

LDHA/B EM wt LMM Analysis

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```
#Sample: Mouse Optic Nerve  
#Immunogold (LDHA or LDHB) stained TEM images  
#Animal line: LDHABfl, LDHAB KO under CNP-Cre promotor  
#mut = LDHA and LDHB KO  
#ctr = wt littermates  
#Gold = Gold of LDHA and LDHB, respectively
```

```
## Loading required package: tidyverse
```

```
## -- Attaching core tidyverse packages ----- tidyverse 2.0.0 --
```

```
## v dplyr      1.1.2      v readr      2.1.4
```

```
## v forcats   1.0.0      v stringr   1.5.0
```

```
## v ggplot2    3.4.2      v tibble    3.2.1
```

```
## v lubridate  1.9.2      v tidyr     1.3.0
```

```
## v purrr      1.0.1
```

```
## -- Conflicts ----- tidyverse_conflicts() --
```

```
## x dplyr::filter() masks stats::filter()
```

```
## x dplyr::lag()     masks stats::lag()
```

```
## i Use the conflicted package (<http://conflicted.r-lib.org/>) to force all conflicts to become errors
```

```
## Loading required package: readxl
```

```
##
```

```
## Loading required package: ggpubr
```

```
##
```

```
## Loading required package: lme4
```

```
##
```

```
## Loading required package: Matrix
```

```
##
```

```
##
```

```
## Attaching package: 'Matrix'
```

```
##
```

```
##
```

```
## The following objects are masked from 'package:tidyr':
```

```
##
```

```
##      expand, pack, unpack
```

```
##
```

```
##
```

```
## Loading required package: here
```

```
##
```

```
## here() starts at /Users/erik/Documents/R-Projects/LDHAB-Oligodendrocytes
```

```
##
```

```
## Loading required package: emmeans
```

```

##
## Loading required package: performance
##
## Loading required package: interactions
##
## Loading required package: lmerTest
##
##
## Attaching package: 'lmerTest'
##
##
## The following object is masked from 'package:lme4':
##
##     lmer
##
## The following object is masked from 'package:stats':
##
##     step
##
## Loading required package: DHARMA
##
## This is DHARMA 0.4.6. For overview type '?DHARMA'. For recent changes, type news(package = 'DHARMA')
##
## Loading required package: reshape2
##
##
## Attaching package: 'reshape2'
##
##
## The following object is masked from 'package:tidyr':
##
##     smiths
##
## Loading required package: simr
##
##
## Attaching package: 'simr'
##
##
## The following object is masked from 'package:lme4':
##
##     getData
##
##
## The following object is masked from 'package:stringr':
##
##     fixed

## [1] "tidyverse : 2.0.0"      "readxl : 1.4.2"        "ggpubr : 0.6.0"
## [4] "lme4 : 1.1.33"         "here : 1.0.1"          "emmeans : 1.8.7"
## [7] "performance : 0.10.4" "interactions : 1.1.5" "lmerTest : 3.1.3"

```

```
## [10] "DHARMA : 0.4.6"          "reshape2 : 1.4.4"          "simr : 1.0.7"
```

```
#Imports excel file
file = here::here("LDHAB_EM_ON_Quantification.xlsx")

ldha <- read_excel(path = file, sheet = "OL - LDHA") %>%
  group_by(Animal, Nr) %>%
  summarise(
    Image = first(Image),
    Genotype = first(Genotype),
    OligoCellBodyArea = sum(OligoCellBodyArea),
    OligoNucleusArea = sum(OligoNucleusArea),
    OligoArea = OligoCellBodyArea-OligoNucleusArea,
    OligoGold = sum(OligoGold)
  ) %>%
  full_join(
    read_excel(path = file, sheet = "Axons - LDHA")) %>%
  mutate(AxonDiameter = sqrt(AxonArea/pi)*2,
    FiberDiameter = sqrt(FiberArea/pi)*2,
    gRatio = AxonDiameter/FiberDiameter,
    gRatio = AxonDiameter/FiberDiameter,
    MyelinArea = FiberArea-AxonArea
  )
```

```
## 'summarise()' has grouped output by 'Animal'. You can override using the
## '.groups' argument.
## Joining with 'by = join_by(Animal, Nr, Image, Genotype)'
```

```
ldha
```

```
## # A tibble: 1,086 x 21
## # Groups:   Animal [8]
##   Animal   Nr Image      Genotype OligoCellBodyArea OligoNucleusArea OligoArea
##   <chr> <dbl> <chr>      <chr>          <dbl>          <dbl>      <dbl>
## 1 0888     1 36_0888_2~ mut          20.6           15.0         5.59
## 2 0888     2 36_0888_4~ mut          15.1            8.61         6.44
## 3 0888     3 36_0888_7~ mut          14.3            8.87         5.44
## 4 0888     4 36_0888_9~ mut          39.1           30.5         8.66
## 5 0888     5 36_0888_1~ mut          31.9           16.0        15.9
## 6 0891     1 36_0891_1~ ctr          31.5           26.3         5.22
## 7 0891     2 36_0891_3~ ctr          38.1           17.1         21
## 8 0891     3 36_0891_5~ ctr          51.2           31.2        20.0
## 9 0891     4 36_0891_1~ ctr          29.0           24.6         4.38
## 10 0891    5 36_0891_1~ ctr          36.5           24.6        11.9
## # i 1,076 more rows
## # i 14 more variables: OligoGold <dbl>, Scale <chr>, AxonArea <dbl>,
## #   AxonGold <dbl>, FiberArea <dbl>, MyelinGold <dbl>, AstrocyteGold <dbl>,
## #   AstrocyteArea <dbl>, GapJunctionGold <dbl>, GapJunctionLength <dbl>,
## #   AxonDiameter <dbl>, FiberDiameter <dbl>, gRatio <dbl>, MyelinArea <dbl>
```

```
ldha_ctr <- ldha %>% subset(subset = Genotype == "ctr") %>%
  dplyr::select(Animal, Image, AxonArea, AxonGold, MyelinArea, MyelinGold, AstrocyteArea, AstrocyteGold)
  group_by(Image) %>%
```

```

summarize(Animal = first(Animal),
  across(matches("Gold|Area"),
    list(mean = ~ mean(., na.rm = TRUE)),
    .names = "{.fn}_{.col}"),
    .groups = "drop") %>%
rename_with(~ sub("mean_", "", .x), .cols = starts_with("mean_")) %>%
pivot_longer(
  cols = matches("(Area|Gold)"),
  names_to = c("Type", ".value"),
  names_pattern = "(.*) (Area|Gold)"
) %>%
add_column(StainingPerArea = .$Gold/.$Area) %>%
na.omit() %>%
rename(Staining = Gold)
#write.csv(ldha_ctr, file = here("ldha_ctr.csv"), row.names = FALSE)
data <- ldha_ctr

# Fit a Linear Mixer Model
model <- lmer(StainingPerArea ~ Type + (1|Animal) + (1|Animal:Type), data = data)

# Results Cell Type
summary(model) # Check the model summary

```

```

## Linear mixed model fit by REML. t-tests use Satterthwaite's method [
## lmerModLmerTest]
## Formula: StainingPerArea ~ Type + (1 | Animal) + (1 | Animal:Type)
## Data: data
##
## REML criterion at convergence: 717.6
##
## Scaled residuals:
## Min 1Q Median 3Q Max
## -2.9011 -0.4911 -0.0692 0.3470 3.4856
##
## Random effects:
## Groups Name Variance Std.Dev.
## Animal:Type (Intercept) 1.6992 1.3035
## Animal (Intercept) 0.9542 0.9768
## Residual 3.3075 1.8187
## Number of obs: 172, groups: Animal:Type, 16; Animal, 4
##
## Fixed effects:
## Estimate Std. Error df t value Pr(>|t|)
## (Intercept) 8.1981 0.8560 9.1119 9.578 4.68e-06 ***
## TypeAxon -1.4121 0.9912 8.2049 -1.425 0.191167
## TypeMyelin -5.8094 0.9912 8.2049 -5.861 0.000343 ***
## TypeOligo -6.4662 1.0413 9.9895 -6.210 0.000101 ***
## ---
## Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Correlation of Fixed Effects:
## (Intr) TypAxn TypMyl
## TypeAxon -0.582

```

```
## TypeMyelin -0.582 0.503
## TypeOligo -0.554 0.479 0.479
```

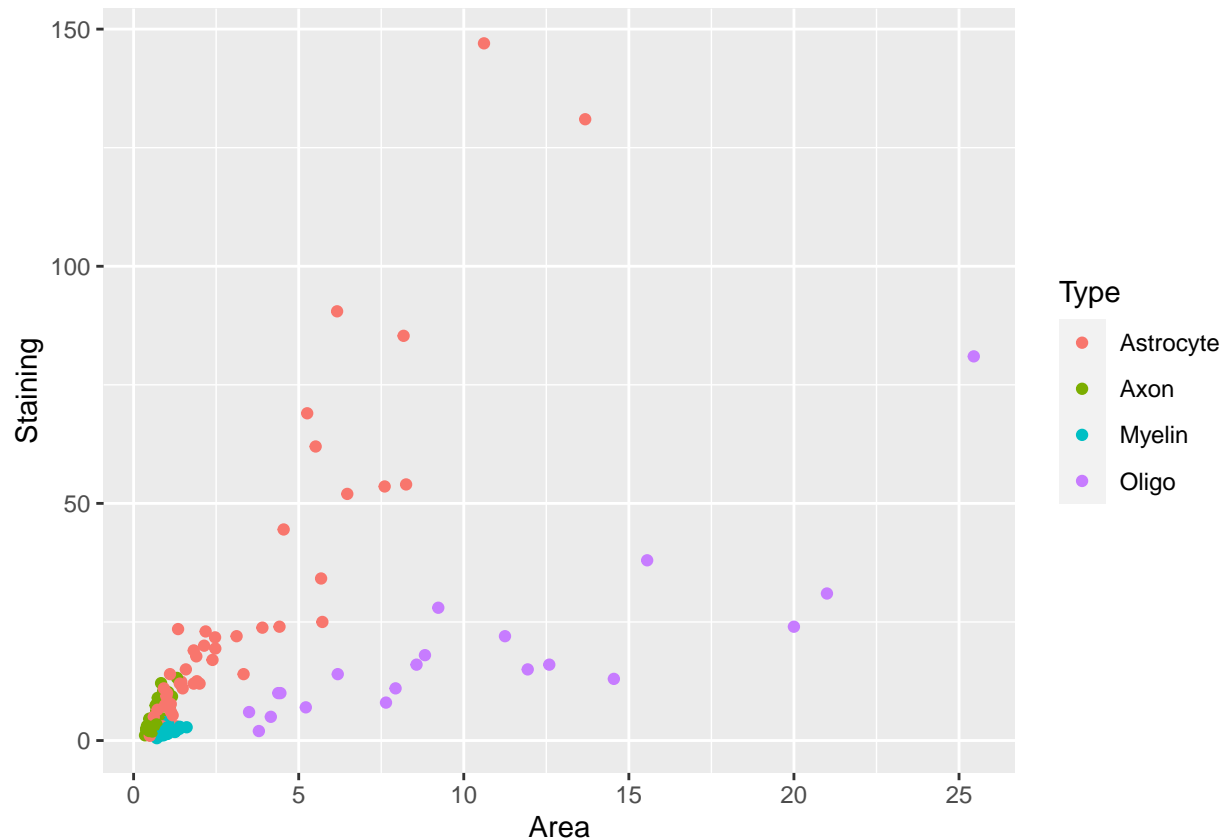
```
anova(model) # Compute ANOVA
```

```
## Type III Analysis of Variance Table with Satterthwaite's method
##      Sum Sq Mean Sq NumDF  DenDF F value    Pr(>F)
## Type 195.86  65.286     3 8.9349  19.738 0.0002785 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```
emm <- emmeans(model, ~ Type) # Compute the estimated marginal means
pairs(emm) # Perform pairwise comparisons
```

```
## contrast      estimate    SE    df t.ratio p.value
## Astrocyte - Axon      1.412 0.991   8.3   1.425 0.5185
## Astrocyte - Myelin     5.809 0.991   8.3   5.861 0.0015
## Astrocyte - Oligo      6.466 1.041  10.1   6.210 0.0005
## Axon - Myelin          4.397 0.988   8.2   4.449 0.0087
## Axon - Oligo           5.054 1.039  10.0   4.866 0.0031
## Myelin - Oligo         0.657 1.039  10.0   0.632 0.9192
##
## Degrees-of-freedom method: kenward-roger
## P value adjustment: tukey method for comparing a family of 4 estimates
```

