col = "white", fill = "seagreen") +
  geom_line(data = df_predicted.m4, aes(y = predicted),
            color = "grey30", linetype = 1, linewidth = 0.6) +
  theme_bw() + ylab("Acoustic diversity") + xlab("Acoustic richness") +
  labs(colour = "Clade") +
  scale_y_continuous(breaks = c(2.5, 5, 7.5, 10, 12.5)) +
  theme(panel.grid.major = element_blank(), panel.grid.minor = element_blank())
# Stitch plots together
combined <- (p1|p2)/(p3|p4) & theme(legend.position = "bottom")
combined + plot_layout(guides = "collect") + plot_annotation(tag_levels = 'A')
```



Part 2: Relative brain size and signal complexity scores

#### 2.1. Importing data and tree again; starting with a fresh workspace

```
# Start with a fresh R environment
rm(list = ls())

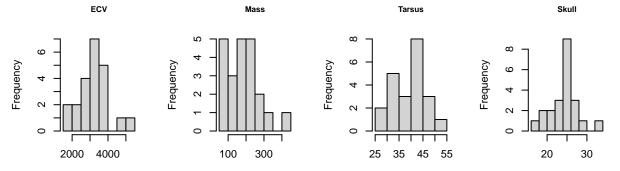
# Import the tree
tree <- read.nexus("Ligon.et.al._UltrametricTree") # Import the tree as .nexus
# Import the data
data <- read.csv("Paradisaeidae_Brain.Data.csv") # Import the dataframe as .csv

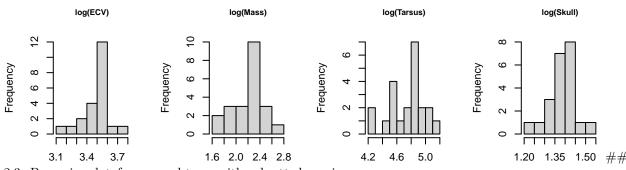
# Let's take a quick look at the data
str(data, 4)
max(data$ECV) # Largest brain is Lycocorax pyrrhopterus with 5048.42 mm^3
min(data$ECV) # Smallest brain is Cicinnurus regius with 1557.87 mm^3
mean(data$ECV) # Our mean brain size is 3218.609 mm^3...
sd(data$ECV) # with a standard deviation of 896.6828 mm^3</pre>
```

#### 2.2. Inspection of variables

```
# Log-transform body mass and brain mass
data$logECV <- log10(data$ECV)
data$logMass <- log10(data$body.mass)
data$logTarsus <- log10(data$tarsus.length^3)
data$logSkull <- log10(data$skull.length)</pre>
```

```
par(mfrow = c(2, 4))
hist(data$ECV, main = "ECV", cex.main = .75, xlab = NULL)
hist(data$body.mass, main = "Mass", cex.main = .75, xlab = NULL)
hist(data$tarsus.length, main = "Tarsus", cex.main = .75, xlab = NULL)
hist(data$skull.length, main = "Skull", cex.main = .75, xlab = NULL)
hist(data$logECV, main = "log(ECV)", cex.main = .75, xlab = NULL)
hist(data$logMass, main = "log(Mass)", cex.main = .75, xlab = NULL)
hist(data$logTarsus, main = "log(Tarsus)", cex.main = .75, xlab = NULL)
hist(data$logSkull, main = "log(Skull)", cex.main = .75, xlab = NULL)
```





2.3. Preparing dataframes and trees with subsetted species

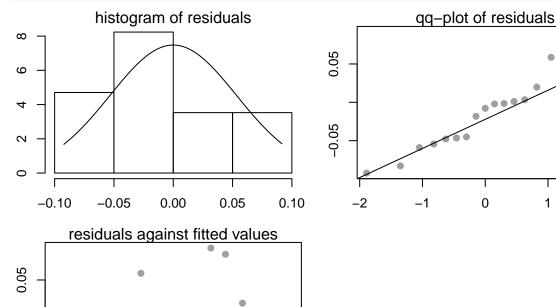
Now we have two data sets and two phylogenetic trees; one pair for all bird of paradise species, and another pair for only the core birds of paradise. We will use these two data sets to investigate any associations between brain size and behavioral complexity

#### 2.4.1 PGLS models including body mass as a predictor

```
m1<- pgls(logECV ~ behavioral.diversity.ligon + logMass,</pre>
          data = comparative_data_poly, lambda = 1)
# Diagnostics
diagnostics.plot(m1)
```

1

2



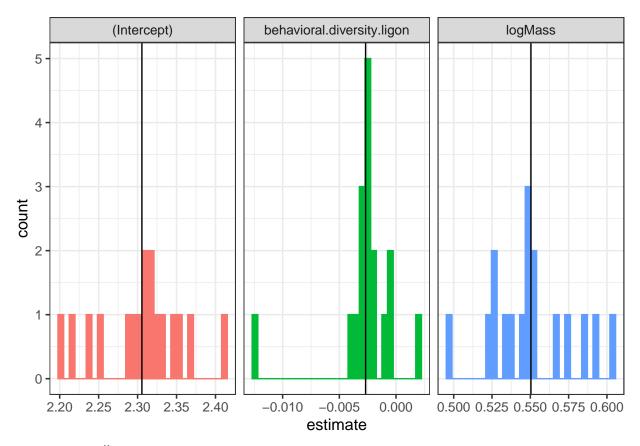
-0.05

```
3.3
                   3.4
                             3.5
                                      3.6
# Inspect the output
summary(m1)
# Formal test of normality
res1 <- residuals(m1, phylo = TRUE)</pre>
shapiro.test(res1)
# Phylogenetic sensitivity test using the sensiPhy package
sensi.m1 <- influ_phylm2(logECV ~ behavioral.diversity.ligon + logMass,</pre>
                          phy = comparative_data_poly$phy,
                          data = comparative_data_poly$data, model = "BM",
```

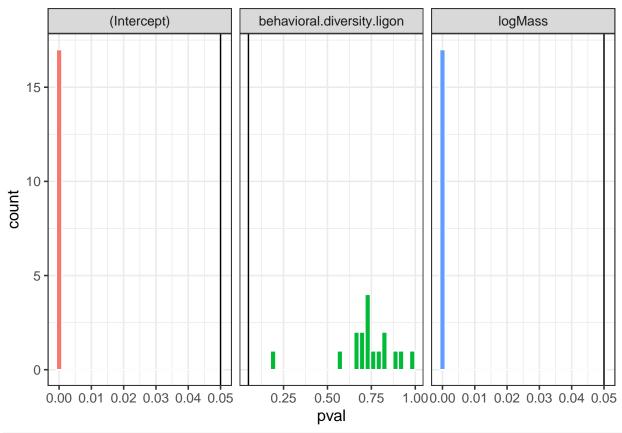
```
## Used dataset has 17 species that match data and phylogeny
# Check full model estimates and compare to initial estimates:
sensi.m1$full.model.estimates
# test for influential species:
summary_influ2(sensi.m1)$estimates
# Visual sensitivity diagnostics
sensi_plot2(sensi.m1)
```

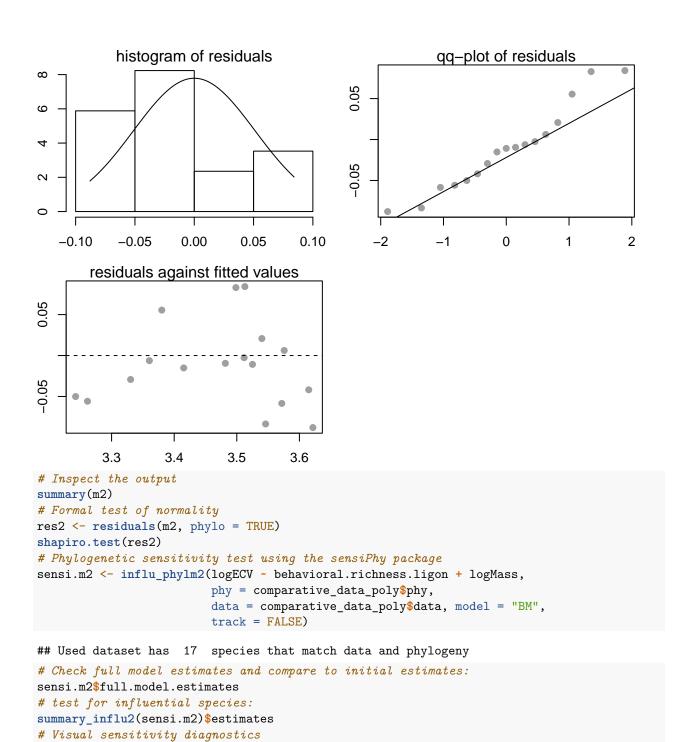
## `stat\_bin()` using `bins = 30`. Pick better value with `binwidth`.

track = FALSE)



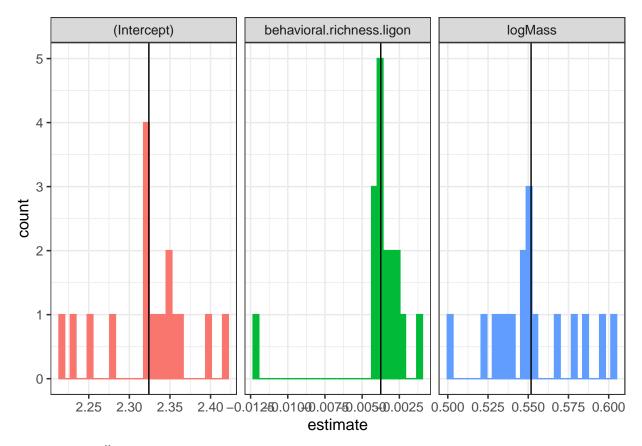
## `stat\_bin()` using `bins = 30`. Pick better value with `binwidth`.



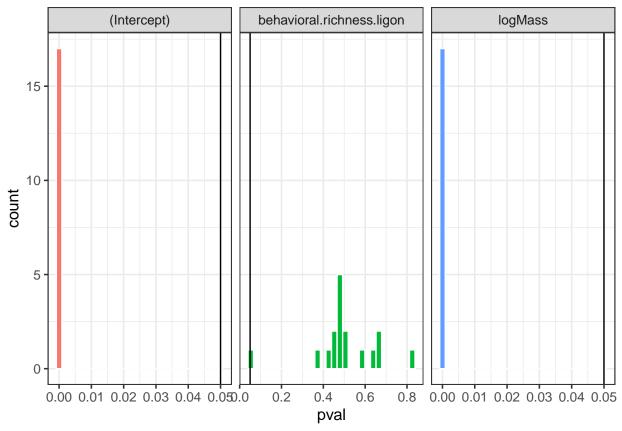


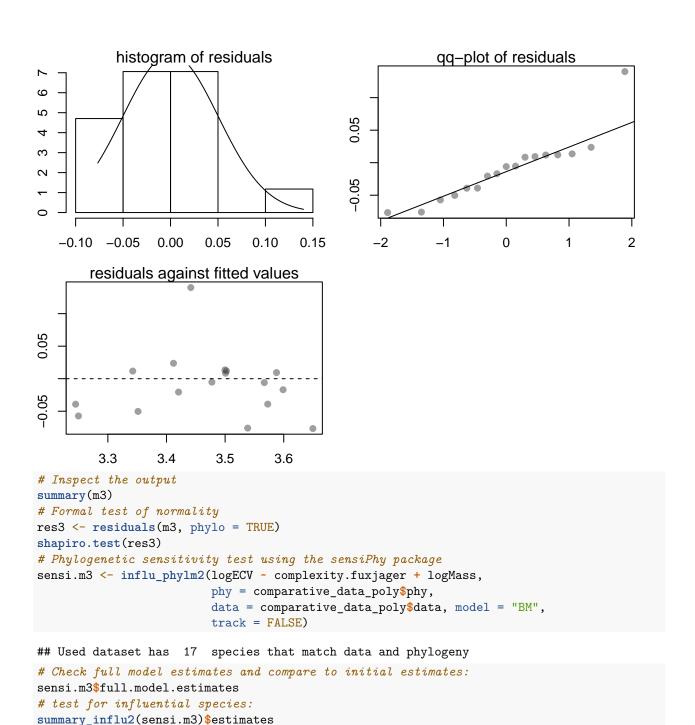
## `stat\_bin()` using `bins = 30`. Pick better value with `binwidth`.

sensi\_plot2(sensi.m2)



## `stat\_bin()` using `bins = 30`. Pick better value with `binwidth`.

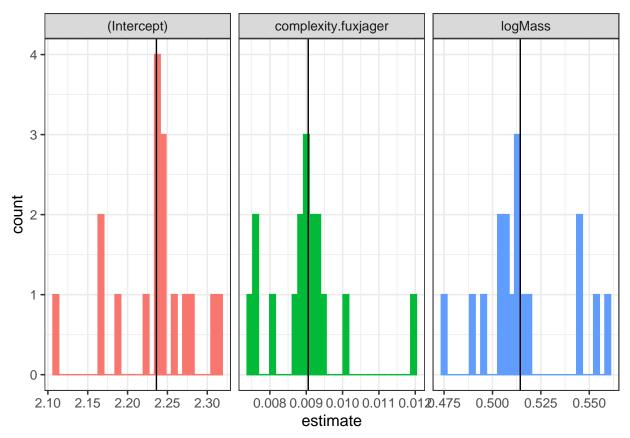




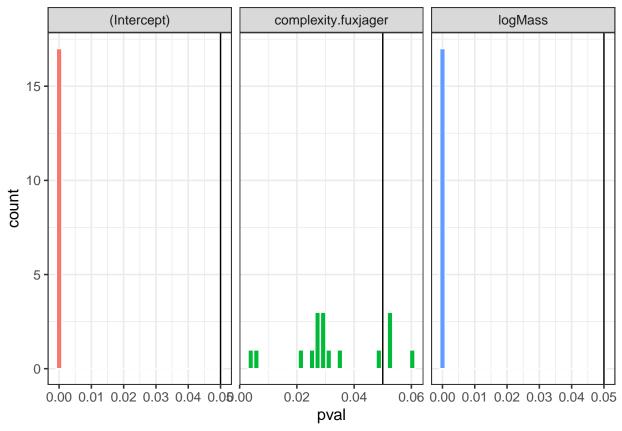
```
## `stat_bin()` using `bins = 30`. Pick better value with `binwidth`.
```

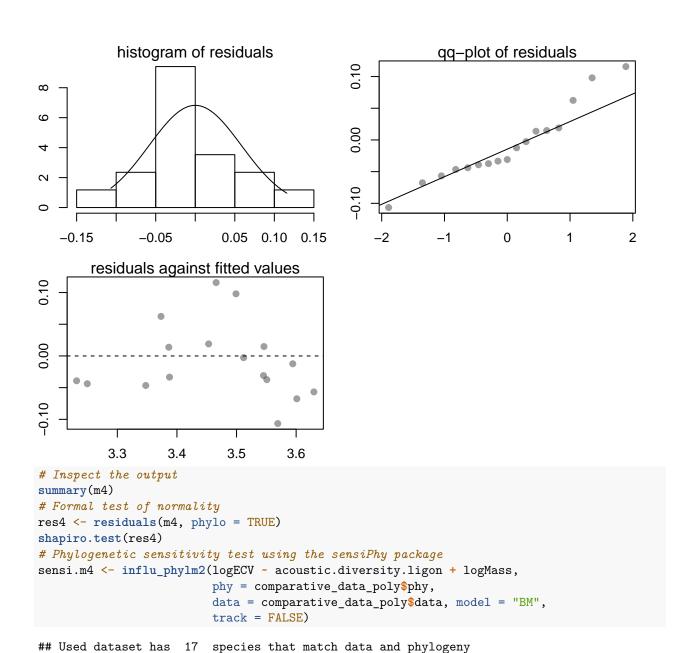
# Visual sensitivity diagnostics

sensi\_plot2(sensi.m3)



## `stat\_bin()` using `bins = 30`. Pick better value with `binwidth`.



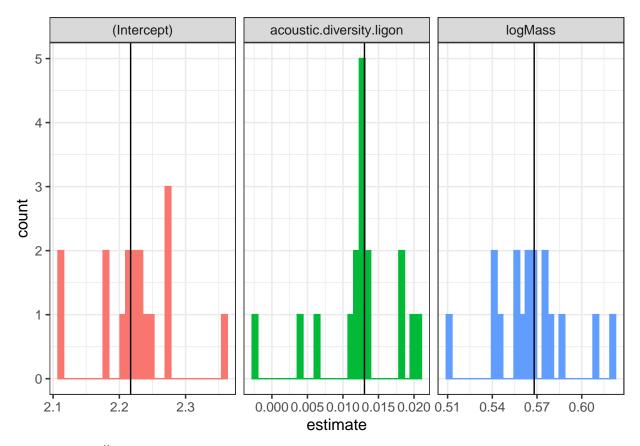