```
ggplot(data, aes(x = Area, y = Staining, color = Type)) +
  geom_point() +
  labs(x = "Area", y = "Staining", color = "Type")
```



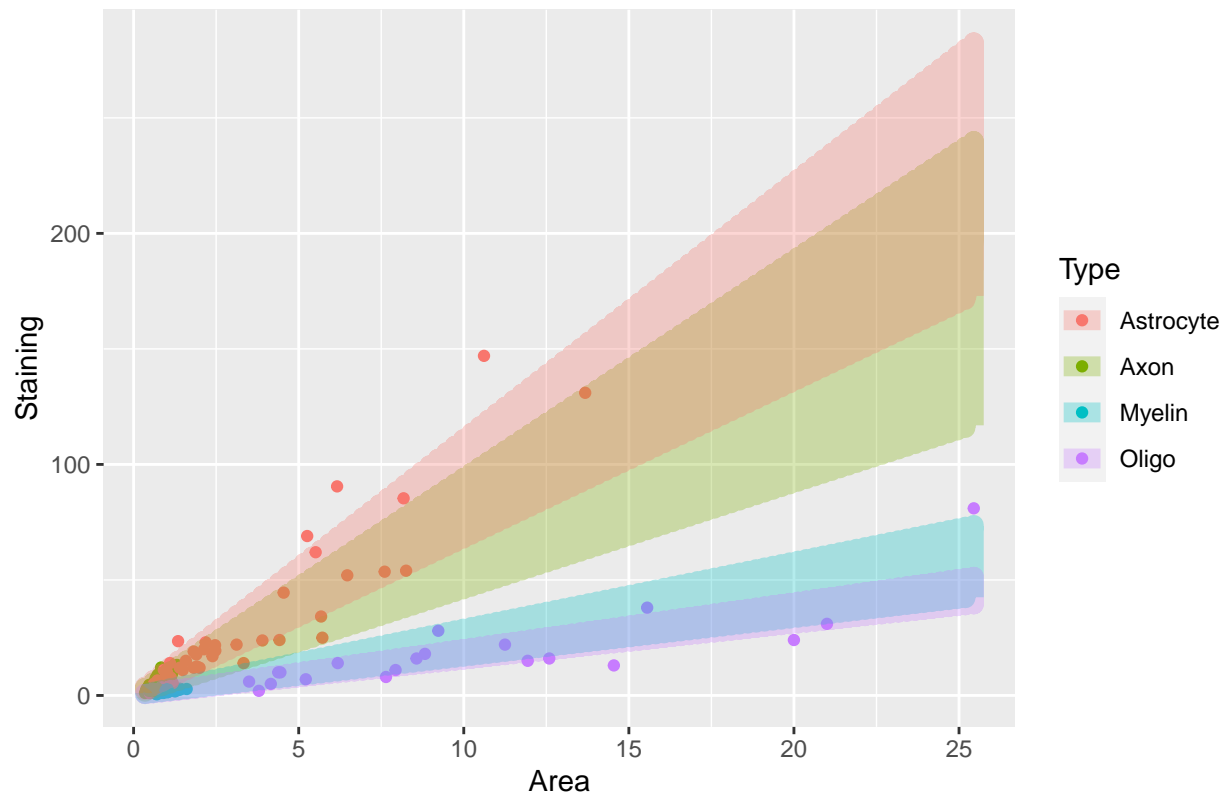
```
# Create a new dataset for predictions
prediction <- expand.grid(Area = seq(min(data$Area), max(data$Area), length.out = 100),
                          Type = unique(data$Type),
                          Animal = unique(data$Animal))
```

```
# Add predictions from the models
prediction$Staining <- predict(model, newdata = prediction) * prediction$Area
prediction$StainingDensity <- predict(model, newdata = prediction)
```

```
# Plot the data and the fitted models
ggplot(data, aes(x = Area, y = Staining, color = Type)) +
  geom_point() +
  geom_line(data = prediction, aes(x = Area, y = Staining, color = Type), linetype = "solid", size = 3.5) +
  labs(x = "Area", y = "Staining", color = "Type", title = "LDHA - Images")
```

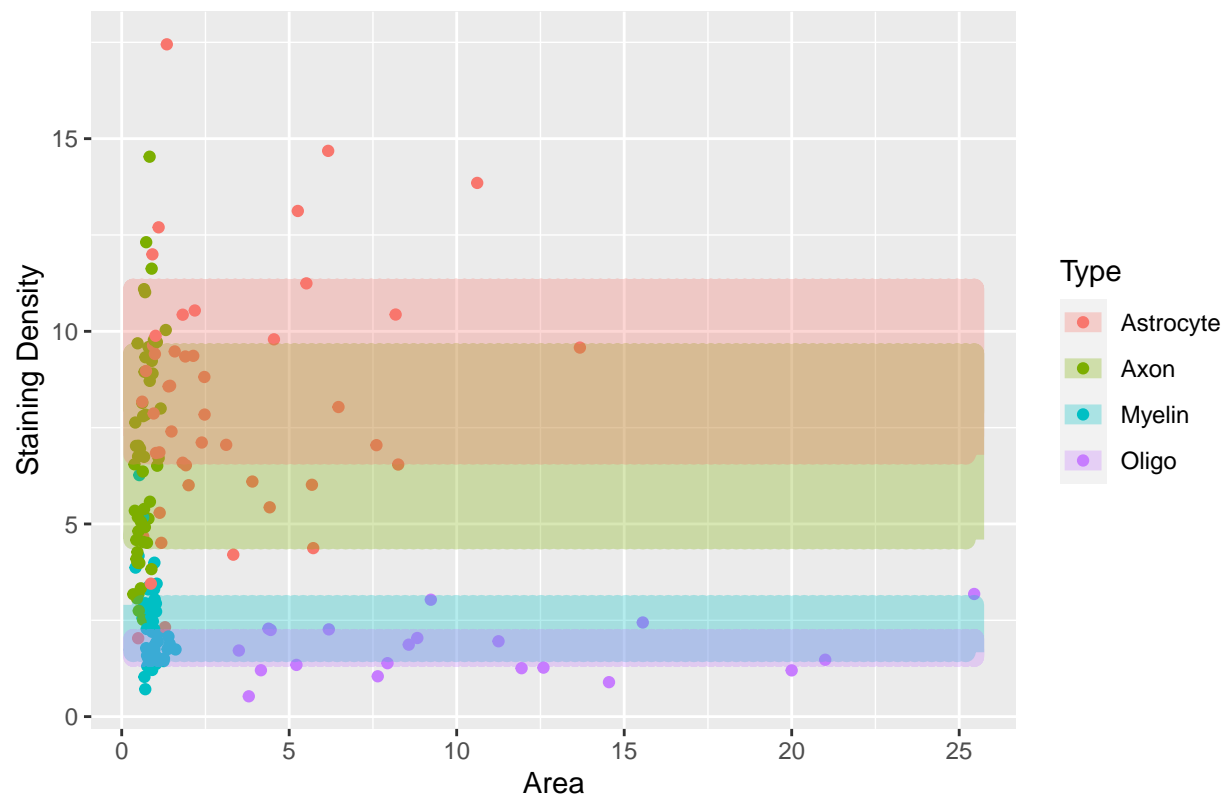
```
## Warning: Using 'size' aesthetic for lines was deprecated in ggplot2 3.4.0.
## i Please use 'linewidth' instead.
## This warning is displayed once every 8 hours.
## Call 'lifecycle::last_lifecycle_warnings()' to see where this warning was
## generated.
```

LDHA – Images



```
ggplot(data, aes(x = Area, y = StainingPerArea, color = Type)) +
  geom_point() +
  geom_line(data = prediction, aes(x = Area, y = StainingDensity, color = Type), linetype = "solid", size = 1) +
  labs(x = "Area", y = "Staining Density", color = "Type", title = "LDHA - Images")
```

LDHA – Images

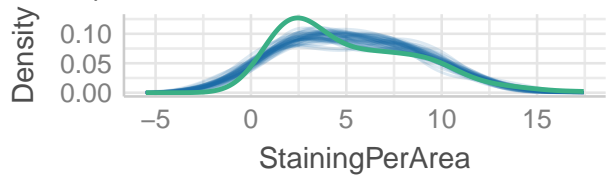


```
# Visual check of model assumptions
check_model(model)
```

```
## Not enough model terms in the conditional part of the model to check for
## multicollinearity.
```


Posterior Predictive Check

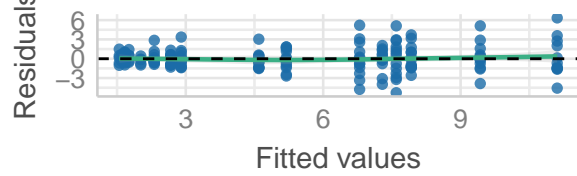
Model-predicted lines should resemble observed data



— Observed data — Model-predicted data

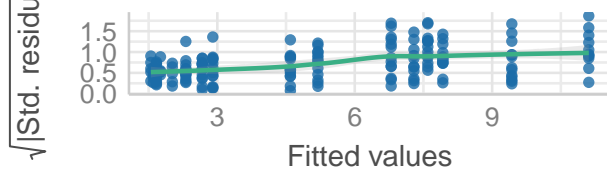
Linearity

Reference line should be flat and horizontal



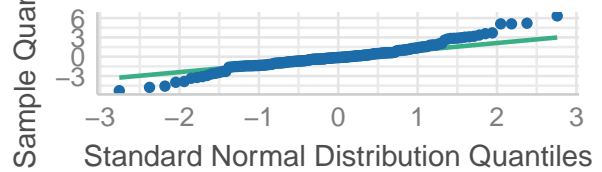
Homogeneity of Variance

Reference line should be flat and horizontal



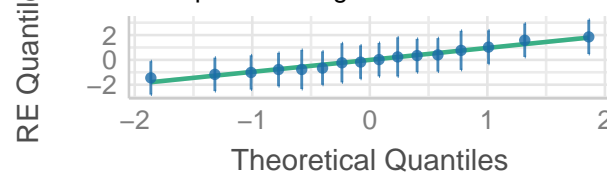
Normality of Residuals

Points should fall along the line



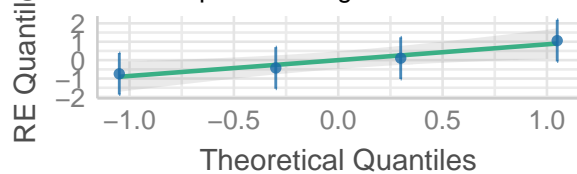
Normality of Random Effects (Animal:Type)

Dots should be plotted along the line

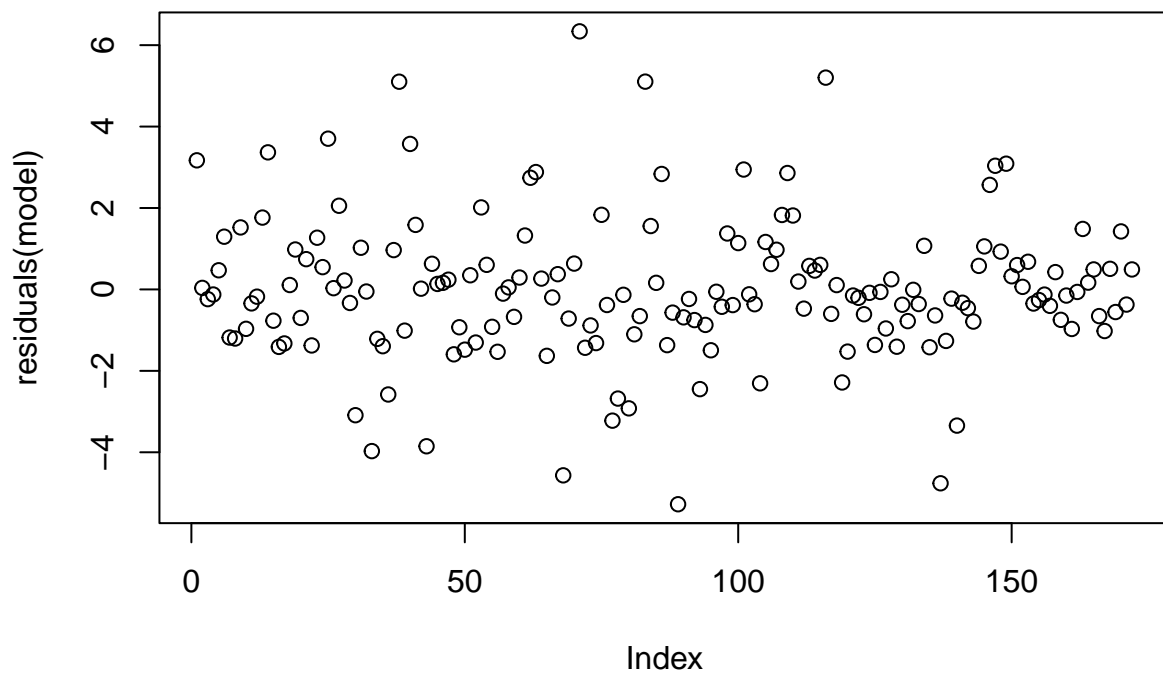


Normality of Random Effects (Animal)

Dots should be plotted along the line

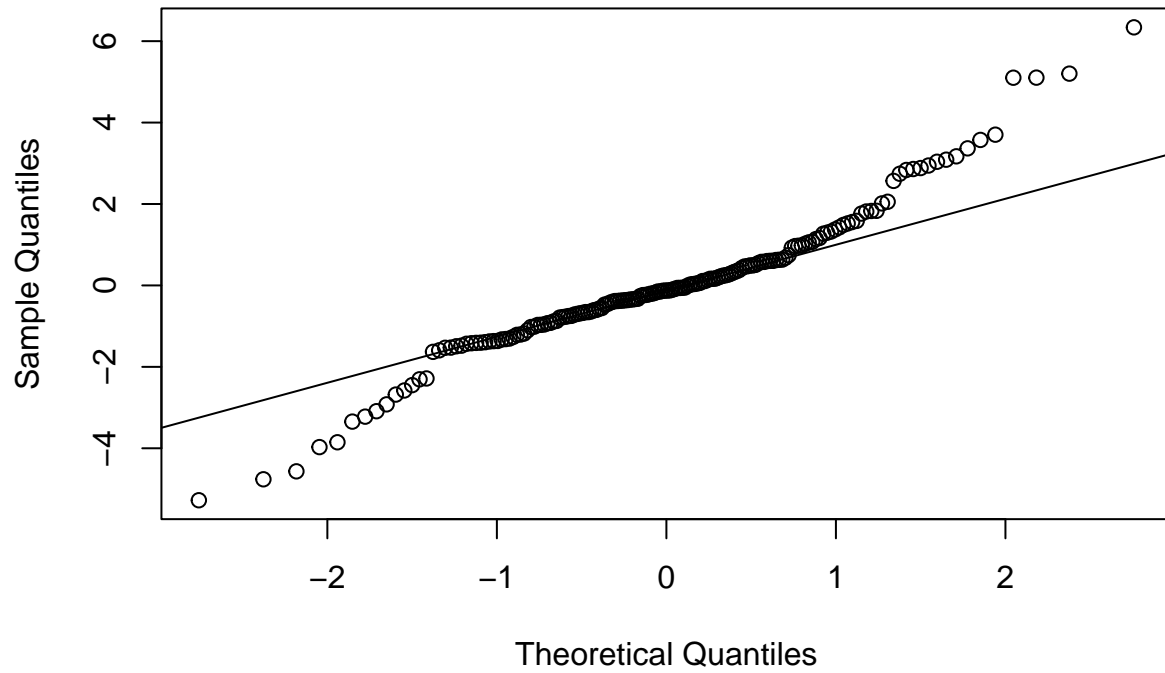


```
# Check residuals
plot(residuals(model))
```



```
qqnorm(resid(model))  
qqline(resid(model))
```

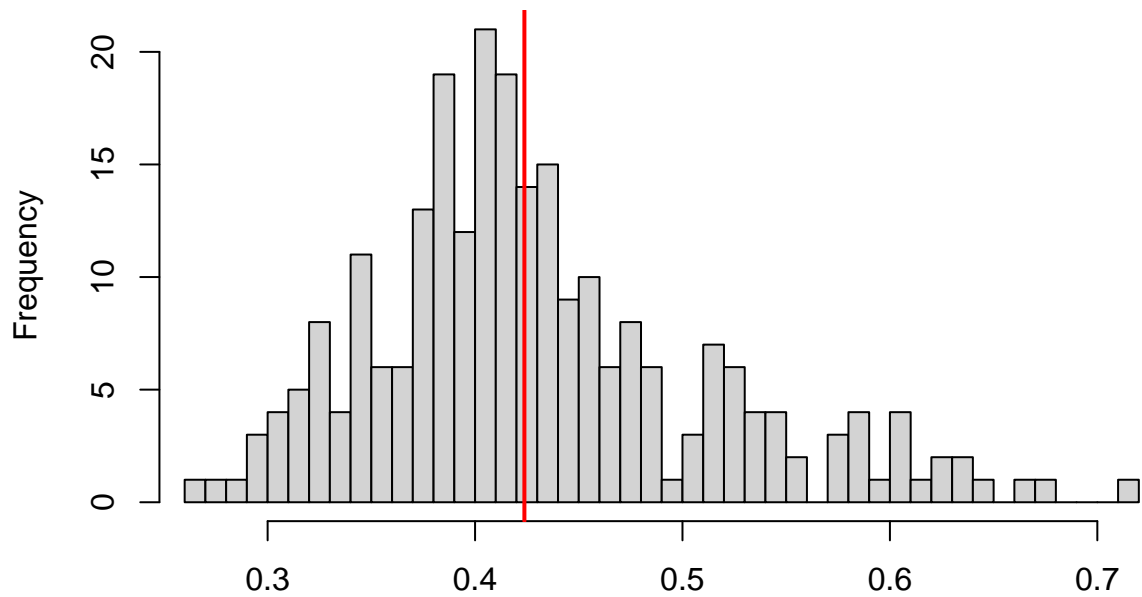
Normal Q-Q Plot



```
# Create simulated residuals
simulationOutput <- simulateResiduals(fittedModel = model)

# Check for dispersion
testDispersion(simulationOutput)
```

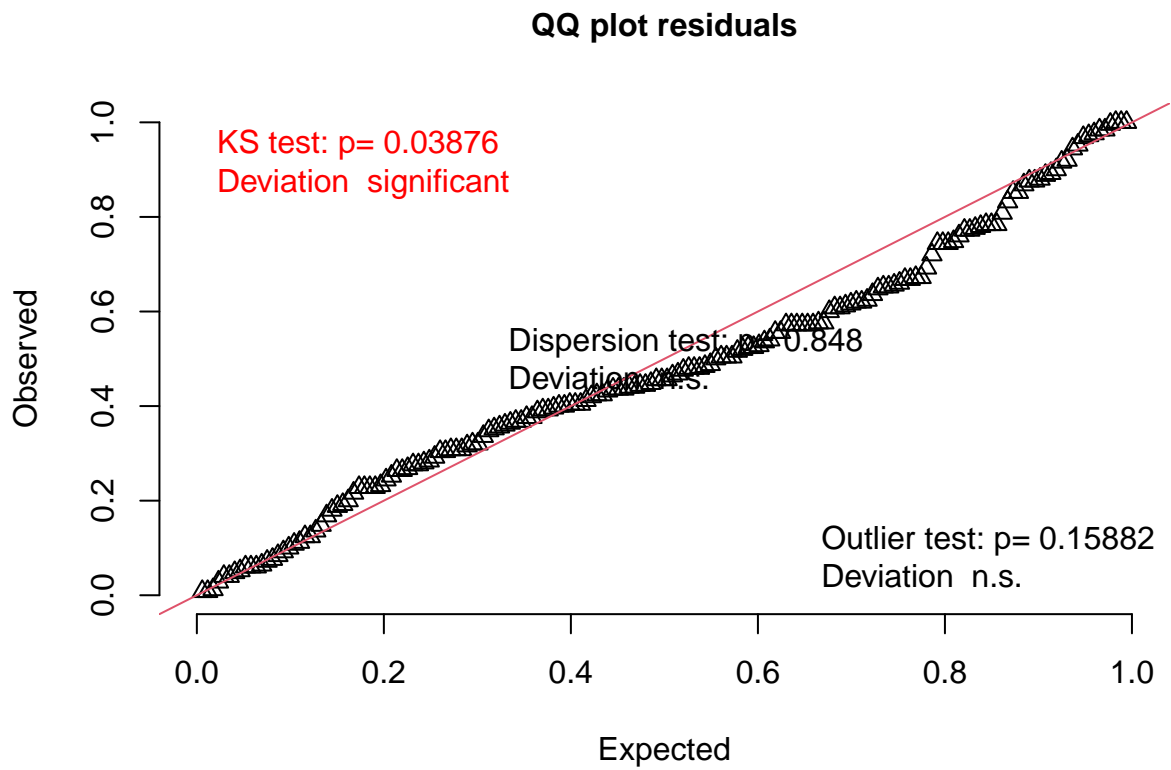
**DHARMA nonparametric dispersion test via sd of
residuals fitted vs. simulated**



Simulated values, red line = fitted model. p-value (two.sided) = 0.848

```
##
## DHARMA nonparametric dispersion test via sd of residuals fitted vs.
## simulated
##
## data: simulationOutput
## dispersion = 0.98515, p-value = 0.848
## alternative hypothesis: two.sided

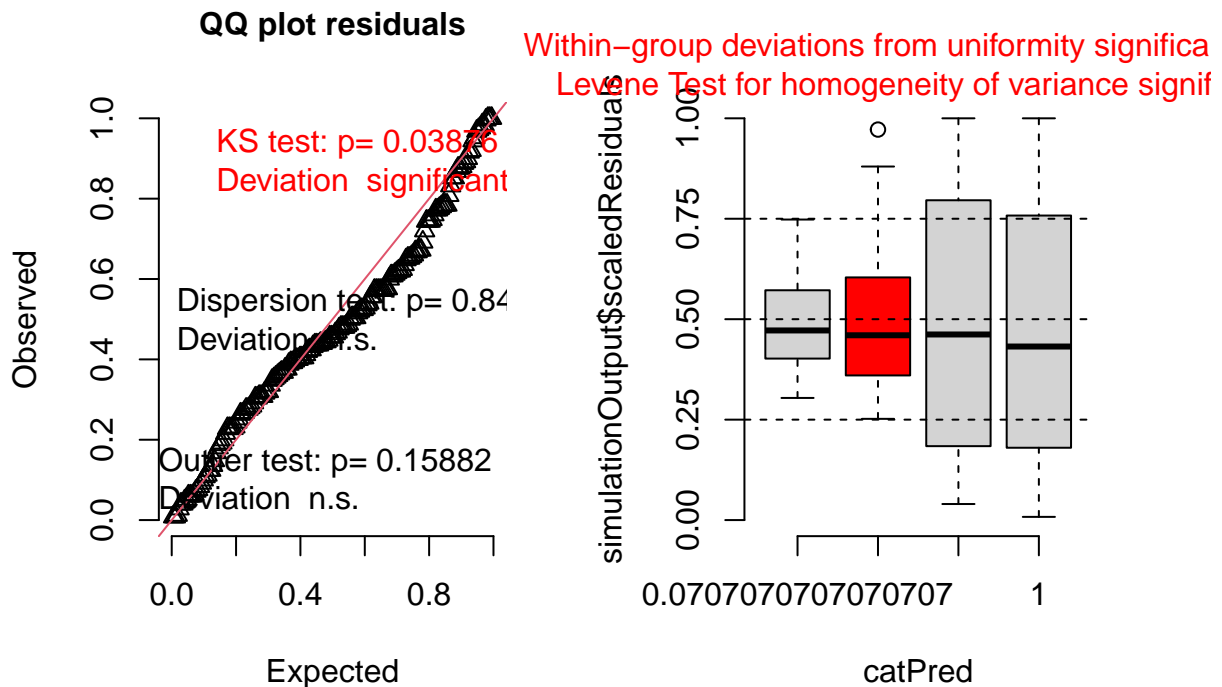
# Check for uniformity of residuals
testUniformity(simulationOutput)
```



```
##  
## One-sample Kolmogorov-Smirnov test  
##  
## data: simulationOutput$scaledResiduals  
## D = 0.10707, p-value = 0.03876  
## alternative hypothesis: two-sided
```

```
# Create diagnostic plots  
plot(simulationOutput)
```

DHARMA residual



```
# Averages over each image
# Note: Because there is only one oligo quantified per image, no StDev needs to be
# taken for oligodendrocytes at this level.
ldhaImages <- ldha %>%
  dplyr::select(-OligoCellBodyArea, -OligoNucleusArea, -matches("Gap")) %>%
  mutate(AxonGoldDensity = AxonGold/AxonArea,
         MyelinGoldDensity = MyelinGold/MyelinArea,
         AstrocyteGoldDensity = AstrocyteGold/AstrocyteArea,
         OligoGoldDensity = OligoGold/OligoArea,
         OligoGold = OligoGold) %>%
  group_by(Image) %>%
  summarize(Animal = first(Animal),
           Image = first(Image),
           Genotype = first(Genotype),
           across(matches("Gold|Area"),
                list(mean = ~ mean(.,na.rm = TRUE),
                     StDev = ~ sd(., na.rm = TRUE)),
                .names = "{.fn}_{.col}"),
           .groups = "drop") %>%
  arrange(Genotype)
ldhaImages
```

```
## # A tibble: 147 x 29
##   Image      Animal Genotype mean_OligoArea StDev_OligoArea mean_OligoGold
##   <chr>      <chr>  <chr>      <dbl>         <dbl>         <dbl>
## 1 36-0891-1 0891   ctr         NaN           NA            NaN
```

```
## 2 36-0891-10 0891 ctr NaN NA NaN
## 3 36-0891-11 0891 ctr NaN NA NaN
## 4 36-0891-12 0891 ctr NaN NA NaN
## 5 36-0891-13 0891 ctr NaN NA NaN
## 6 36-0891-2 0891 ctr NaN NA NaN
## 7 36-0891-3 0891 ctr NaN NA NaN
## 8 36-0891-4 0891 ctr NaN NA NaN
## 9 36-0891-5 0891 ctr NaN NA NaN
## 10 36-0891-6 0891 ctr NaN NA NaN
## # i 137 more rows
## # i 23 more variables: StDev_OligoGold <dbl>, mean_AxonArea <dbl>,
## # StDev_AxonArea <dbl>, mean_AxonGold <dbl>, StDev_AxonGold <dbl>,
## # mean_FiberArea <dbl>, StDev_FiberArea <dbl>, mean_MyelinGold <dbl>,
## # StDev_MyelinGold <dbl>, mean_AstrocyteGold <dbl>,
## # StDev_AstrocyteGold <dbl>, mean_AstrocyteArea <dbl>,
## # StDev_AstrocyteArea <dbl>, mean_MyelinArea <dbl>, ...
```

```
# Averages over each animal
# SEM for error propagation
# StDev for Oligodendrocytes (because it is the first averaging)
ldhaAnimals <- ldhaImages %>%
  group_by(Animal) %>%
  summarize(Animal = first(Animal),
            ImageNr = n(),
            Genotype = first(Genotype),
            across(matches("^mean"),
              list(mean = ~ mean(., na.rm = TRUE),
                   StDev = ~ sd(., na.rm = TRUE),
                   SEM = ~ sd(., na.rm = TRUE) / sqrt(sum(!is.na(.)))
              ),
            .names = "{.fn}_{.col}"
          ),
            .groups = "drop") %>%
  rename_with(~ sub("mean_mean_", "mean_", .x), .cols = starts_with("mean_mean_")) %>%
  rename_with(~ sub("StDev_mean_", "StDev_", .x), .cols = starts_with("StDev_mean_")) %>%
  rename_with(~ sub("SEM_mean_", "SEM_", .x), .cols = starts_with("SEM_mean_")) %>%
  arrange(Genotype)
ldhaAnimals
```