```
# Check full model estimates and compare to initial estimates:
sensi.m4$full.model.estimates
# test for influential species:
```

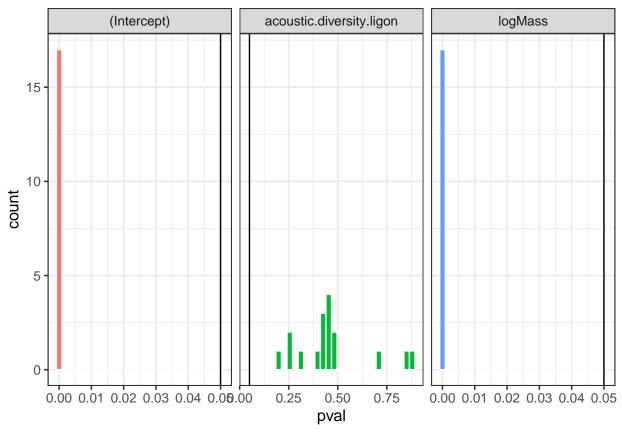
summary\_influ2(sensi.m4)\$estimates

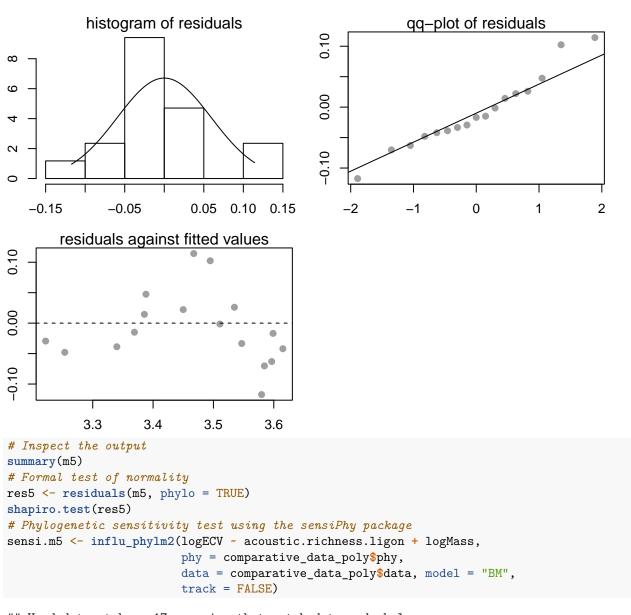
# Visual sensitivity diagnostics
sensi\_plot2(sensi.m4)

## `stat\_bin()` using `bins = 30`. Pick better value with `binwidth`.



## `stat\_bin()` using `bins = 30`. Pick better value with `binwidth`.

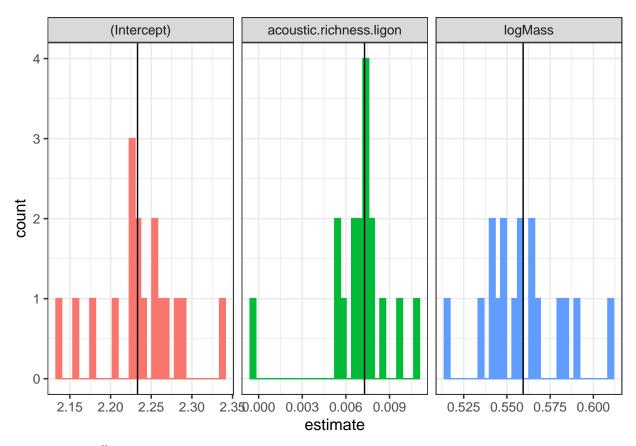




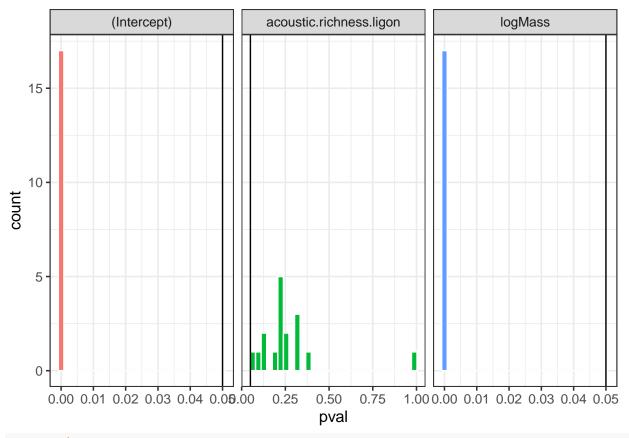
```
## Used dataset has 17 species that match data and phylogeny
```

```
# Check full model estimates and compare to initial estimates:
sensi.m5$full.model.estimates
# test for influential species:
summary_influ2(sensi.m5)$estimates
# Visual sensitivity diagnostics
sensi_plot2(sensi.m5)
```

## `stat\_bin()` using `bins = 30`. Pick better value with `binwidth`.

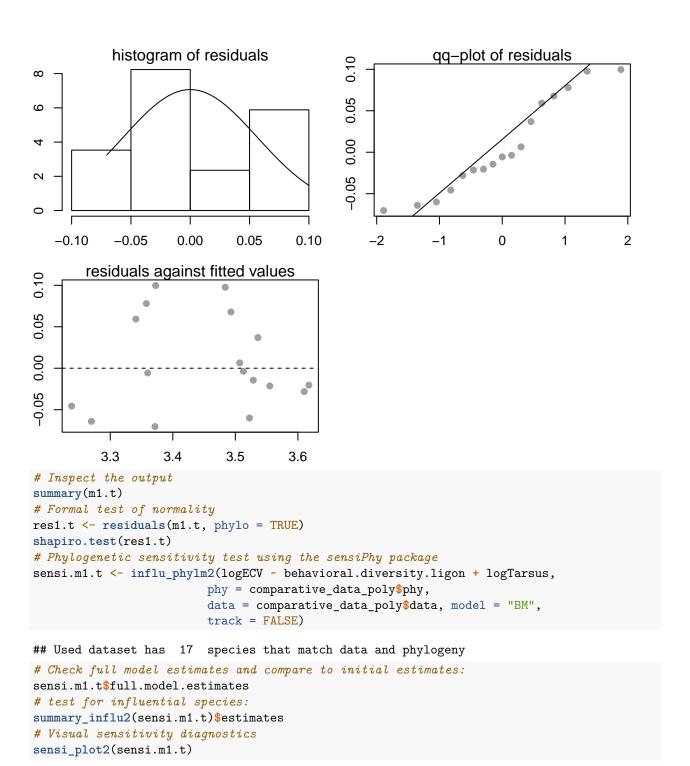


## `stat\_bin()` using `bins = 30`. Pick better value with `binwidth`.

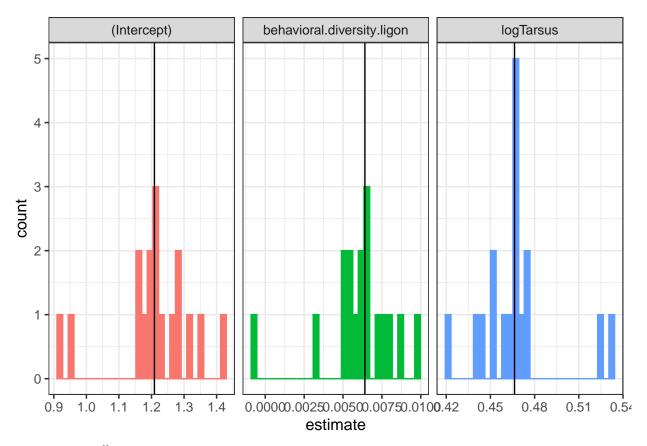


sensi.m5\$sensi.estimates

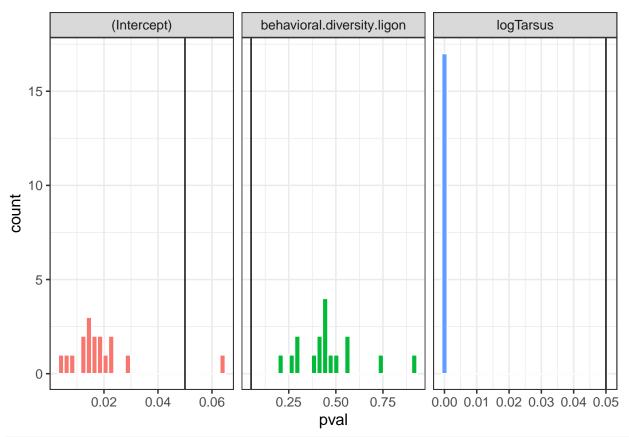
### 2.4.2 Repeat analyses using tarsus cubed as a metric of body size

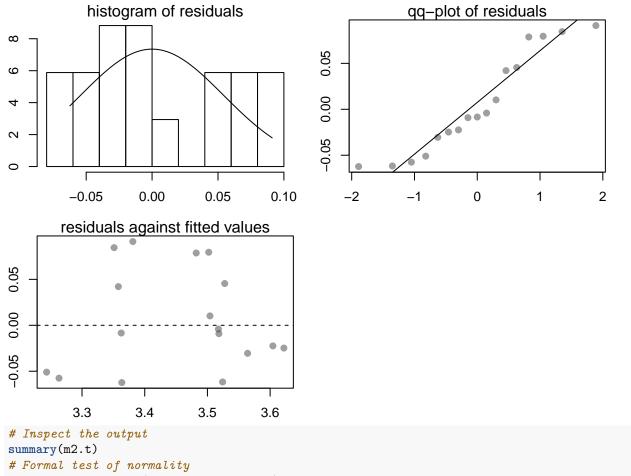


## `stat\_bin()` using `bins = 30`. Pick better value with `binwidth`.



## `stat\_bin()` using `bins = 30`. Pick better value with `binwidth`.



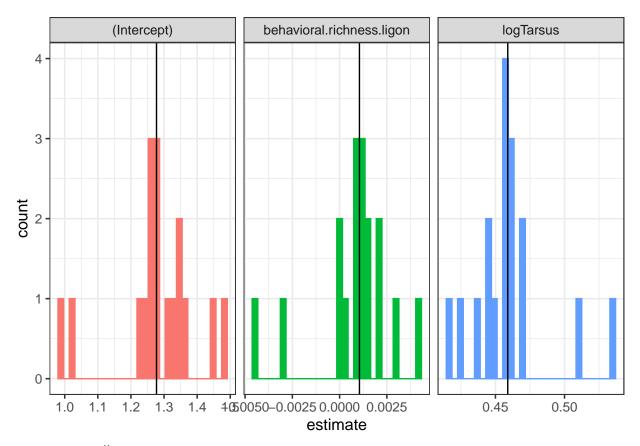