```
## # A tibble: 8 x 42
##   Animal ImageNr Genotype mean_OligoArea StDev_OligoArea SEM_OligoArea
##   <chr>      <int> <chr>      <dbl>          <dbl>          <dbl>
## 1 0891         18 ctr         12.5           7.87           3.52
## 2 0893         18 ctr         11.1           3.18           1.42
## 3 0895         18 ctr          7.98           4.56           2.04
## 4 0896         18 ctr          9.63           8.97           4.01
## 5 0888         21 mut          8.40           4.38           1.96
## 6 0892         19 mut          7.76           4.08           1.67
## 7 0894         18 mut          6.76           3.01           1.35
## 8 0899         17 mut          5.45           1.90           0.851
## # i 36 more variables: mean_OligoGold <dbl>, StDev_OligoGold <dbl>,
## # SEM_OligoGold <dbl>, mean_AxonArea <dbl>, StDev_AxonArea <dbl>,
## # SEM_AxonArea <dbl>, mean_AxonGold <dbl>, StDev_AxonGold <dbl>,
## # SEM_AxonGold <dbl>, mean_FiberArea <dbl>, StDev_FiberArea <dbl>,
```

```
## # SEM_FiberArea <dbl>, mean_MyelinGold <dbl>, StDev_MyelinGold <dbl>,
## # SEM_MyelinGold <dbl>, mean_AstrocyteGold <dbl>, StDev_AstrocyteGold <dbl>,
## # SEM_AstrocyteGold <dbl>, mean_AstrocyteArea <dbl>, ...
```

```
# Averages over each genotype
```

```
ldhaGenotype <- ldhaAnimals %>%
  group_by(Genotype) %>%
  summarize(AnimalNr = n(),
            ImageNr = sum(ImageNr),
            across(matches("^mean"),
              list(mean = ~ mean(., na.rm = TRUE),
                   StDev = ~ sd(., na.rm = TRUE),
                   SEM = ~ sd(., na.rm = TRUE) / sqrt(sum(!is.na(.)))
              ),
            .names = "{.fn}_{.col}"
          ),
            .groups = "drop") %>%
  rename_with(~ sub("mean_mean_", "mean_", .x), .cols = starts_with("mean_mean_")) %>%
  rename_with(~ sub("StDev_mean_", "StDev_", .x), .cols = starts_with("StDev_mean_")) %>%
  rename_with(~ sub("SEM_mean_", "SEM_", .x), .cols = starts_with("SEM_mean_"))

ldhaGenotype
```

```
## # A tibble: 2 x 42
##   Genotype AnimalNr ImageNr mean_OligoArea StDev_OligoArea SEM_OligoArea
##   <chr>      <int>   <int>         <dbl>         <dbl>         <dbl>
## 1 ctr         4     72         10.3          1.95          0.974
## 2 mut         4     75          7.09          1.29          0.643
## # i 36 more variables: mean_OligoGold <dbl>, StDev_OligoGold <dbl>,
## # SEM_OligoGold <dbl>, mean_AxonArea <dbl>, StDev_AxonArea <dbl>,
## # SEM_AxonArea <dbl>, mean_AxonGold <dbl>, StDev_AxonGold <dbl>,
## # SEM_AxonGold <dbl>, mean_FiberArea <dbl>, StDev_FiberArea <dbl>,
## # SEM_FiberArea <dbl>, mean_MyelinGold <dbl>, StDev_MyelinGold <dbl>,
## # SEM_MyelinGold <dbl>, mean_AstrocyteGold <dbl>, StDev_AstrocyteGold <dbl>,
## # SEM_AstrocyteGold <dbl>, mean_AstrocyteArea <dbl>, ...
```

```
df_gRatio <- ldha %>%
  dplyr::select(Animal, Image, Genotype, AxonDiameter, FiberDiameter, gRatio) %>%
  filter(!is.na(FiberDiameter)) %>% # Exclude all rows that don't contain gRatio measurements
  filter(!grepl("Neg", Image)) %>% # Excludes negative controls
  mutate(gRatio = AxonDiameter/FiberDiameter) %>%
  mutate(Genotype = as.factor(Genotype),
         Animal = as.factor(Animal))
df_gRatio
```

```
## # A tibble: 1,030 x 6
## # Groups:   Animal [8]
##   Animal Image Genotype AxonDiameter FiberDiameter gRatio
##   <fct> <chr>   <fct>         <dbl>         <dbl> <dbl>
## 1 0888 36-0888-1 mut         1.42          2.35  0.603
## 2 0888 36-0888-1 mut         1.06          1.66  0.635
## 3 0888 36-0888-1 mut         0.980         1.69  0.581
## 4 0888 36-0888-1 mut         1.34          1.84  0.730
```



```
## 5 0888 36-0888-1 mut 0.768 1.11 0.689
## 6 0888 36-0888-1 mut 0.451 0.789 0.571
## 7 0888 36-0888-1 mut 0.931 1.58 0.589
## 8 0888 36-0888-1 mut 0.749 1.08 0.692
## 9 0888 36-0888-1 mut 0.579 1.05 0.552
## 10 0888 36-0888-1 mut 0.627 1.05 0.596
## # i 1,020 more rows
```

```
# Fit a Linear Mixer Model
```

```
model <- lmer(gRatio ~ AxonDiameter * Genotype + (1 | Animal), data = df_gRatio)
```

```
# Predict the fiber diameter
```

```
df_gRatio$EstimatedGRatio <- predict(model, newdata = df_gRatio)
```

```
# Compute the estimated g-Ratio
```

```
df_gRatio$EstimatedFiberDiameter <- df_gRatio$AxonDiameter / df_gRatio$EstimatedGRatio
```

```
# Results
```

```
summary(model) # Check the model summary
```

```
## Linear mixed model fit by REML. t-tests use Satterthwaite's method [
## lmerModLmerTest]
## Formula: gRatio ~ AxonDiameter * Genotype + (1 | Animal)
## Data: df_gRatio
##
## REML criterion at convergence: -2585.6
##
## Scaled residuals:
## Min 1Q Median 3Q Max
## -3.4113 -0.6431 0.0656 0.6896 2.9205
##
## Random effects:
## Groups Name Variance Std.Dev.
## Animal (Intercept) 0.001402 0.03744
## Residual 0.004519 0.06722
## Number of obs: 1030, groups: Animal, 8
##
## Fixed effects:
## Estimate Std. Error df t value Pr(>|t|)
## (Intercept) 5.795e-01 2.058e-02 8.318e+00 28.160 1.51e-09 ***
## AxonDiameter 5.583e-02 9.638e-03 1.022e+03 5.793 9.22e-09 ***
## Genotypectr 4.852e-02 2.907e-02 8.282e+00 1.669 0.1324
## AxonDiameter:Genotypectr -2.829e-02 1.329e-02 1.022e+03 -2.129 0.0335 *
## ---
## Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Correlation of Fixed Effects:
## (Intr) AxnDmt Gntypc
## AxonDiametr -0.389
## Genotypectr -0.708 0.276
## AxnDmtr:Gnt 0.282 -0.725 -0.387
```

```
anova(model) # Compute ANOVA
```

```
## Type III Analysis of Variance Table with Satterthwaite's method
##              Sum Sq Mean Sq NumDF DenDF F value Pr(>F)
## AxonDiameter    0.177915  0.177915     1 1022.41 39.3701 5.169e-10 ***
## Genotype         0.012586  0.012586     1    8.28  2.7851  0.13241
## AxonDiameter:Genotype 0.020488  0.020488     1 1022.41  4.5338  0.03347 *
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```
# Compute the estimated marginal means for the interaction
```

```
emm_int <- emmeans(model, ~ Genotype:AxonDiameter)
summary(emm_int)
```

```
## Genotype AxonDiameter emmean SE df lower.CL upper.CL
## mut      0.849 0.627 0.019 6.00 0.581 0.673
## ctr      0.849 0.651 0.019 5.99 0.605 0.698
##
## Degrees-of-freedom method: kenward-roger
## Confidence level used: 0.95
```

```
pairs(emm_int) # Perform pairwise comparisons
```

```
## contrast estimate
## mut AxonDiameter0.848593945928665 - ctr AxonDiameter0.848593945928665 -0.0245
## SE df t.ratio p.value
## 0.0268 6 -0.914 0.3958
##
## Degrees-of-freedom method: kenward-roger
```

```
# Test the fit
```

```
AIC(model)
```

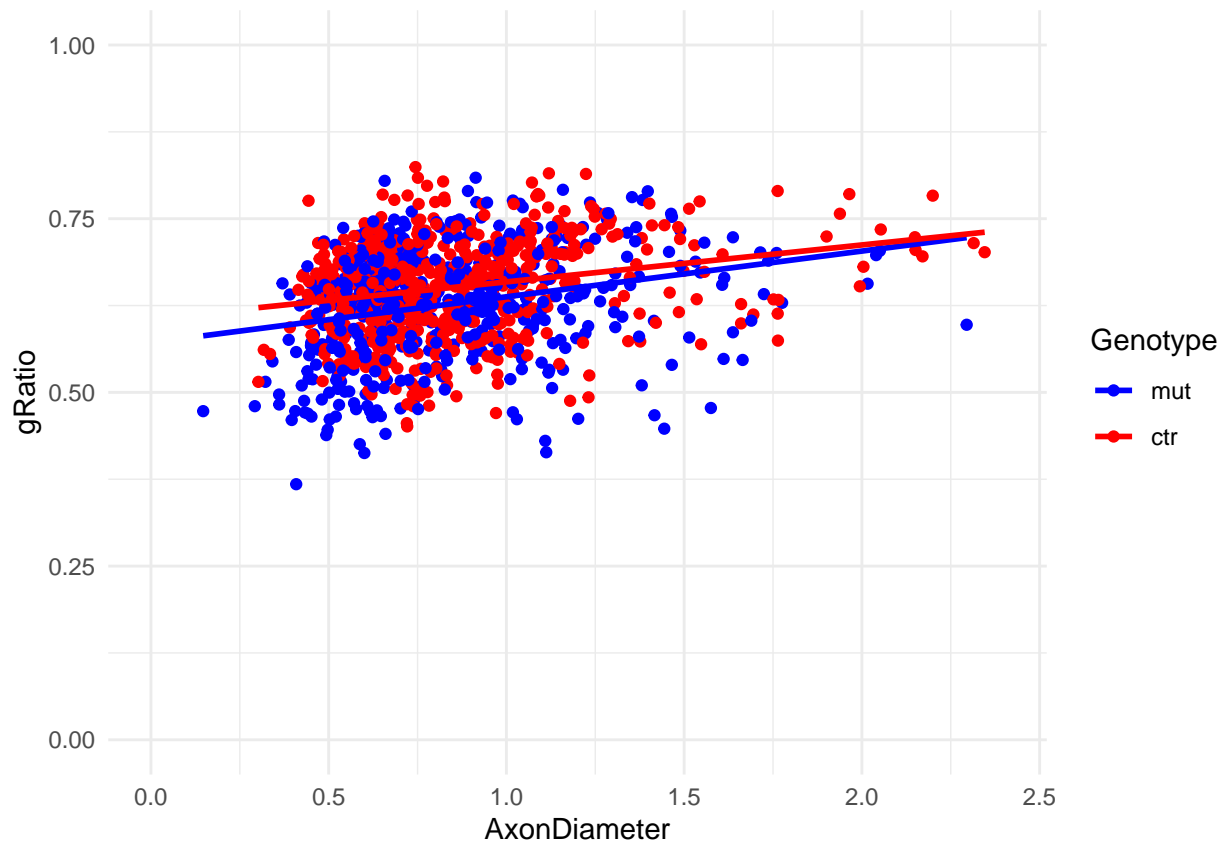
```
## [1] -2573.551
```

```
best_model <- lmerTest::step(model, direction="both")
summary(best_model)
```

```
##          Length Class Mode
## random 7      anova list
## fixed  7      anova list
```

```
data <- df_gRatio
ggplot(data, aes(x = AxonDiameter, y = gRatio, color = Genotype)) +
  geom_point() +
  geom_smooth(method = "lm", aes(group = Genotype), se = FALSE) +
  labs(x = "AxonDiameter", y = "gRatio", color = "Genotype") +
  scale_color_manual(values = c("ctr" = "red", "mut" = "blue")) +
  xlim(0, 2.4) +
  ylim(0, 1) +
  theme_minimal()
```

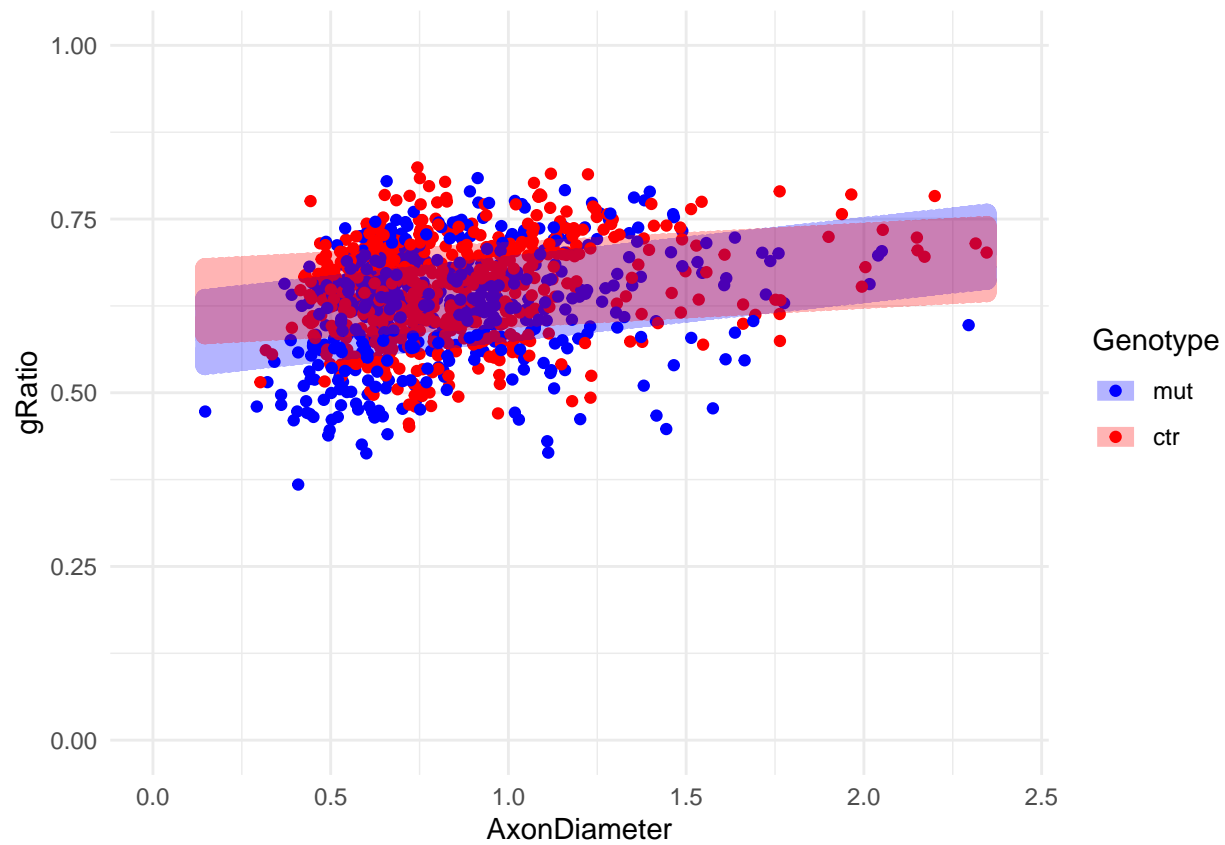
```
## 'geom_smooth()' using formula = 'y ~ x'
```



```
# Create a new dataset for predictions
prediction <- expand.grid(AxonDiameter = seq(min(data$AxonDiameter), max(data$AxonDiameter), length.out = 100),
  Animal = unique(data$Animal),
  Genotype = unique(data$Genotype))

# Add predictions from the models
prediction$Pred_Model <- predict(model, newdata = prediction)
prediction$gRatio <- prediction$Pred_Model

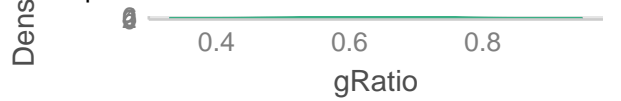
# Plot the data and the fitted models
ggplot(data, aes(x = AxonDiameter, y = gRatio, color = Genotype)) +
  geom_point() +
  geom_line(data = prediction, aes(y = gRatio), linetype = "solid", size = 3.5, alpha = 0.3) +
  labs(x = "AxonDiameter", y = "gRatio", color = "Genotype") +
  xlim(0, 2.4) +
  ylim(0, 1) +
  scale_color_manual(values = c("ctr" = "red", "mut" = "blue")) +
  theme_minimal()
```



```
# Visual check of model assumptions  
check_model(model)
```

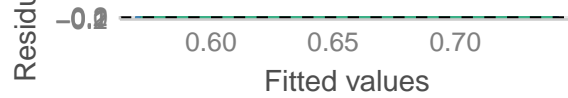
Posterior Predictive Check

Model-predicted lines should resemble observed data



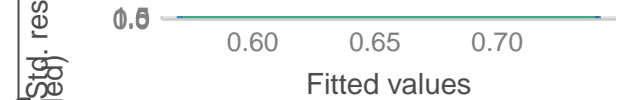
Linearity

Reference line should be flat and horizontal



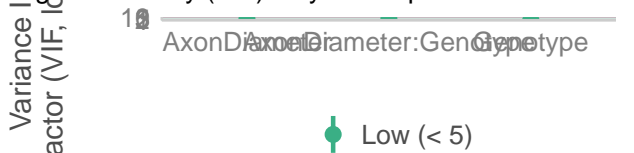
Homogeneity of Variance

Reference line should be flat and horizontal



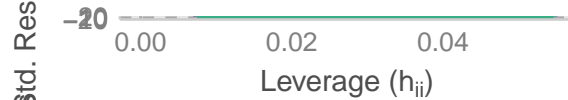
Collinearity

High collinearity (VIF) may inflate parameter uncertainty



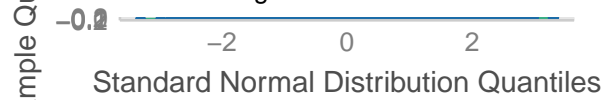
Influential Observations

Points should be inside the contour lines



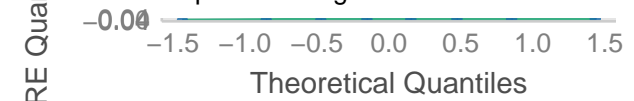
Normality of Residuals

Points should fall along the line



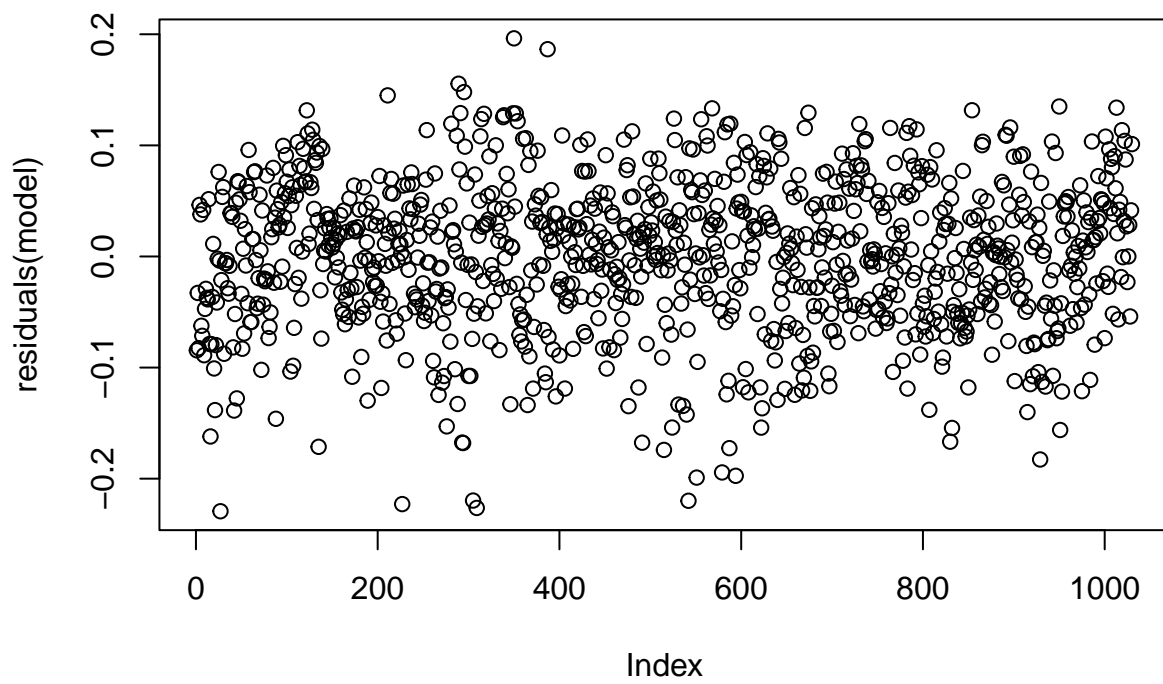
Normality of Random Effects (Animal)

Points should be plotted along the line



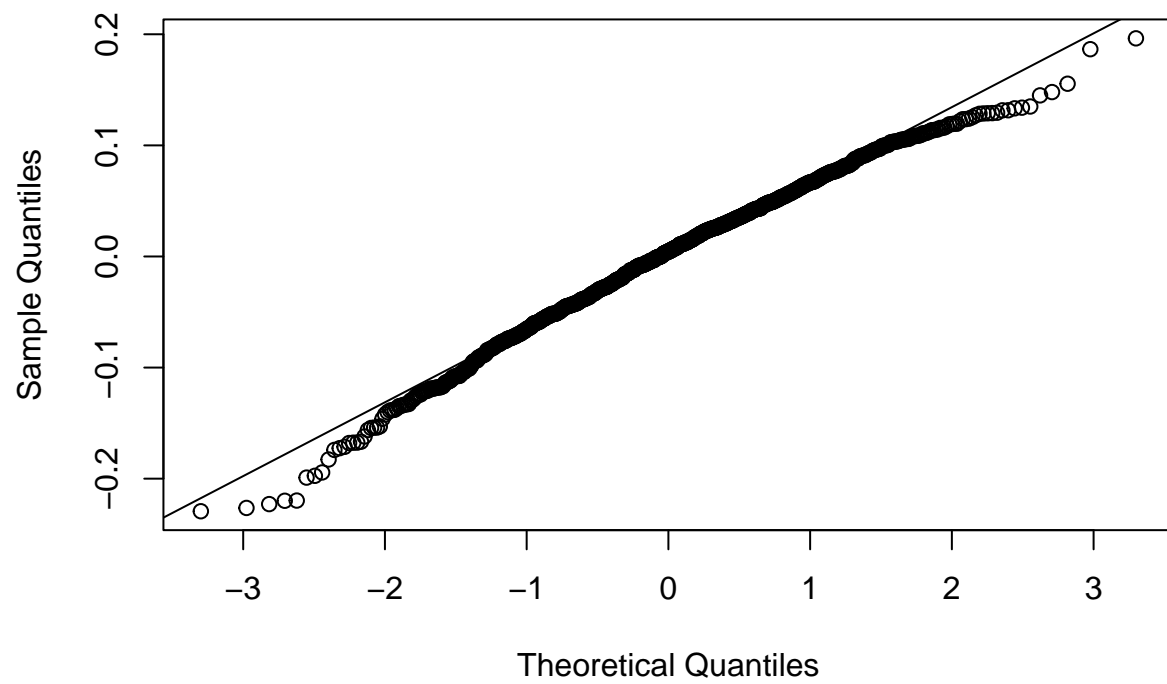
```
# Check residuals
```

```
plot(residuals(model))
```



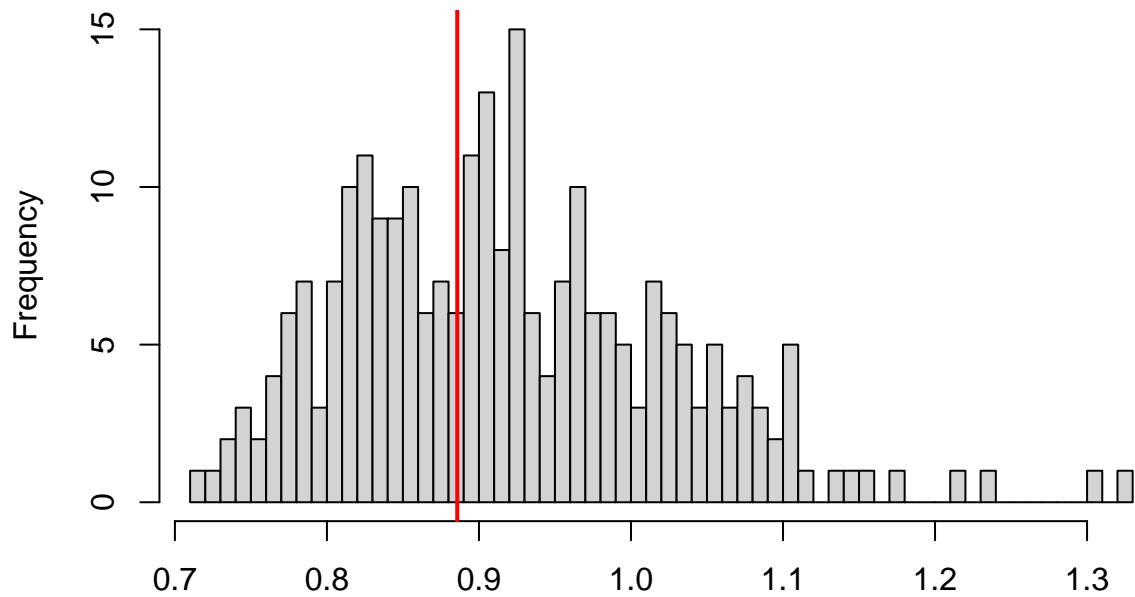
```
qqnorm(resid(model))  
qqline(resid(model))
```

Normal Q-Q Plot



```
# Create simulated residuals  
simulationOutput <- simulateResiduals(fittedModel = model)  
  