```
# Check full model estimates and compare to initial estimates:
sensi.m2.t$full.model.estimates
# test for influential species:
summary_influ2(sensi.m2.t)$estimates
# Visual sensitivity diagnostics
```

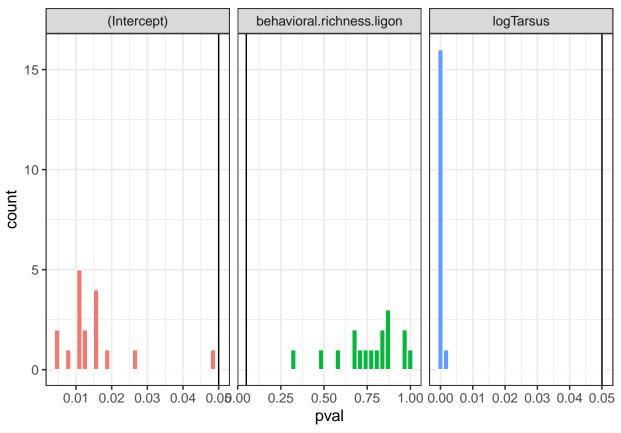
## `stat\_bin()` using `bins = 30`. Pick better value with `binwidth`.

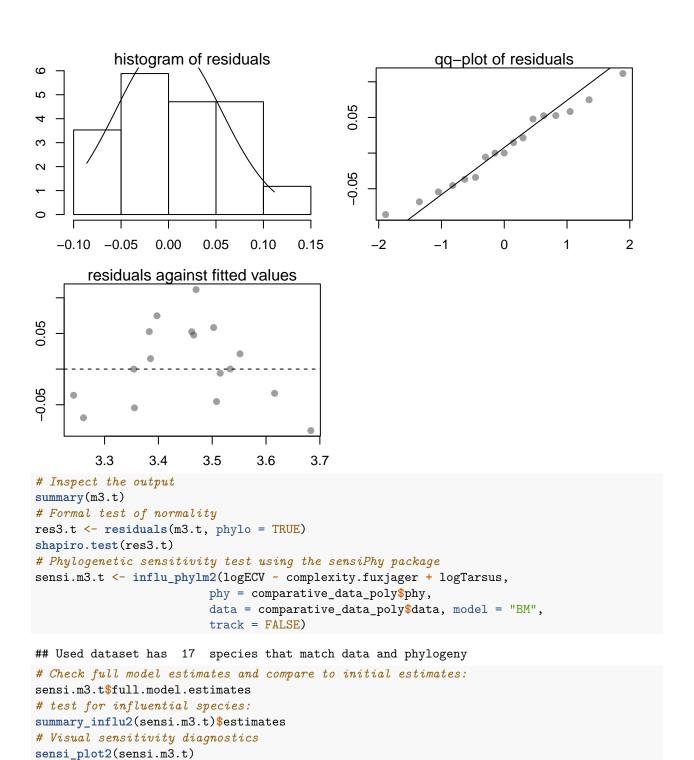
## Used dataset has 17 species that match data and phylogeny

sensi\_plot2(sensi.m2.t)

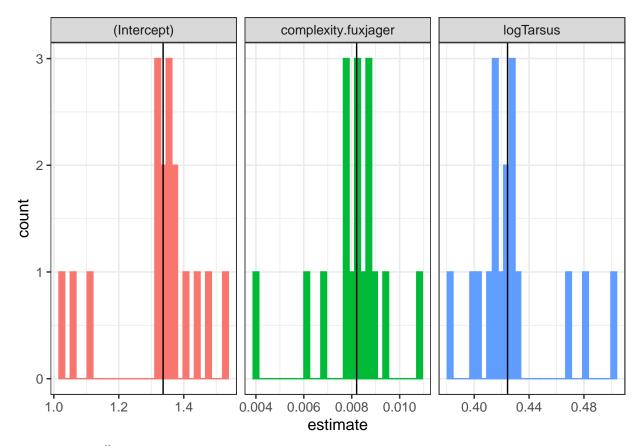


## `stat\_bin()` using `bins = 30`. Pick better value with `binwidth`.

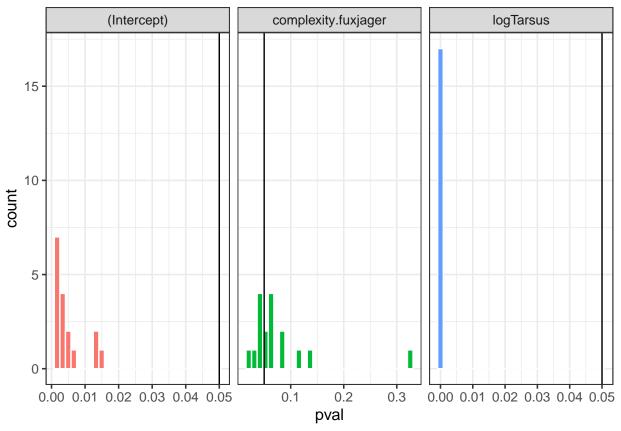


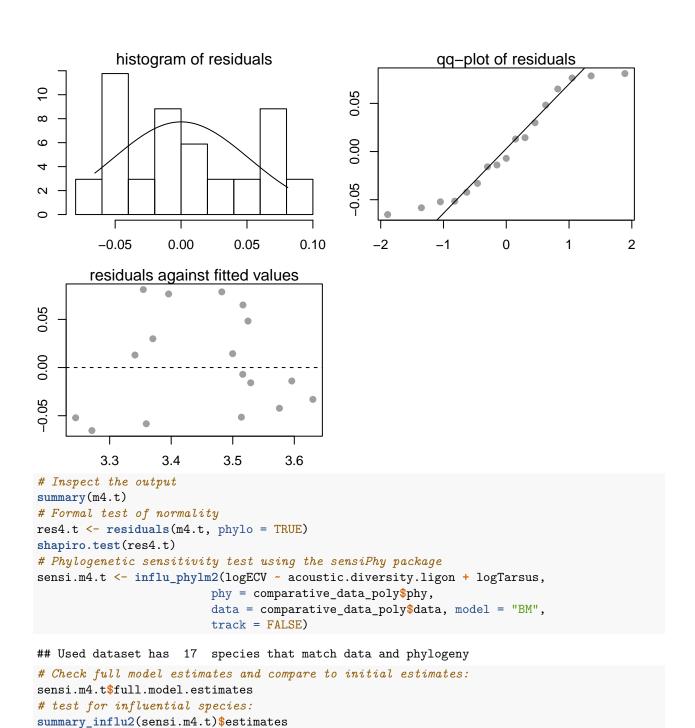


## `stat\_bin()` using `bins = 30`. Pick better value with `binwidth`.

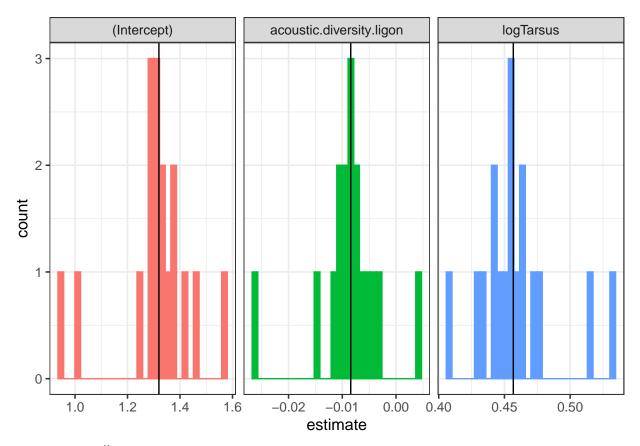


## `stat\_bin()` using `bins = 30`. Pick better value with `binwidth`.

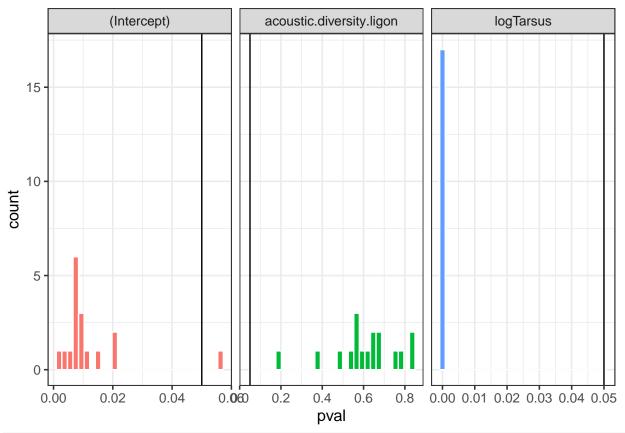


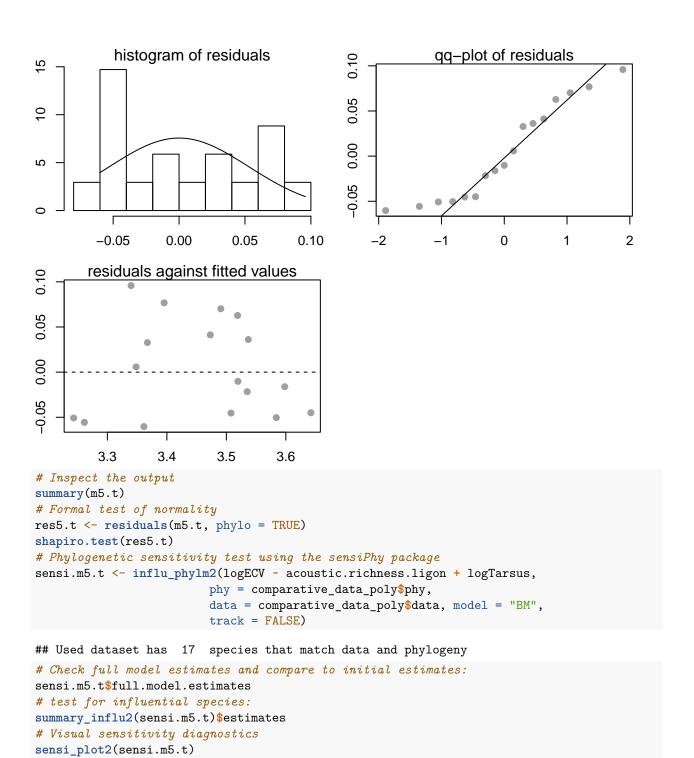