# Check for dispersion  
testDispersion(simulationOutput)
```

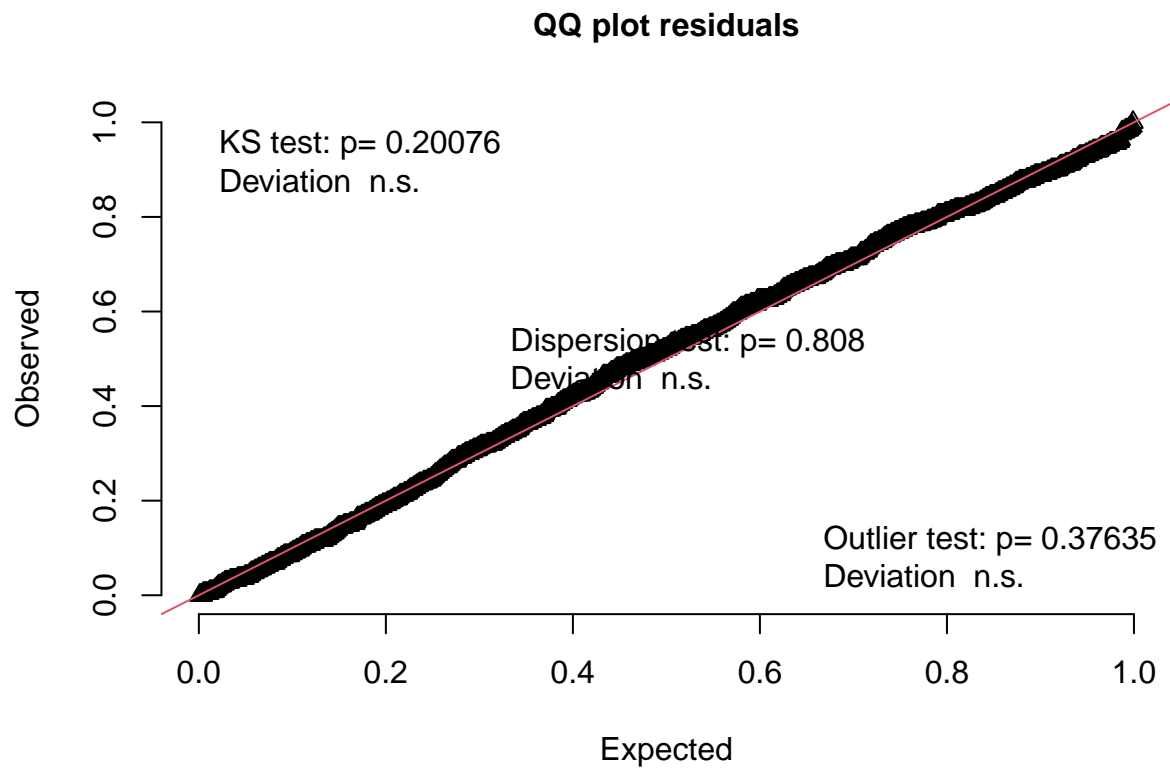
**DHARMA nonparametric dispersion test via sd of
residuals fitted vs. simulated**



Simulated values, red line = fitted model. p-value (two.sided) = 0.808

```
##
## DHARMA nonparametric dispersion test via sd of residuals fitted vs.
## simulated
##
## data: simulationOutput
## dispersion = 0.96358, p-value = 0.808
## alternative hypothesis: two.sided

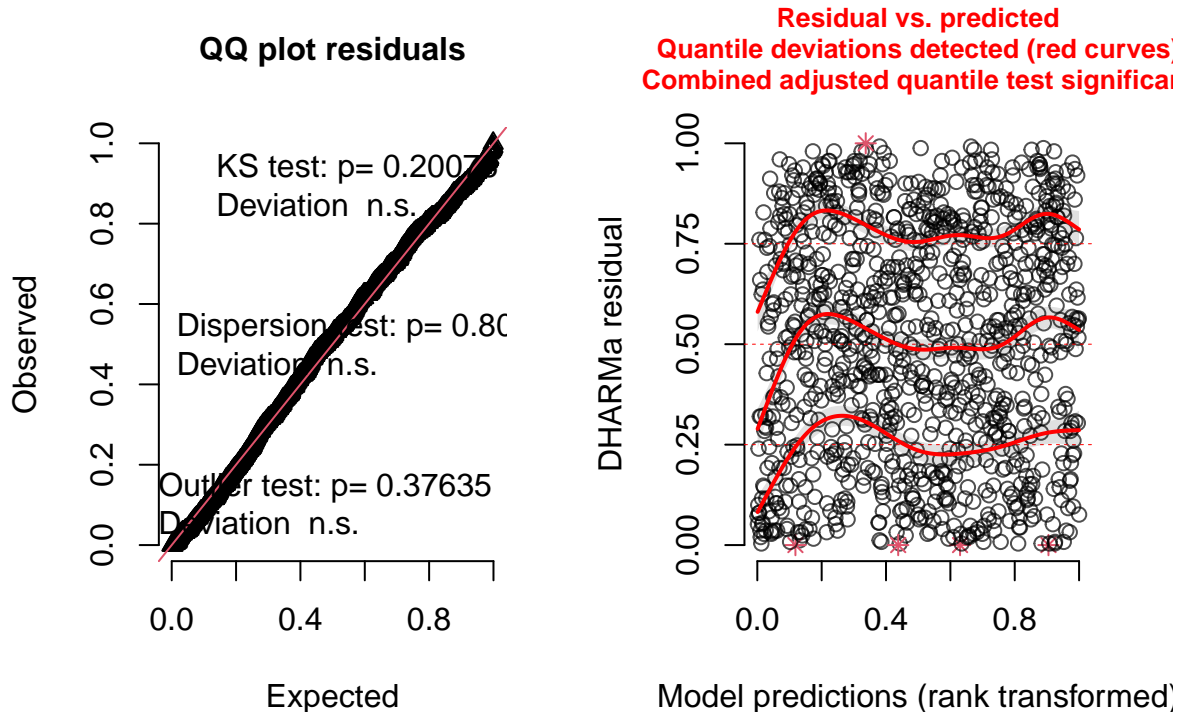
# Check for uniformity of residuals
testUniformity(simulationOutput)
```

```
##  
## One-sample Kolmogorov-Smirnov test  
##  
## data: simulationOutput$scaledResiduals  
## D = 0.033398, p-value = 0.2008  
## alternative hypothesis: two-sided
```

```
# Create diagnostic plots  
plot(simulationOutput)
```

DHARMA residual



```
#Imports excel file
rnaFile = here::here("LDHAB_RNAscope_Quantification.xlsx")

ldha_Rna <- read_excel(path = rnaFile, sheet = "LDHA") %>%
  mutate(CellID = row_number()) %>%
  pivot_longer(
    cols = -CellID, # Exclude CellID from the reshaping
    names_to = c("Genotype", "Animal"), # New column names
    names_pattern = "(wt|KO) (.*)" # Regular expression to match and separate genotype and animal number
  ) %>%
  rename(RnaDots = value)
ldha_Rna$Genotype[which(ldha_Rna$Genotype == "KO")] <- "mut"

ldha_Rna <- ldha_Rna %>%
  mutate(Animal = paste(Genotype, Animal, sep = " - "))

# Convert Genotype to factor
ldha_Rna$Genotype <- as.factor(ldha_Rna$Genotype)

# Negative Binomial GLMM
model <- glmer.nb(RnaDots ~ Genotype + (1|Animal), data = ldha_Rna)

# Results Cell Type
summary(model) # Check the model summary
```

```
## Generalized linear mixed model fit by maximum likelihood (Laplace
## Approximation) [glmerMod]
## Family: Negative Binomial(15.8185) ( log )
## Formula: RnaDots ~ Genotype + (1 | Animal)
## Data: ldha_Rna
##
##      AIC      BIC   logLik deviance df.resid
## 22334.7 22361.2 -11163.3 22326.7    5518
##
## Scaled residuals:
##      Min       1Q   Median       3Q      Max
## -1.7077 -0.6486 -0.0872  0.5307  6.0643
##
## Random effects:
## Groups Name      Variance Std.Dev.
## Animal (Intercept) 0.004419 0.06647
## Number of obs: 5522, groups: Animal, 6
##
## Fixed effects:
##              Estimate Std. Error z value Pr(>|z|)
## (Intercept)  1.17682    0.04064  28.956  <2e-16 ***
## Genotypewt  -0.05823    0.05693  -1.023    0.306
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Correlation of Fixed Effects:
##              (Intr)
## Genotypewt -0.714
```

```
anova(model) # Compute ANOVA
```

```
## Analysis of Variance Table
##              npar Sum Sq Mean Sq F value
## Genotype      1 1.0466  1.0466  1.0466
```

```
# Obtain the EMMS
emm <- emmeans(model, ~ Genotype)
pairs(emm) # Perform pairwise comparisons
```

```
## contrast estimate      SE df z.ratio p.value
## mut - wt    0.0582 0.0569 Inf  1.023  0.3064
##
## Results are given on the log (not the response) scale.
```

```
# Transform the estimates
emm_exp <- regrid(emm, transform = "response")

# Print the results
summary(emm_exp)
```

```
## Genotype response      SE df asymp.LCL asymp.UCL
## mut              3.24 0.132 Inf    2.99    3.5
```

```
## wt          3.06 0.122 Inf      2.82      3.3
##
## Confidence level used: 0.95
```

```
# Calculate contrasts
contrasts <- contrast(emm_exp, method = "pairwise")

# Print the results
summary(contrasts)
```

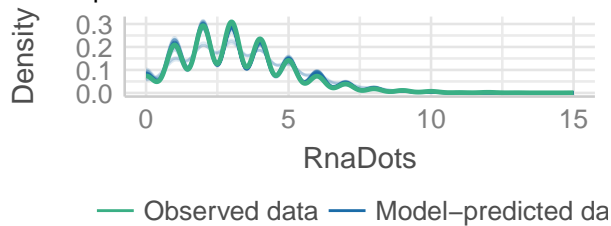
```
## contrast estimate SE df z.ratio p.value
## mut - wt      0.183 0.18 Inf   1.021  0.3070
```