```
# Visual sensitivity diagnostics
sensi_plot2(sensi.m4.t)
```

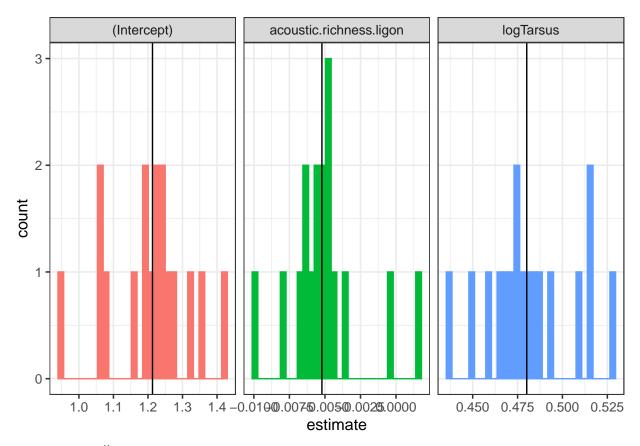


## `stat\_bin()` using `bins = 30`. Pick better value with `binwidth`.

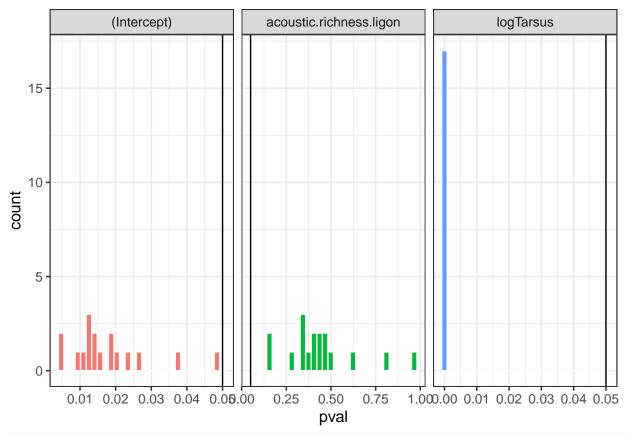




## `stat\_bin()` using `bins = 30`. Pick better value with `binwidth`.



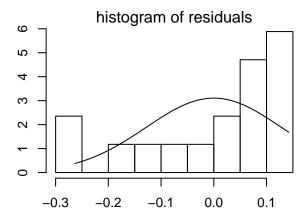
## `stat\_bin()` using `bins = 30`. Pick better value with `binwidth`.

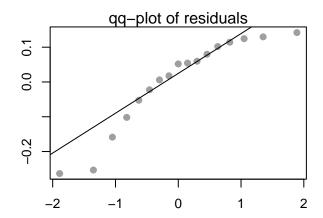


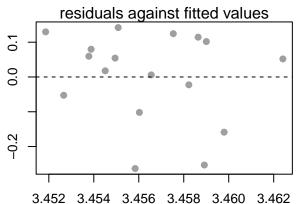
sensi.m5.t\$sensi.estimates

We also want to run the same set of models without controlling for body size so we can test if any of these metrics correlate with absolute brain size.

#### 2.5. PGLS models not including body mass as a predictor

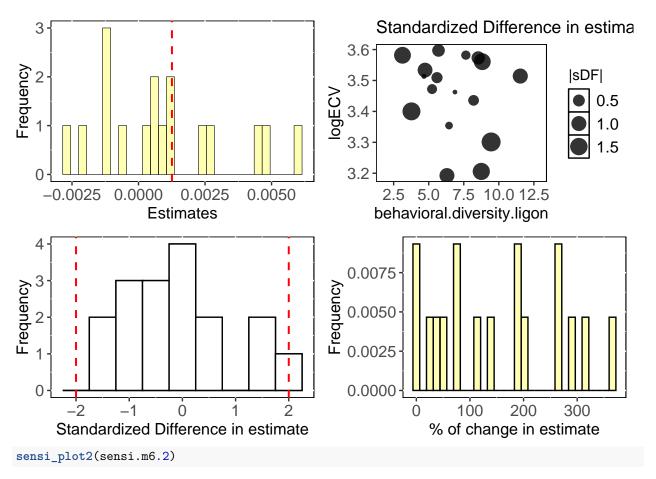




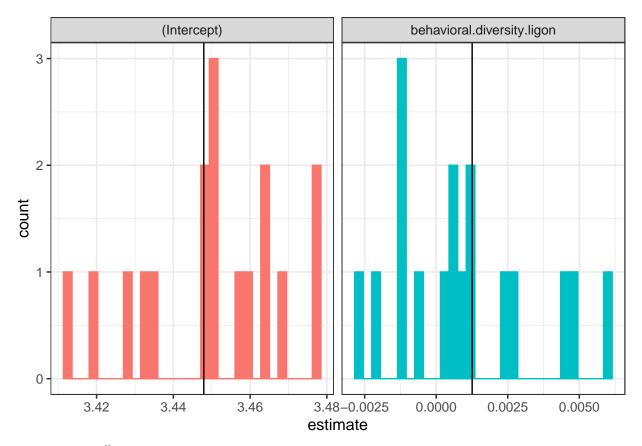


```
## Used dataset has 17 species that match data and phylogeny
```

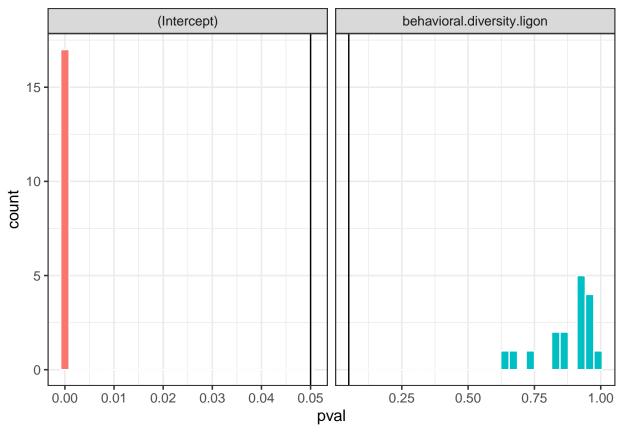
```
# Check full model estimates and compare to initial estimates:
sensi.m6$full.model.estimates
# test for influential species:
summary(sensi.m6)
# Visual sensitivity diagnostics
sensi_plot(sensi.m6)
```

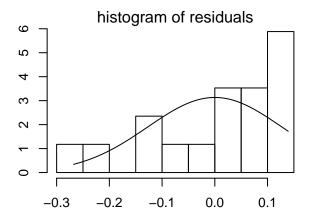


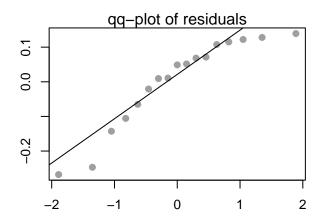
## `stat\_bin()` using `bins = 30`. Pick better value with `binwidth`.

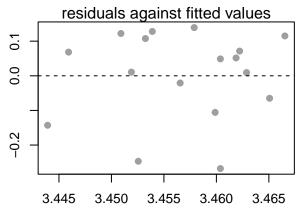


## `stat\_bin()` using `bins = 30`. Pick better value with `binwidth`.

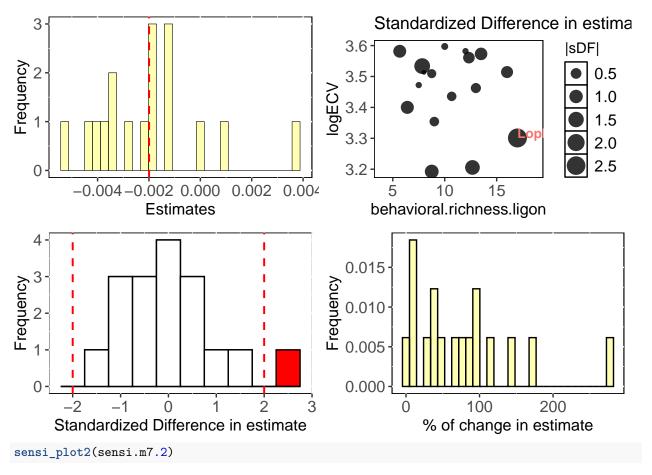




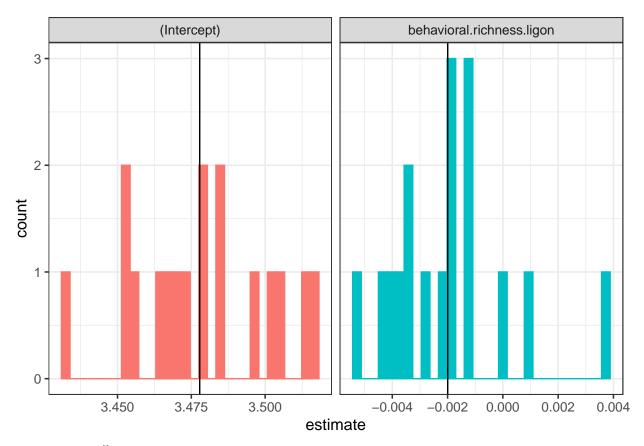




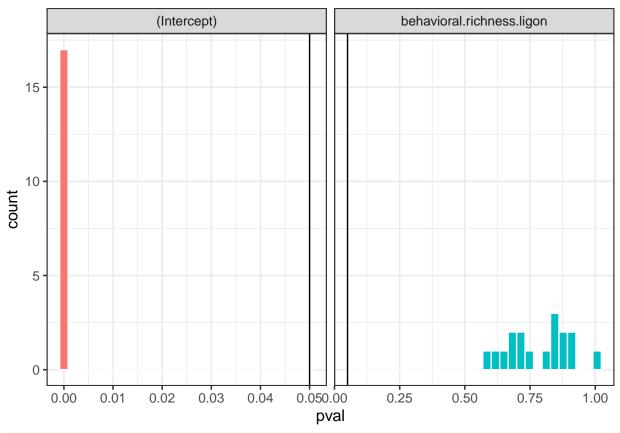
```
# Check full model estimates and compare to initial estimates:
sensi.m7$full.model.estimates
# test for influential species:
summary(sensi.m7)
summary_influ2(sensi.m7.2)$estimates
# Visual sensitivity diagnostics
sensi_plot(sensi.m7)
```

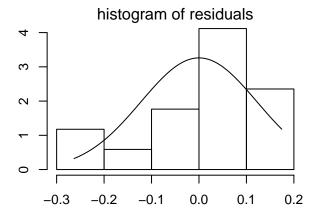


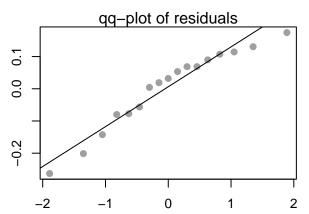
## `stat\_bin()` using `bins = 30`. Pick better value with `binwidth`.

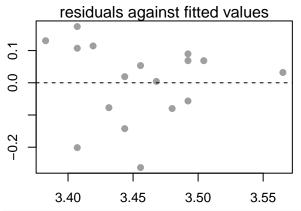


## `stat\_bin()` using `bins = 30`. Pick better value with `binwidth`.

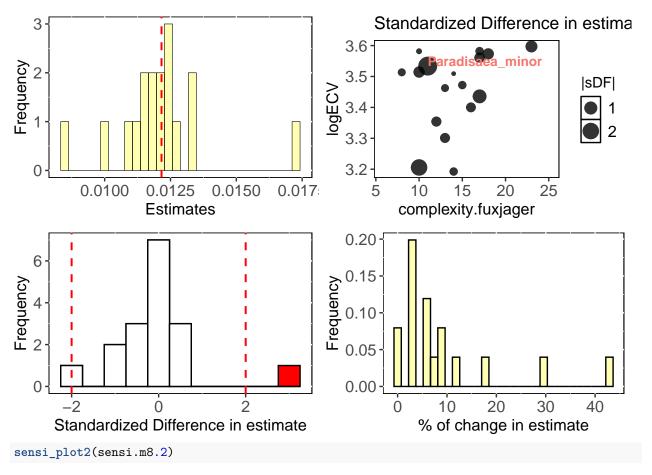




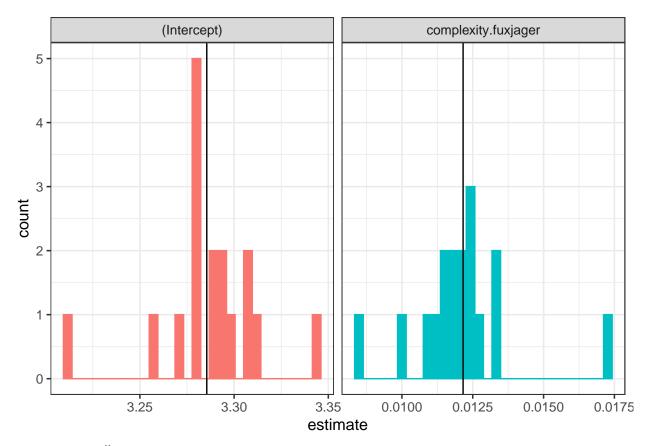




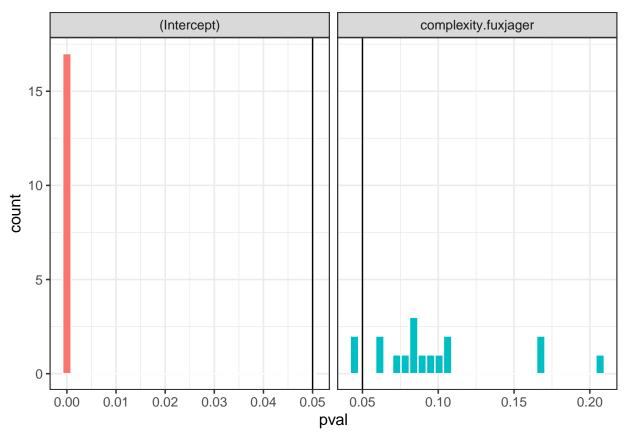
```
# Check full model estimates and compare to initial estimates:
sensi.m8$full.model.estimates
# test for influential species:
summary(sensi.m8)
summary_influ2(sensi.m8.2)$estimates
# Visual sensitivity diagnostics
sensi_plot(sensi.m8)
```

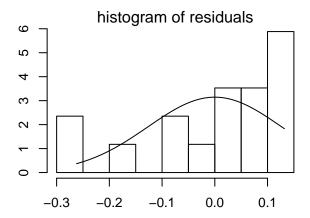


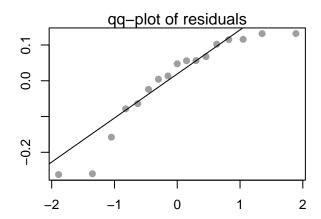
## `stat\_bin()` using `bins = 30`. Pick better value with `binwidth`.

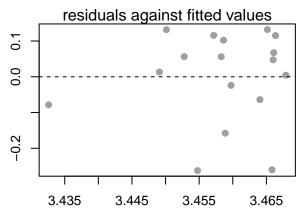


## `stat\_bin()` using `bins = 30`. Pick better value with `binwidth`.

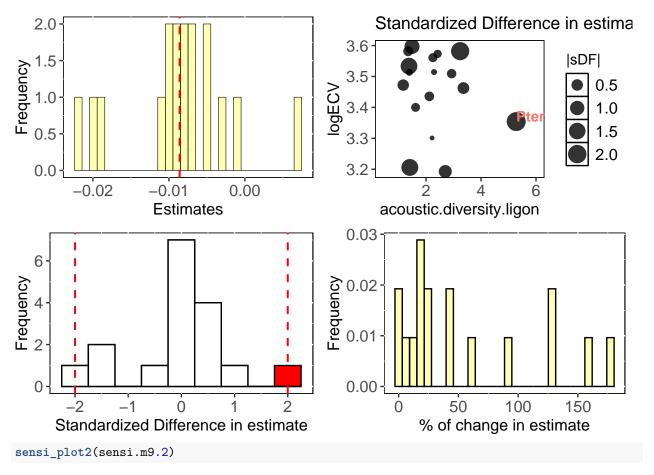




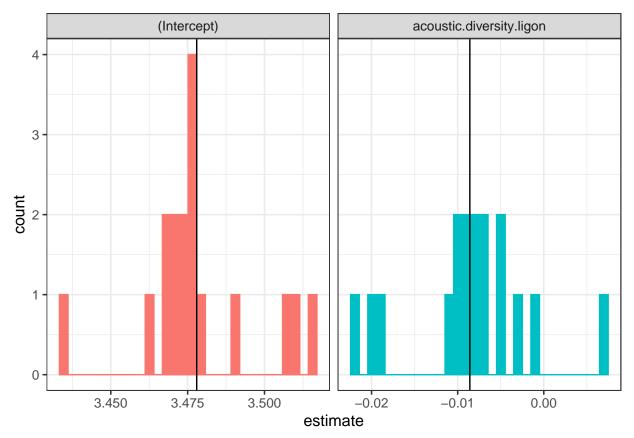




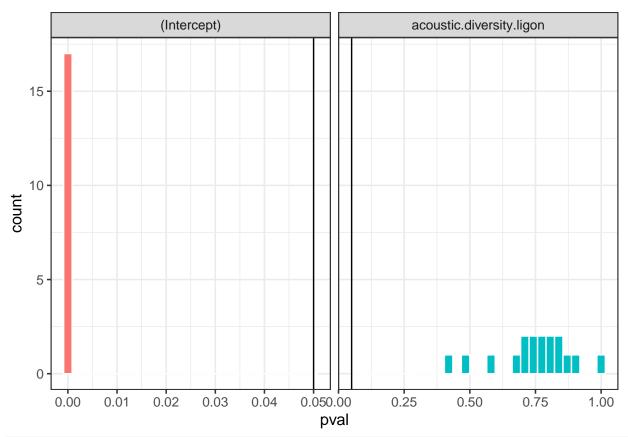
```
# Check full model estimates and compare to initial estimates:
sensi.m9$full.model.estimates
# test for influential species:
summary(sensi.m9)
# Visual sensitivity diagnostics
sensi_plot(sensi.m9)
```

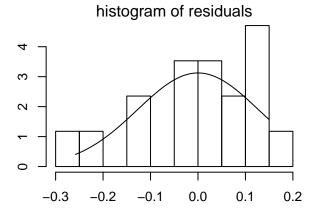


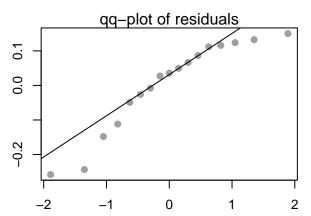
## `stat\_bin()` using `bins = 30`. Pick better value with `binwidth`.

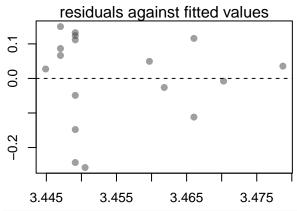


## `stat\_bin()` using `bins = 30`. Pick better value with `binwidth`.

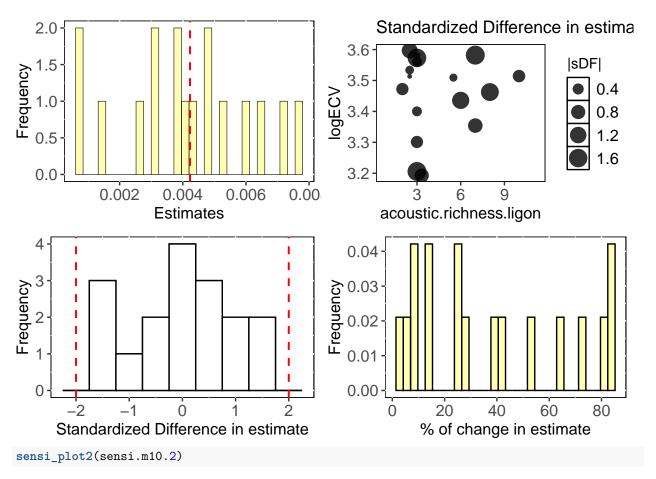




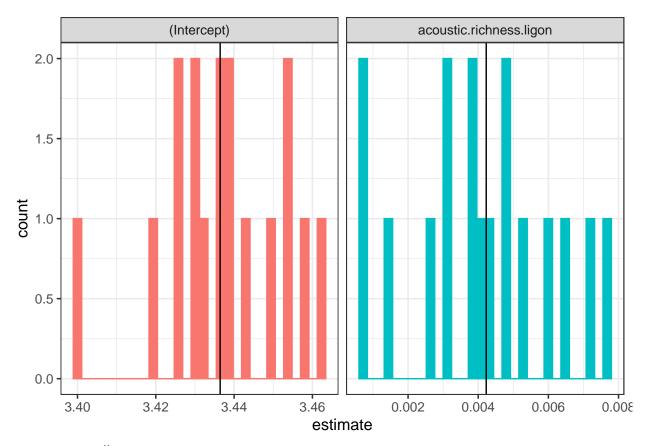




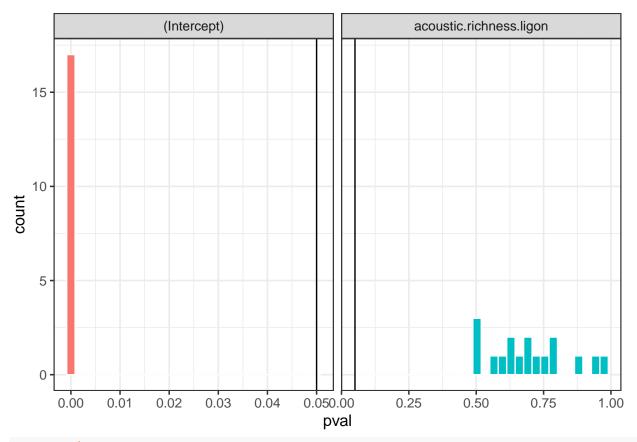
```
## Used dataset has 17 species that match data and phylogeny
# Check full model estimates and compare to initial estimates:
sensi.m10$full.model.estimates
# test for influential species:
summary(sensi.m10)
# Visual sensitivity diagnostics
sensi_plot(sensi.m10)
```



## `stat\_bin()` using `bins = 30`. Pick better value with `binwidth`.



## `stat\_bin()` using `bins = 30`. Pick better value with `binwidth`.



sensi.m10\$sensi.estimates

#### 2.6. Plotting

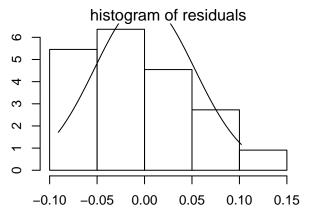
```
# Plot behavioral diversity
p1 <- ggplot(data.poly, aes(y = logECV, x = behavioral.diversity.ligon)) +</pre>
  geom_point(shape = 16, size = 2, alpha = 1, col = "#1B9E77") +
  theme bw() +
  geom_text_repel(aes(label = species_number),
                  size = 2,
                  box.padding = 0.15,
                  point.padding = 0.15) +
  ylab(expression(log[10]~(ECV)~"["*mm^3*"]")) +
  xlab("Behavioral diversity") +
  labs(colour = "Clade") +
  theme(panel.grid.major = element_blank(),
        panel.grid.minor = element_blank())
# Plot behavioral richness
p2 <- ggplot(data.poly, aes(y = logECV, x = behavioral.richness.ligon)) +
  geom_point(shape = 16, size = 2, alpha = 1, col = "#1B9E77") +
  theme_bw() +
  geom_text_repel(aes(label = species_number),
                  size = 2,
                  box.padding = 0.15,
                  point.padding = 0.15) +
 ylab(NULL) +
```

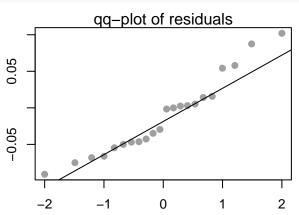
```
# ylab(expression(log[10]~(ECV)~"["*mm^3*"]")) +
  xlab("Behavioral richness") +
  labs(colour = "Clade") +
  scale_x_continuous(breaks = c(7.5, 10, 12.5, 15)) +
  theme(panel.grid.major = element_blank(),
        panel.grid.minor = element_blank())
# Plot behavioral complexity
# Generate predicted values while keeping logMass constant (e.g., at its mean)
mean_logMass <- mean(data.poly$logMass, na.rm = TRUE)</pre>
# Create a new data frame with the mean logMass for m3
data_for_prediction_m3 <- data.poly %>%
 mutate(logMass = mean_logMass)
# Predict values: Behavioral complexity for m3
m3.fit <- predict(m3, newdata = data_for_prediction_m3)</pre>
# Create data frame with predicted values for m3
df_predicted.m3 <- mutate(data_for_prediction_m3, predicted = m3.fit)</pre>
# We also want to highlight the species that, when dropped,
# result in a non-significant p-value
sp <- c("Cicinnurus magnificus",</pre>
        "Cicinnurus respublica",
        "Paradisaea minor",
        "Parotia lawesii")
# Plot the data, the model predictions, and the custom line
p3 <- ggplot(data.poly, aes(y = logECV, x = complexity.fuxjager)) +
  geom_point(col = "#1B9E77", shape = 16, size = 2, stroke = .75, alpha = 1) +
  geom_line(data = df_predicted.m3, aes(y = predicted),
            color = "black", linetype = 2, linewidth = 0.4) +
  geom_text_repel(aes(label = species_number),
                  size = 2,
                  box.padding = 0.15,
                  point.padding = 0.15) +
  theme_bw() +
 ylab(NULL) +
# ylab(expression(log[10]~(ECV)~"["*mm^3*"]")) +
 xlab("Behavioral complexity") +
  labs(colour = "Clade") +
  theme(panel.grid.major = element_blank(),
        panel.grid.minor = element_blank(),
        legend.position = "none")
# Plot acoustic diversity
p4 <- ggplot(data.poly, aes(y = logECV, x = acoustic.diversity.ligon)) +
  geom_point(shape = 16, size = 2, alpha = 1, col = "#7570B3") +
  theme_bw() +
  geom_text_repel(aes(label = species_number),
                  size = 2,
```

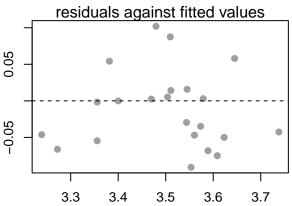
```
box.padding = 0.15,
                    point.padding = 0.15) +
  ylab(expression(log[10]~(ECV)~"["*mm^3*"]")) +
  xlab("Acoustic diversity") +
  labs(colour = "Clade") +
  theme(panel.grid.major = element_blank(),
         panel.grid.minor = element_blank())
# Plot acoustic richness
p5 <- ggplot(data.poly, aes(y = logECV, x = acoustic.richness.ligon)) +
  geom_point(shape = 16, size = 2, alpha = 1, col = "#7570B3") +
  theme_bw() +
  geom_text_repel(aes(label = species_number),
                    size = 2,
                    box.padding = 0.15,
                    point.padding = 0.15) +
  ylab(NULL) +
  xlab("Acoustic richness") +
  labs(colour = "Clade") +
  theme(panel.grid.major = element_blank(),
         panel.grid.minor = element_blank())
combined <- (p1|p2|p3)/(p4|p5|plot_spacer())</pre>
combined + plot_annotation(tag_levels = 'A')
                                     3.6
      3.6
 log_{10} (ECV) [mm^3]
      3.5
                                     3.5
                                                                    3.5
      3.4
                                     3.4
                                                                    3.4
                                                             6
      3.3
                                     3.3
                                                                    3.3
      3.2
                                     3.2 -
                                                                    3.2
                                            7.5 10.0 12.5 15.0
              5.0
                    7.5
                          10.0
                                                                              12
                                                                                   16
                                                                                         20
           Behavioral diversity
                                          Behavioral richness
                                                                        Behavioral complexity
                                    E<sub>3.6</sub>
D
      3.6
  \log_{10} (ECV) [mm^3]
                                       3.5
      3.4
                               12
                                       3.4
      3.3
                                       3.3
      3.2
                                       3.2
                    3
                                                       6
                                                                  10
             Acoustic diversity
                                              Acoustic richness
```

### Part 3: Testing for evolutionary grade shifts between BoP clades

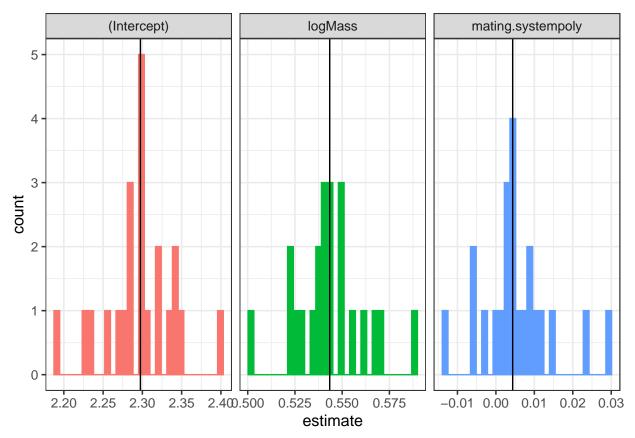
#### 3.1.1. Hypothesis-testing



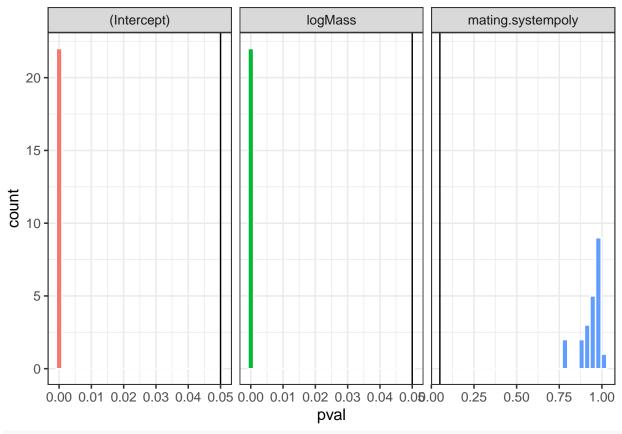


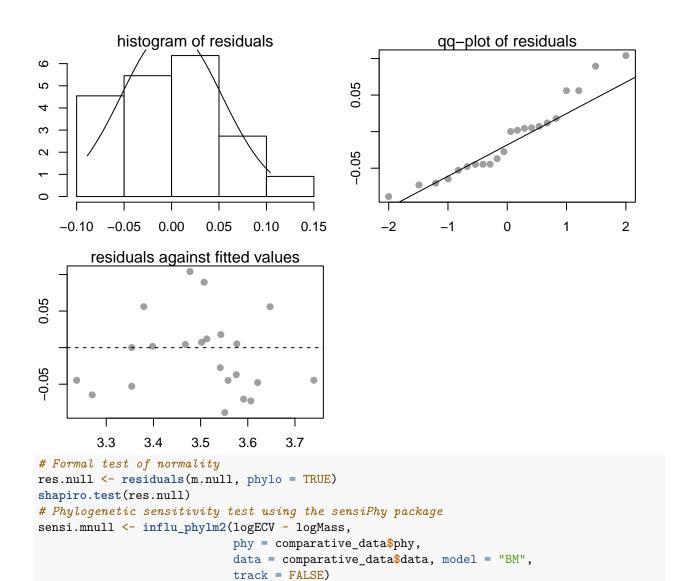