```
# Visual check of model assumptions
check_model(model)
```

```
## Not enough model terms in the conditional part of the model to check for
## multicollinearity.
```

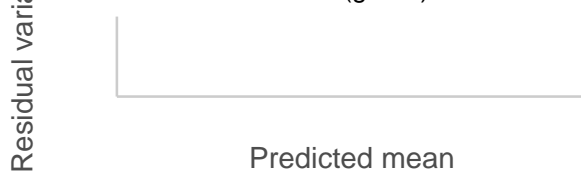
Posterior Predictive Check

Model-predicted lines should resemble observed data



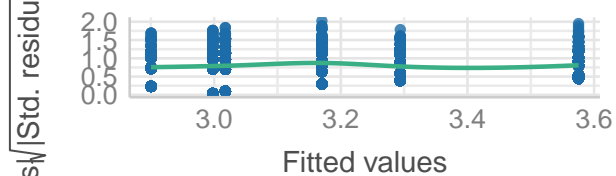
Overdispersion and zero-inflation

Observed residual variance (green) should follow predicted mean



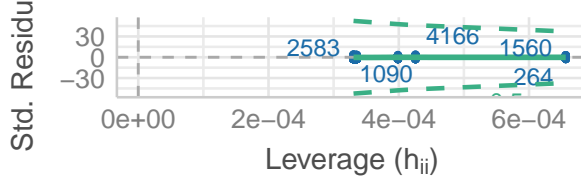
Homogeneity of Variance

Reference line should be flat and horizontal



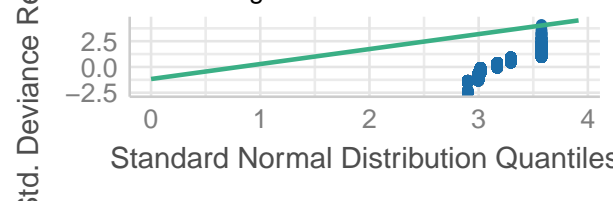
Influential Observations

Points should be inside the contour lines



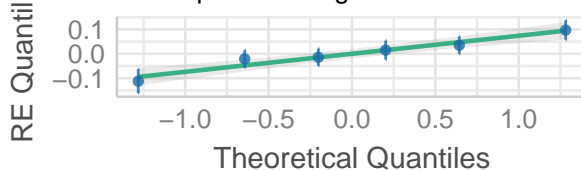
Normality of Residuals

Dots should fall along the line

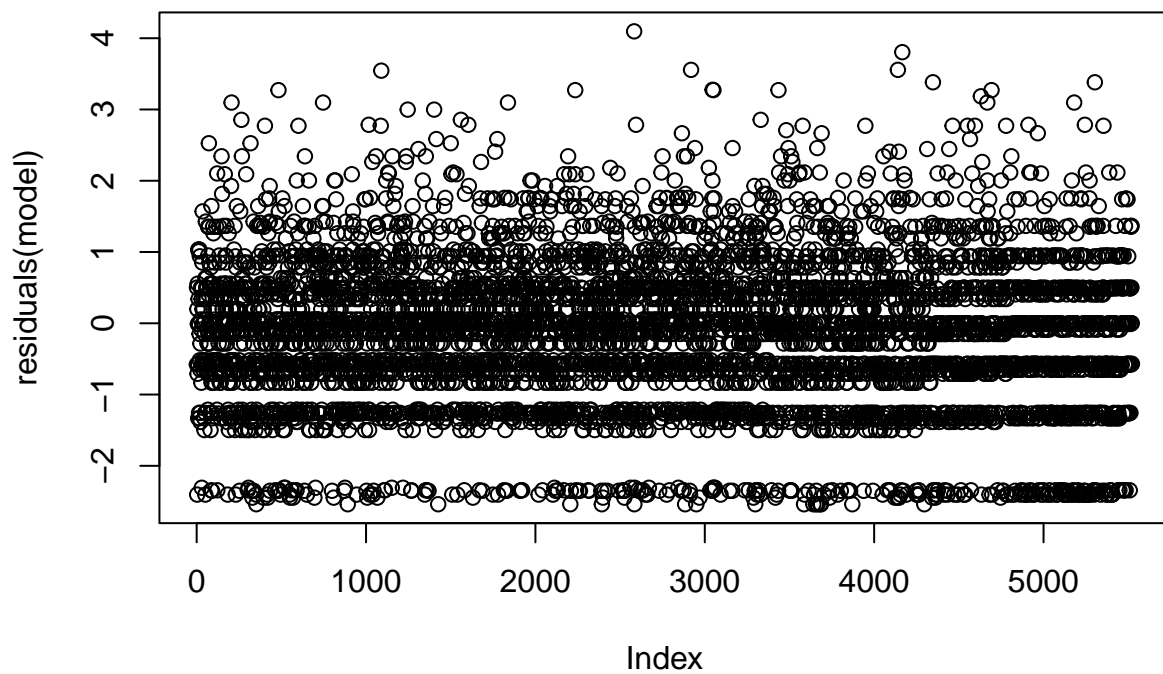


Normality of Random Effects (Animal)

Dots should be plotted along the line

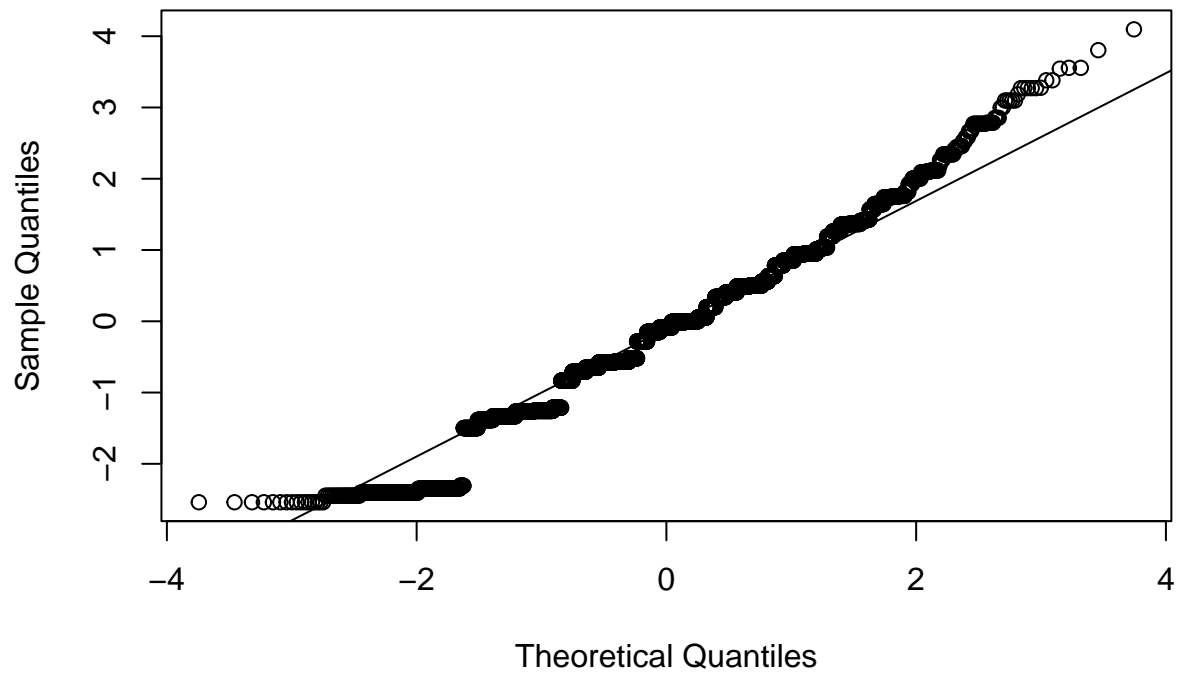


```
# Check residuals
plot(residuals(model))
```



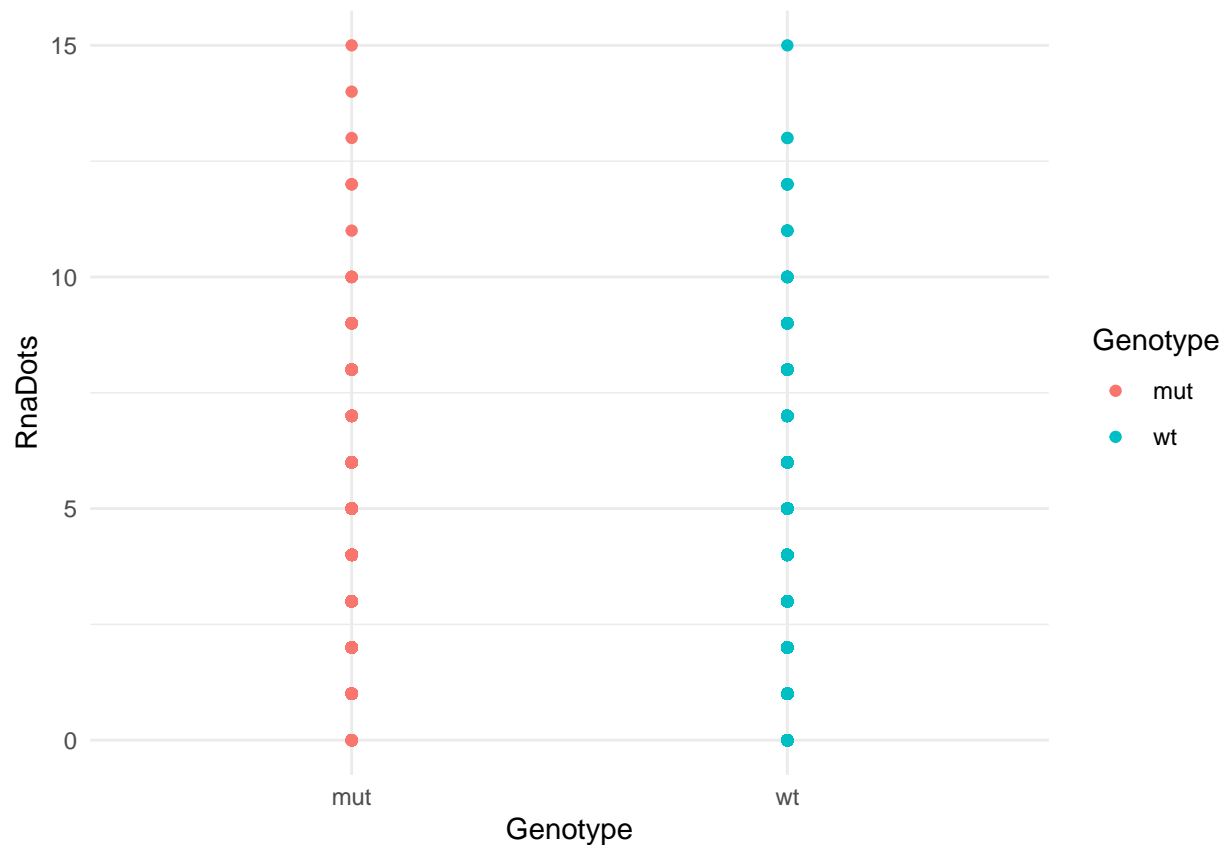
```
qqnorm(resid(model))  
qqline(resid(model))
```

Normal Q-Q Plot



```
data <- ldha_Rna
ggplot(data, aes(x = Genotype, y = RnaDots, color = Genotype)) +
  geom_point() +
  labs(x = "Genotype", y = "RnaDots", color = "Genotype") +
  theme_minimal()
```

```
## Warning: Removed 1228 rows containing missing values ('geom_point()').
```

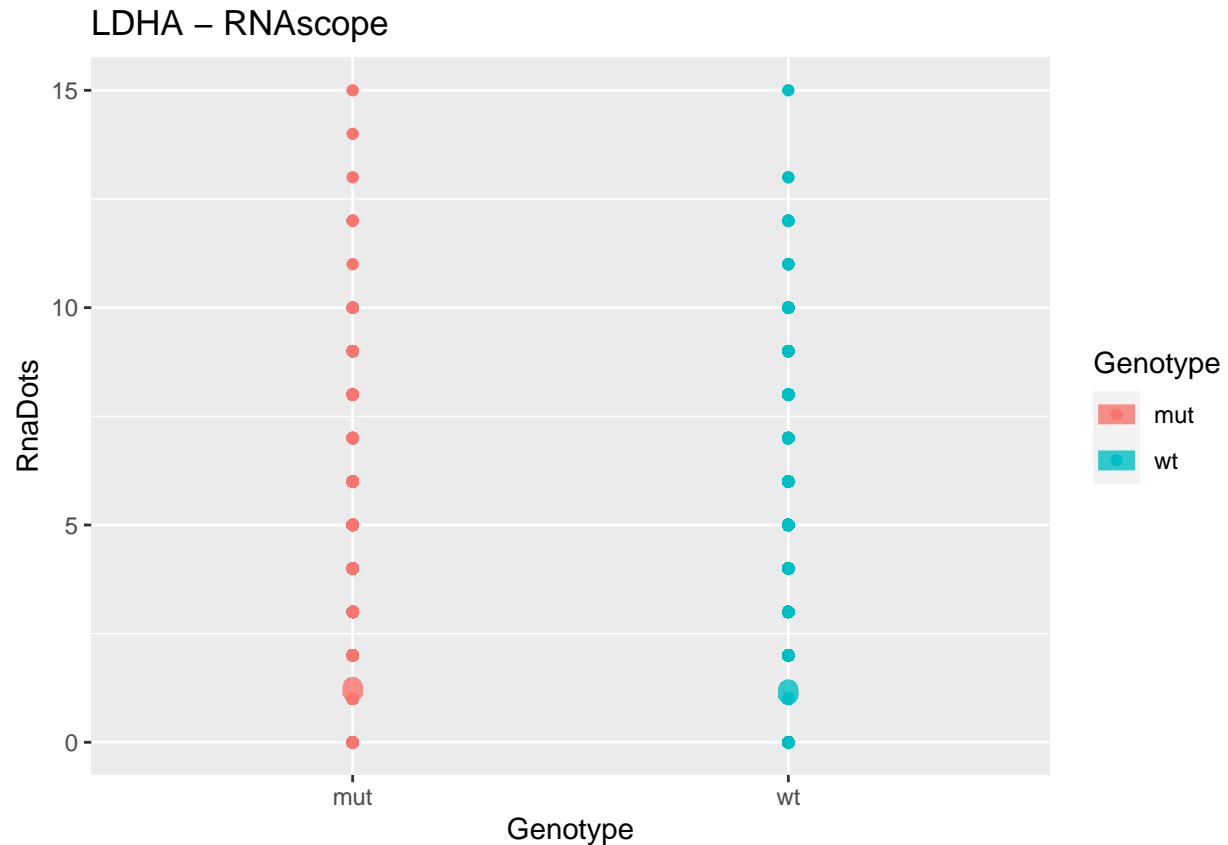


```
# Create a new dataset for predictions
prediction <- expand.grid(Genotype = unique(data$Genotype),
                          Animal = unique(data$Animal))

# Add predictions from the models
prediction$Pred_Model <- predict(model, newdata = prediction)

# Plot the data and the fitted models
ggplot(data, aes(x = Genotype, y = RnaDots, color = Genotype)) +
  geom_point() +
  geom_line(data = prediction, aes(x = Genotype, y = Pred_Model, color = Genotype), linetype = "solid",
            labs(x = "Genotype", y = "RnaDots", color = "Genotype", title = "LDHA - RNAscope"))
```

Warning: Removed 1228 rows containing missing values ('geom_point()').