```
## Used dataset has 22 species that match data and phylogeny
# Check full model estimates and compare to initial estimates:
sensi.mfull$full.model.estimates
# test for influential species:
summary_influ2(sensi.mfull)$estimates
# Visual sensitivity diagnostics
sensi_plot2(sensi.mfull)
```



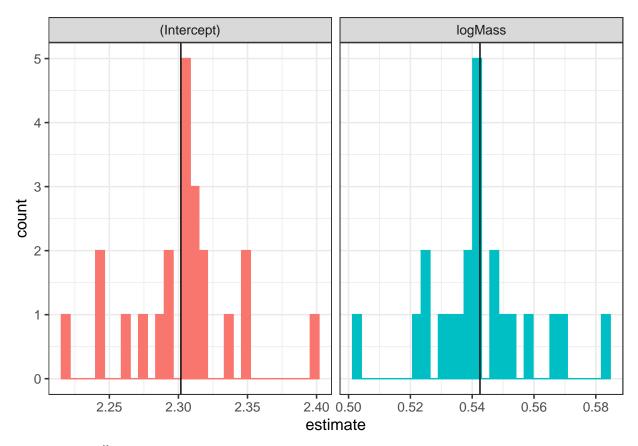
## `stat\_bin()` using `bins = 30`. Pick better value with `binwidth`.



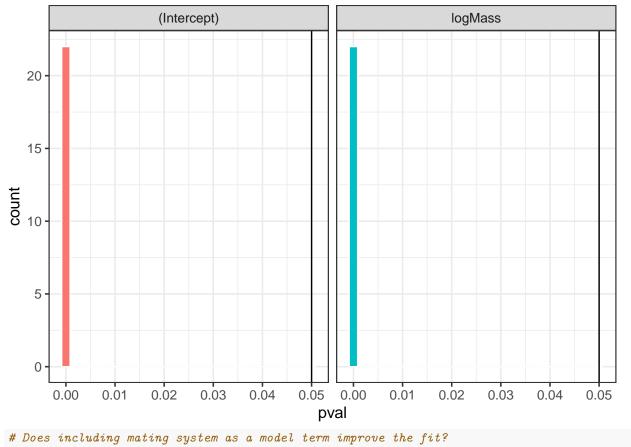


```
## Used dataset has 22 species that match data and phylogeny
```

```
# Check full model estimates and compare to initial estimates:
sensi.mnull$full.model.estimates
# test for influential species:
summary_influ2(sensi.mnull)$estimates
# Visual sensitivity diagnostics
sensi_plot2(sensi.mnull)
```

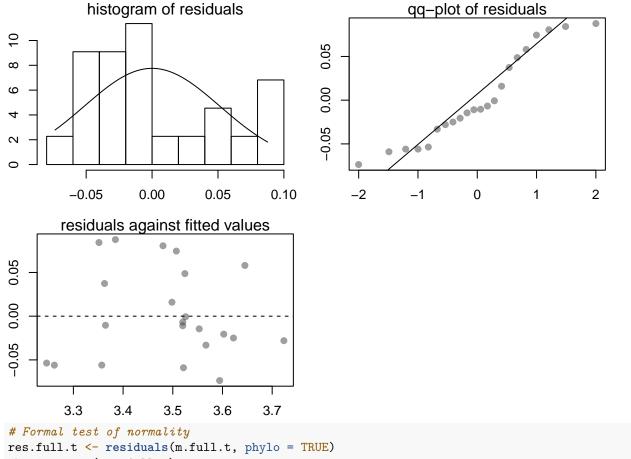


## `stat\_bin()` using `bins = 30`. Pick better value with `binwidth`.



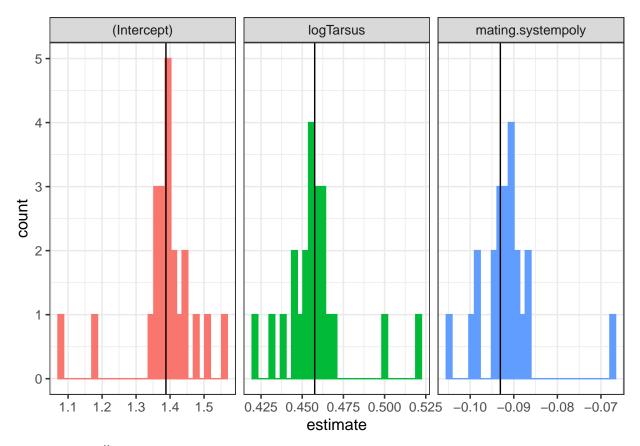
# anova(m.null, m.full) summary(m.null) # Nope

## 3.1.2. We can do the same using tarsus length cubed as a predictor

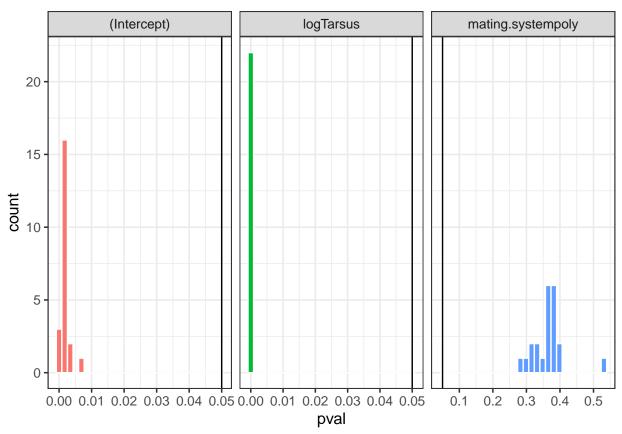


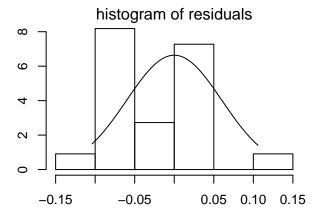
## Used dataset has 22 species that match data and phylogeny
# Check full model estimates and commune to initial estimates:

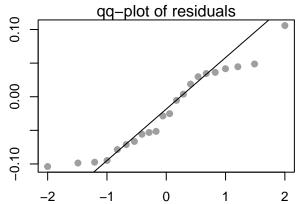
```
# Check full model estimates and compare to initial estimates:
sensi.mfull.t$full.model.estimates
# test for influential species:
summary_influ2(sensi.mfull.t)$estimates
# Visual sensitivity diagnostics
sensi_plot2(sensi.mfull.t)
```

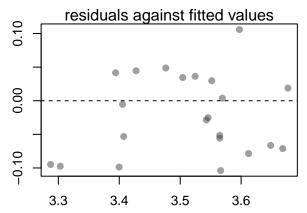


## `stat\_bin()` using `bins = 30`. Pick better value with `binwidth`.

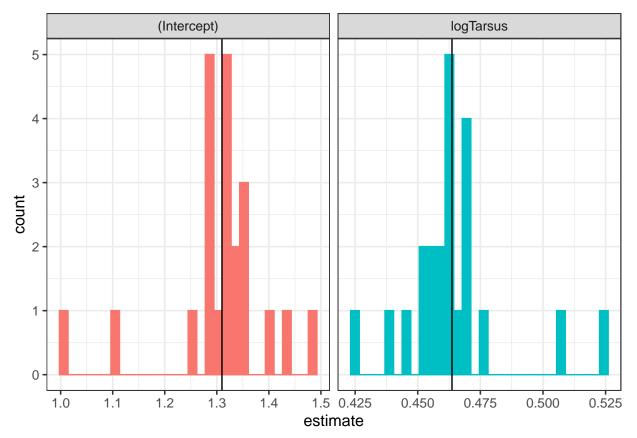




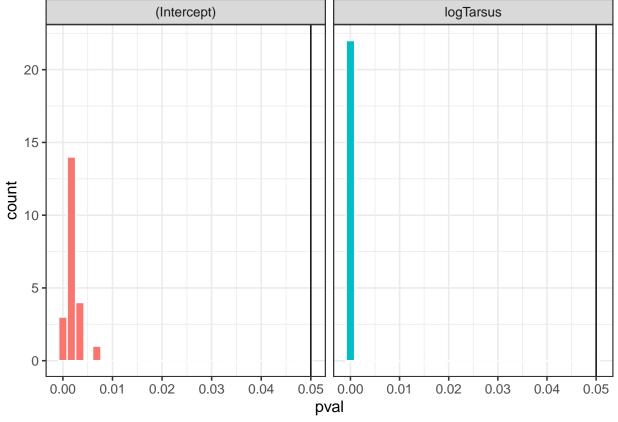




```
# Check full model estimates and compare to initial estimates:
sensi.mnull.t$full.model.estimates
# test for influential species:
summary_influ2(sensi.mnull.t)$estimates
# Visual sensitivity diagnostics
sensi_plot2(sensi.mnull.t)
```



## `stat\_bin()` using `bins = 30`. Pick better value with `binwidth`.



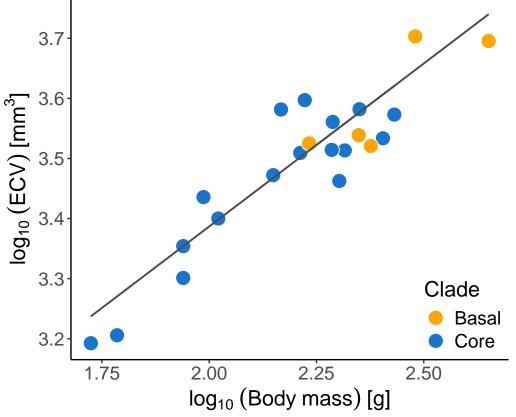
```
# Does including mating system as a model term improve the fit?
anova(m.null.t, m.full.t)
summary(m.null.t) # Nope
```

## 3.2. Plotting results

```
# Predict values
null.fit<- predict(m.null, data)</pre>
# Create data frame for males with predicted values
df_predicted.null <- mutate(data, predicted = null.fit)</pre>
p <- ggplot(data, aes(x = logMass, y = logECV, fill = mating.system)) +</pre>
  geom_point(shape = 21, size = 5, alpha = 1, col = "white") +
  geom_line(data = df_predicted.null, aes(y = null.fit),
            color = "grey30", linetype = 1, linewidth = 0.7) +
  scale_fill_manual(values = c("orange", "dodgerblue3"),
                    labels = c("Basal", "Core")) + # Rename levels here
  theme classic() +
  ylab(expression(log[10]~(ECV)~"["*mm^3*"]")) +
  xlab(expression(log[10]~(Body~mass)~"["*g*"]")) +
  theme(
   axis.text.x = element_text(size = 14),
   axis.text.y = element text(size = 14),
   axis.title.x = element_text(size = 16),
   axis.title.y = element_text(size = 16),
   legend.title = element_text(size = 16),
```

```
legend.text = element_text(size = 14),
legend.position = c(1, 0),
legend.justification = c(1, 0),
legend.background = element_blank()) +
coord_fixed(ratio = 1.4) +
scale_y_continuous(breaks = c(3.2, 3.3, 3.4, 3.5, 3.6, 3.7)) +
theme(
   panel.grid.major = element_blank(),
   panel.grid.minor = element_blank()) +
labs(fill = "Clade")

print(p)
```



```
# For completeness, we also test whether body size predicts display complexity

# Start with a fresh R environment
rm(list = ls())

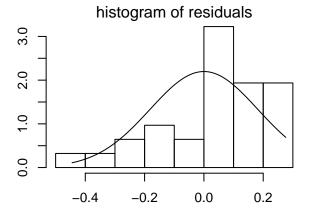
# Call other functions
source("diagnostic_fcns.r")
source("influ_phylm2_Paterno_et_al.R")
source("summary_influ_phylm2_Paterno_et_al.R")
source("plot_influ_phylm2_Paterno_et_al.R")

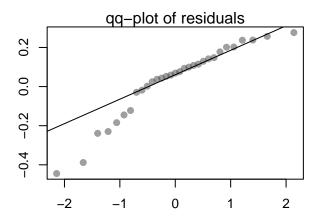
# Load the data again in the fresh environment
df <- read.csv("Paradisaeidae_Brain.Data.Full.csv")
# Load the tree</pre>
```

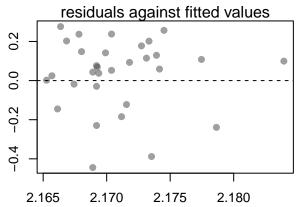
```
tree <- read.nexus("Ligon.et.al._UltrametricTree")</pre>
# Only the core birds of paradise
df.poly <- filter(df, mating.system == "poly")</pre>
# First, run all models with body mass as a response variable
# New comparative data set:
comparative_df <- comparative.data(phy = tree,</pre>
                                      data = df.poly,
                                      names.col = species,
                                      vcv = TRUE,
                                      na.omit = FALSE,
                                      warn.dropped = TRUE)
# Fit model 1
m1 <- pgls(log10(bodymass.frith.g) ~ behavioral.diversity.ligon, data = comparative_df, lambda = 1)
# Diagnostics
diagnostics.plot(m1)
                                                              qq-plot of residuals
            histogram of residuals
                                                0.2
3.0
                                                0.0
2.0
                                                -0.2
1.0
                                                -0.4
0.0
        -0.4
                 -0.2
                           0.0
                                                                        0
                                                                                 1
                                                                                         2
                                    0.2
                                                      -2
                                                               -1
        residuals against fitted values
0.0
-0.2
-0.4
   2.160
               2.170
                            2.180
                                        2.190
# Formal test of normality
res.m1 <- residuals(m1, phylo = TRUE)</pre>
shapiro.test(res.m1)
# Phylogenetic sensitivity test using the sensiPhy package
sensi.m1 <- influ_phylm(log10(bodymass.frith.g) ~ behavioral.diversity.ligon,</pre>
                              phy = comparative_df$phy,
                              data = comparative_df$data, model = "BM",
```

track = FALSE)

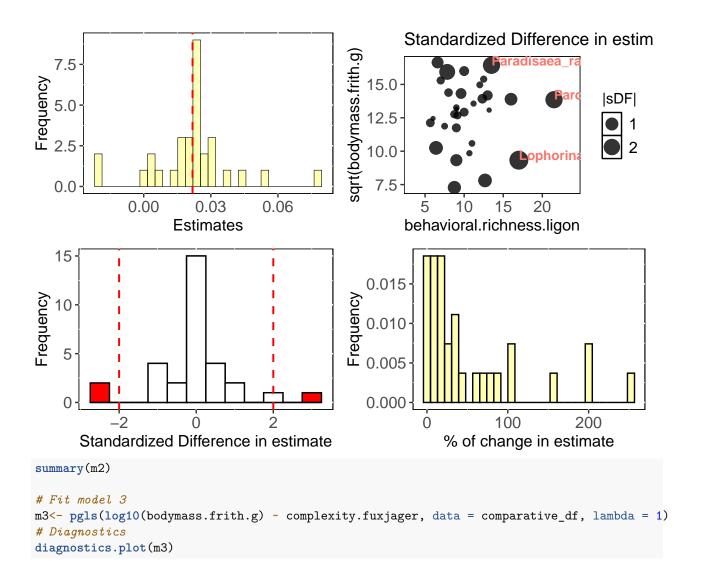
```
## Used dataset has 31 species that match data and phylogeny
# Check full model estimates and compare to initial estimates:
sensi.m1$full.model.estimates
# test for influential species:
summary(sensi.m1)
# Visual sensitivity diagnostics
sensi_plot(sensi.m1)
                                                     Standardized Difference in estima
                                              |sDF|
Frequency
   3
                                                                                      0.5
                                                                                      1.0
                                                                                      1.5
                                                                                      2.0
  0
        0.000
                0.002
                         0.004
                                  0.006
                                                            5
                                                                     10
                   Estimates
                                                     behavioral.diversity.ligon
                                                 0.03
Frequency
                                              Frequency
                                                 0.02
    5
                                                 0.01
                                                 0.00
    0
                        0
                                                                    50
                                                        0
                                                                                100
                                                            % of change in estimate
      Standardized Difference in estimate
summary(m1)
nobs(m1)
# Fit model 2
m2<- pgls(log10(bodymass.frith.g) ~ behavioral.richness.ligon, data = comparative_df, lambda = 1)</pre>
# Diagnostics
diagnostics.plot(m2)
```

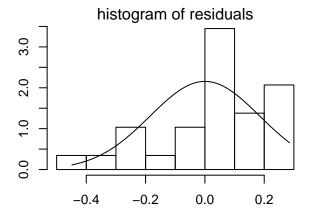


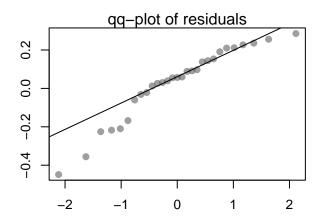


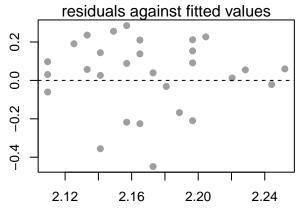


```
## Used dataset has 31 species that match data and phylogeny
# Check full model estimates and compare to initial estimates:
sensi.m2$full.model.estimates
# test for influential species:
summary(sensi.m2)
# Visual sensitivity diagnostics
sensi_plot(sensi.m2)
```

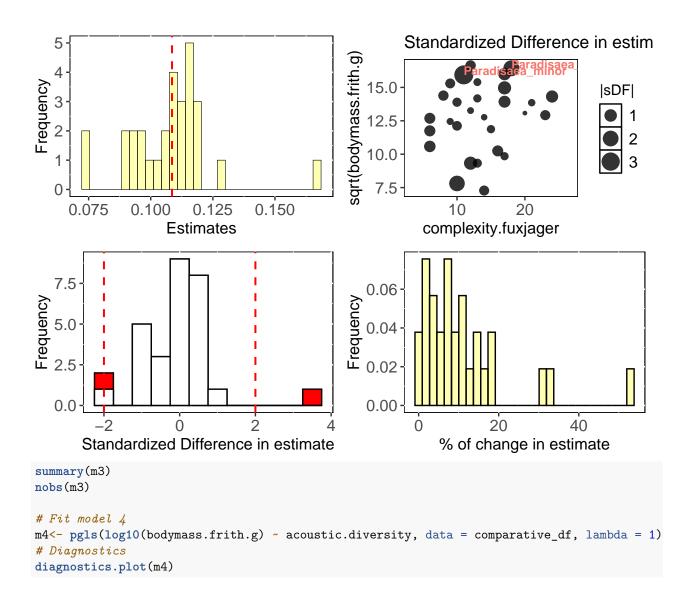


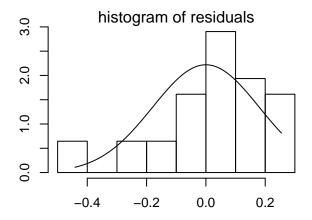


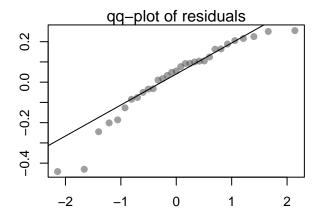


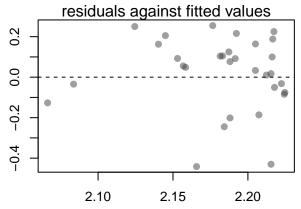


```
## Used dataset has 29 species that match data and phylogeny
# Check full model estimates and compare to initial estimates:
sensi.m3$full.model.estimates
# test for influential species:
summary(sensi.m3)
# Visual sensitivity diagnostics
sensi_plot(sensi.m3)
```

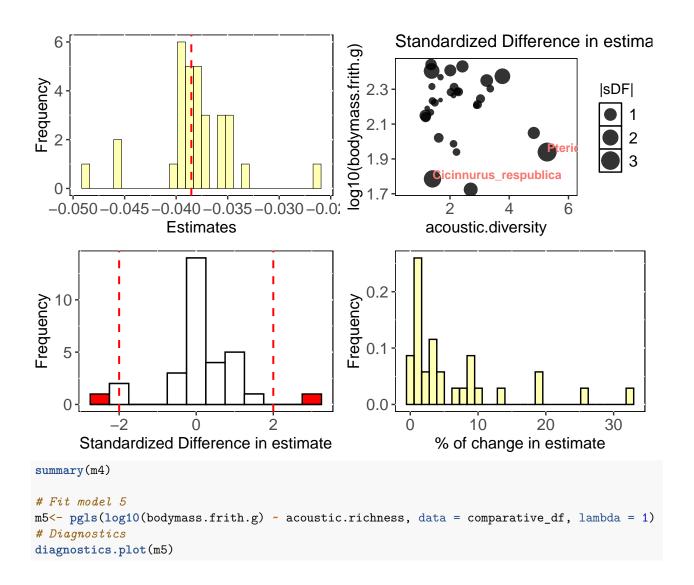


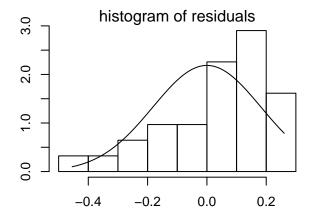


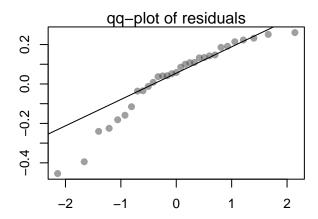


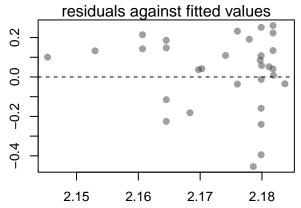


```
## Used dataset has 31 species that match data and phylogeny
# Check full model estimates and compare to initial estimates:
sensi.m4$full.model.estimates
# test for influential species:
summary(sensi.m4)
# Visual sensitivity diagnostics
sensi_plot(sensi.m4)
```

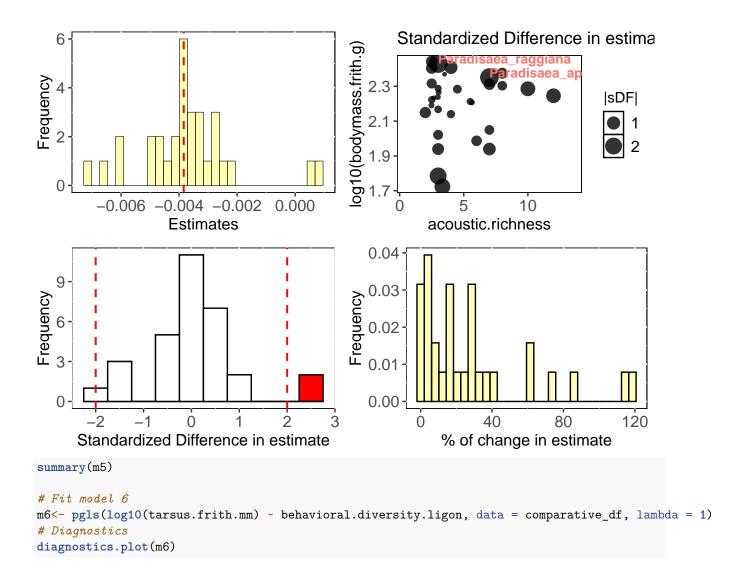


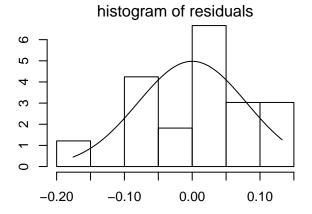


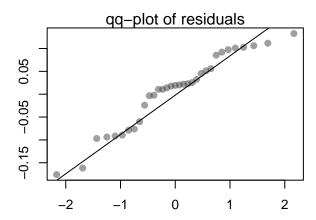


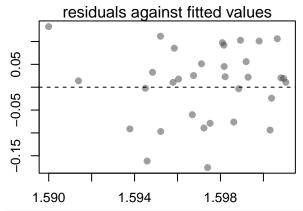


```
## Used dataset has 31 species that match data and phylogeny
# Check full model estimates and compare to initial estimates:
sensi.m5$full.model.estimates
# test for influential species:
summary(sensi.m5)
# Visual sensitivity diagnostics
sensi_plot(sensi.m5)
```



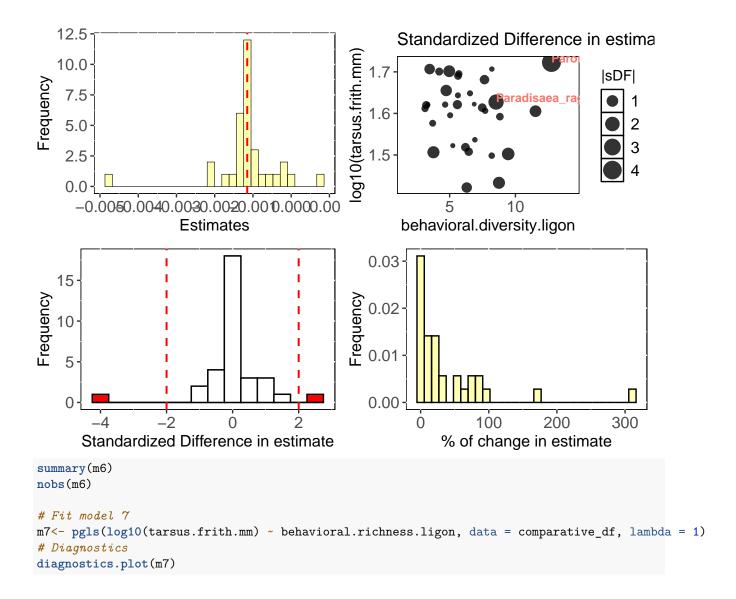


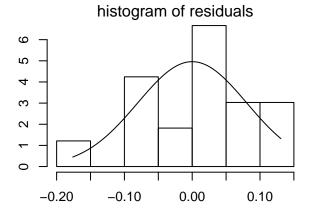


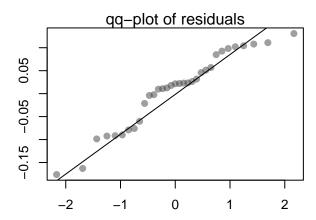


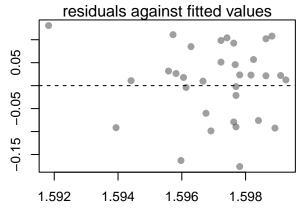
## Used dataset has 33 species that match data and phylogeny

```
# Check full model estimates and compare to initial estimates:
sensi.m6$full.model.estimates
# test for influential species:
summary(sensi.m6)
# Visual sensitivity diagnostics
sensi_plot(sensi.m6)
```



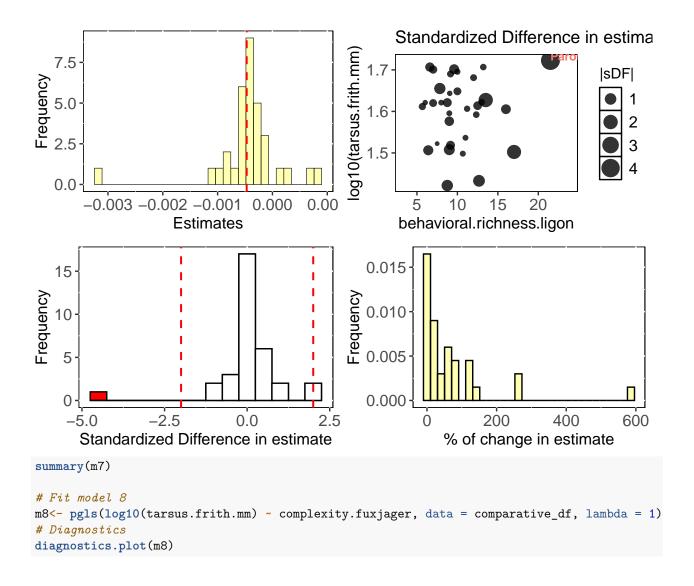


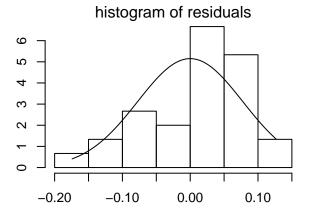


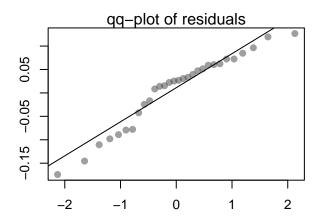


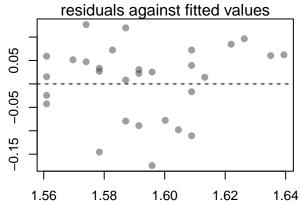
## Used dataset has 33 species that match data and phylogeny

```
# Check full model estimates and compare to initial estimates:
sensi.m7$full.model.estimates
# test for influential species:
summary(sensi.m7)
# Visual sensitivity diagnostics
sensi_plot(sensi.m7)
```

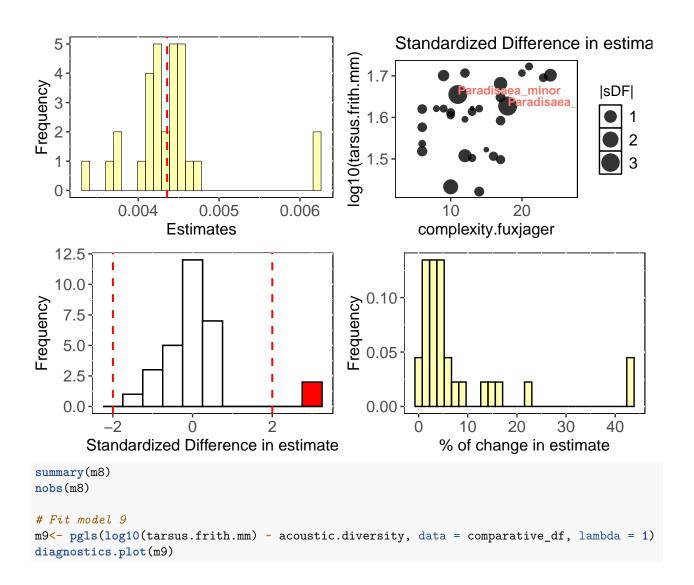


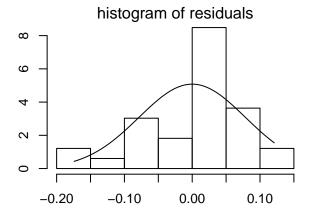


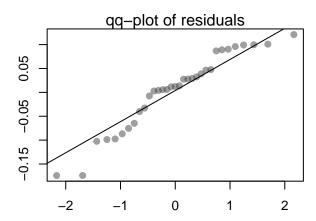


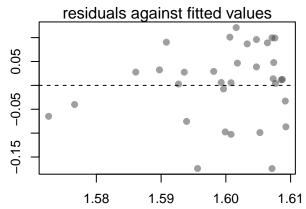


```
## Used dataset has 30 species that match data and phylogeny
# Check full model estimates and compare to initial estimates:
sensi.m8$full.model.estimates
# test for influential species:
summary(sensi.m8)
# Visual sensitivity diagnostics
sensi_plot(sensi.m8)
```





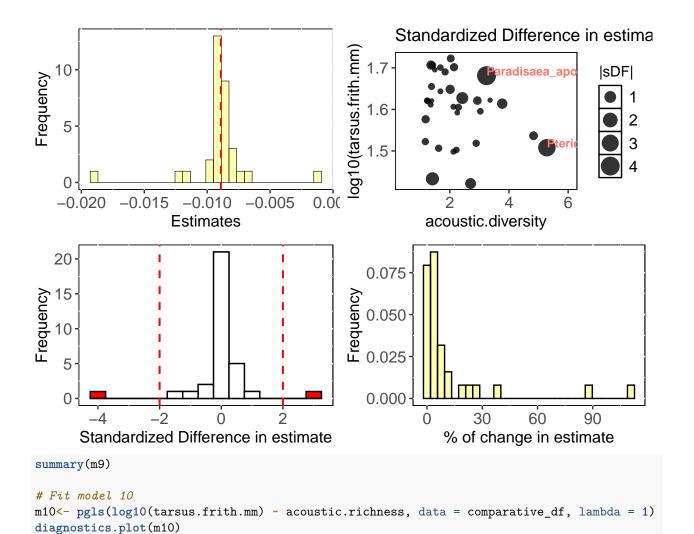


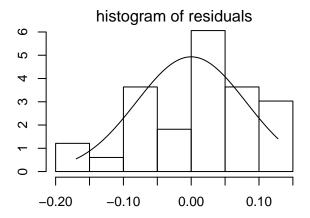


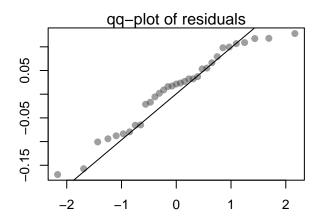
sensi\_plot(sensi.m9)

```
# Check full model estimates and compare to initial estimates:
sensi.m9$full.model.estimates
# test for influential species:
summary(sensi.m9)
# Visual sensitivity diagnostics
```

## Used dataset has 33 species that match data and phylogeny

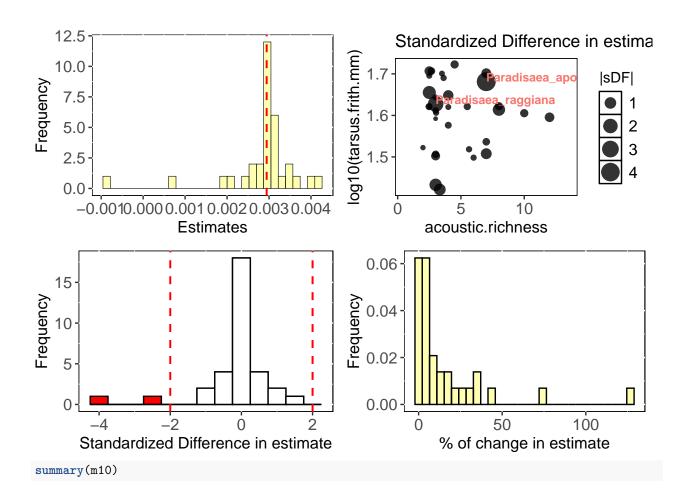






## residuals against fitted values 90.0 - 4.

```
## Used dataset has 33 species that match data and phylogeny
# Check full model estimates and compare to initial estimates:
sensi.m10$full.model.estimates
# test for influential species:
summary(sensi.m10)
# Visual sensitivity diagnostics
sensi_plot(sensi.m10)
```



## END OF DOCUMENT