```
ldhb_Rna <- read_excel(path = rnaFile, sheet = "LDHB") %>%
  mutate(CellID = row_number()) %>%
  pivot_longer(
    cols = -CellID, # Exclude CellID from the reshaping
    names_to = c("Genotype", "Animal"), # New column names
    names_pattern = "(wt|KO) (.*)" # Regular expression to match and separate genotype and animal number
  ) %>%
  rename(RnaDots = value)
ldhb_Rna$Genotype[which(ldhb_Rna$Genotype == "KO")] <- "mut"

ldhb_Rna <- ldhb_Rna %>%
  mutate(Animal = paste(Genotype, Animal, sep = " - "))

# Convert Genotype to factor
ldhb_Rna$Genotype <- as.factor(ldhb_Rna$Genotype) %>%
  relevel(ref = "wt")

# Negative Binomial GLMM
model <- glmer.nb(RnaDots ~ Genotype + (1|Animal), data = ldhb_Rna)

# Results Cell Type
summary(model) # Check the model summary
```

Generalized linear mixed model fit by maximum likelihood (Laplace


```
## Approximation) [glmerMod]
## Family: Negative Binomial(7.9582) (log)
## Formula: RnaDots ~ Genotype + (1 | Animal)
## Data: ldhb_Rna
##
##      AIC      BIC    logLik deviance df.resid
## 24386.1 24412.6 -12189.1 24378.1    5518
##
## Scaled residuals:
##      Min       1Q   Median       3Q      Max
## -1.7374 -0.6801 -0.1744  0.5614  6.2018
##
## Random effects:
## Groups Name      Variance Std.Dev.
## Animal (Intercept) 0.02378  0.1542
## Number of obs: 5522, groups: Animal, 6
##
## Fixed effects:
##              Estimate Std. Error z value Pr(>|z|)
## (Intercept)  1.34241    0.08966  14.973  <2e-16 ***
## Genotypemut -0.03672    0.12708  -0.289    0.773
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Correlation of Fixed Effects:
##              (Intr)
## Genotypemut -0.705
```

```
anova(model) # Compute ANOVA
```

```
## Analysis of Variance Table
##              npar    Sum Sq Mean Sq F value
## Genotype      1 0.083463 0.083463  0.0835
```

```
# Obtain the EMMS
emm <- emmeans(model, ~ Genotype)
pairs(emm) # Perform pairwise comparisons
```

```
## contrast estimate    SE df z.ratio p.value
## wt - mut    0.0367 0.127 Inf  0.289  0.7726
##
## Results are given on the log (not the response) scale.
```

```
# Transform the estimates
emm_exp <- regrid(emm, transform = "response")

# Print the results
summary(emm_exp)
```

```
## Genotype response    SE df asymp.LCL asymp.UCL
## wt                3.83 0.343 Inf    3.16    4.50
## mut                3.69 0.332 Inf    3.04    4.34
```

```
##
## Confidence level used: 0.95

# Calculate contrasts
contrasts <- contrast(emm_exp, method = "pairwise")

# Print the results
summary(contrasts)
```

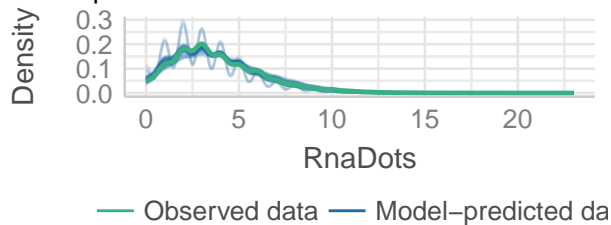
```
## contrast estimate SE df z.ratio p.value
## wt - mut 0.138 0.478 Inf 0.289 0.7726
```

```
# Visual check of model assumptions
check_model(model)
```

```
## Not enough model terms in the conditional part of the model to check for
## multicollinearity.
```

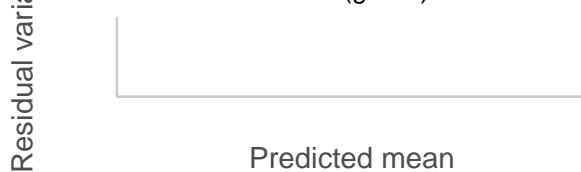
Posterior Predictive Check

Model-predicted lines should resemble observed data



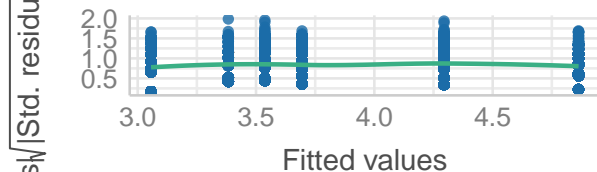
Overdispersion and zero-inflation

Observed residual variance (green) should follow predicted



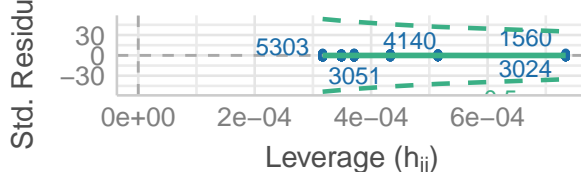
Homogeneity of Variance

Reference line should be flat and horizontal



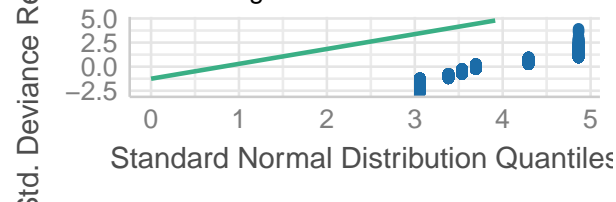
Influential Observations

Points should be inside the contour lines



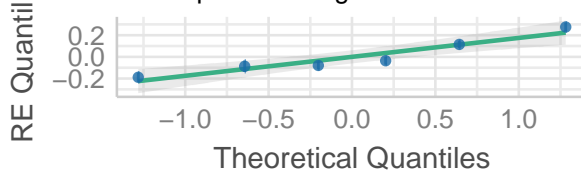
Normality of Residuals

Dots should fall along the line

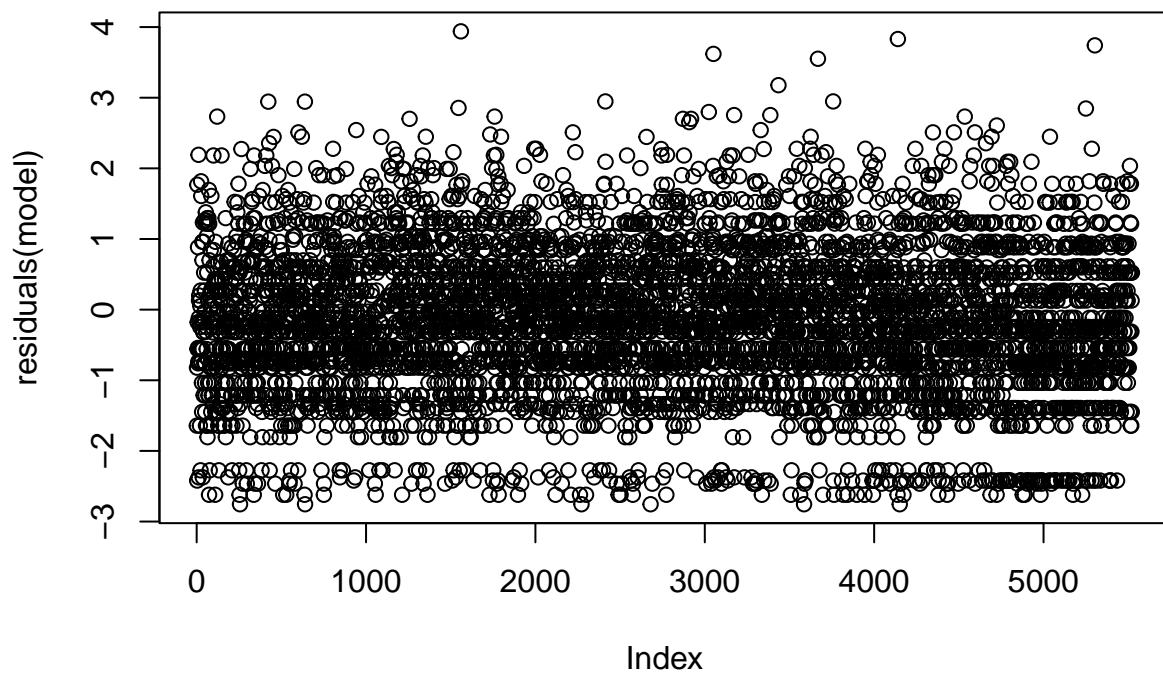


Normality of Random Effects (Animal)

Dots should be plotted along the line

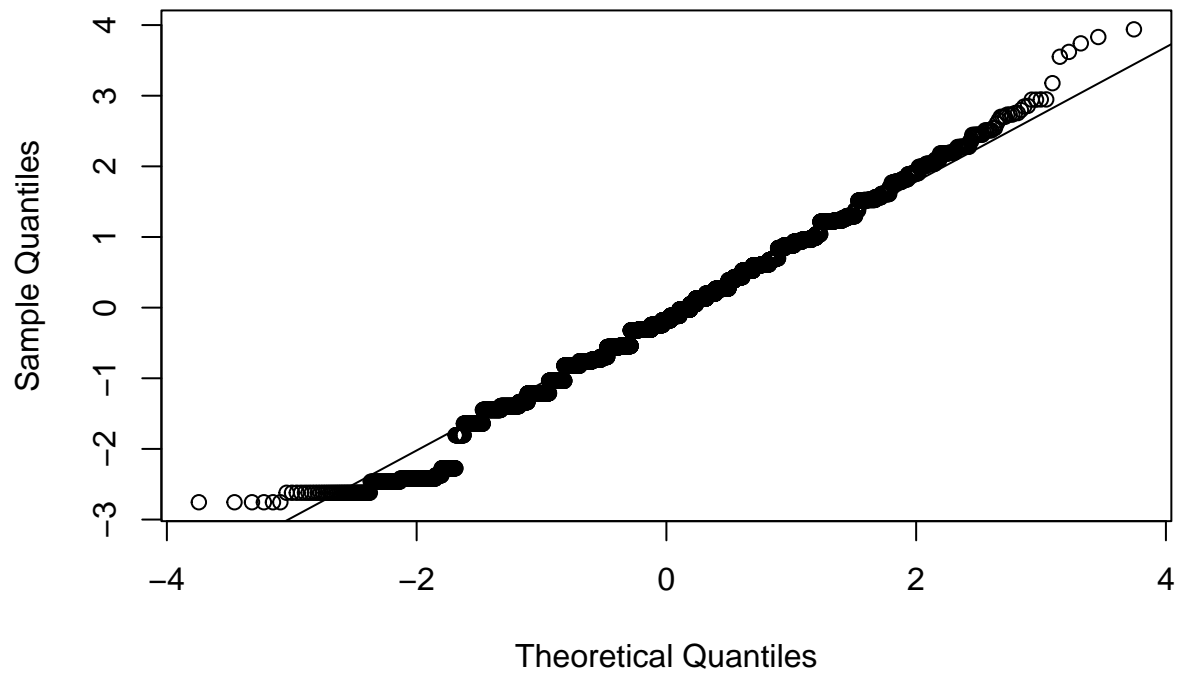


```
# Check residuals
plot(residuals(model))
```



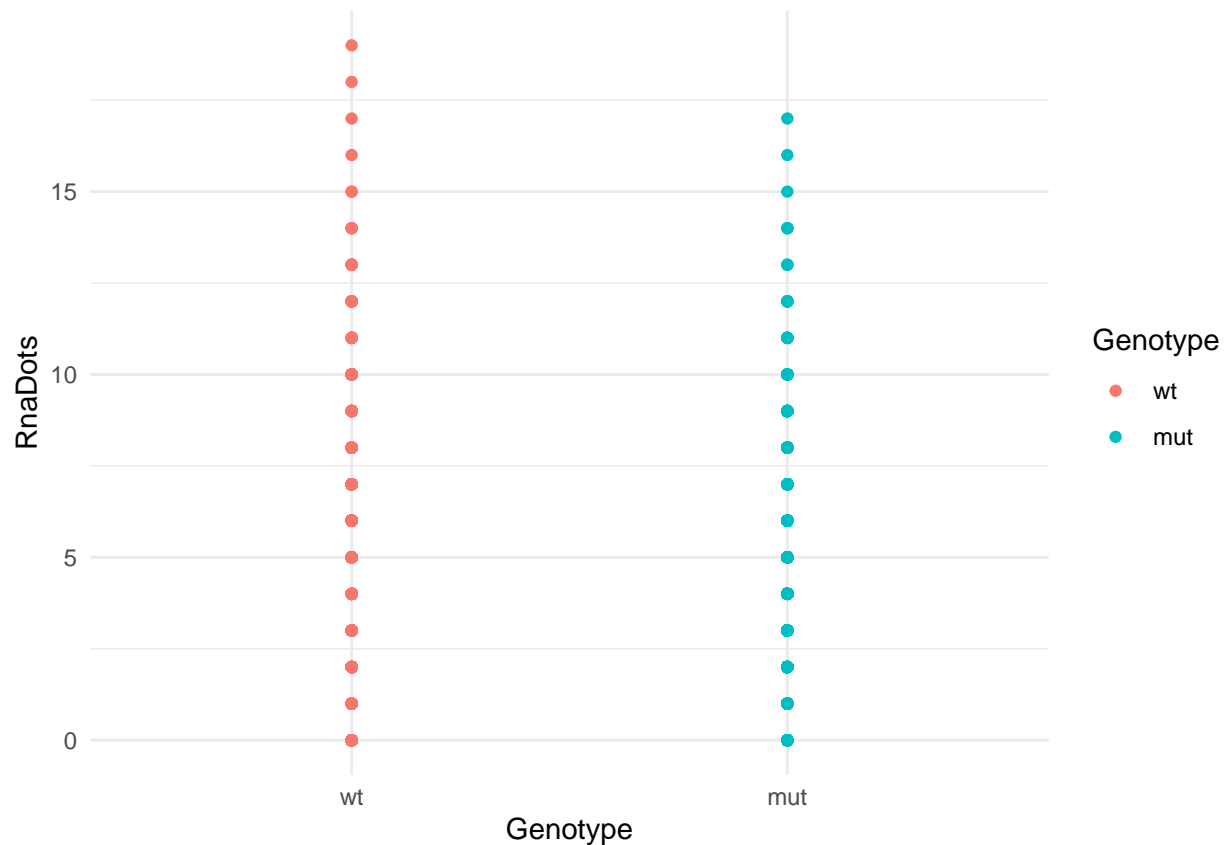
```
qqnorm(resid(model))  
qqline(resid(model))
```

Normal Q-Q Plot



```
data <- ldhb_Rna
ggplot(data, aes(x = Genotype, y = RnaDots, color = Genotype)) +
  geom_point() +
  labs(x = "Genotype", y = "RnaDots", color = "Genotype") +
  theme_minimal()
```

```
## Warning: Removed 1228 rows containing missing values ('geom_point()').
```

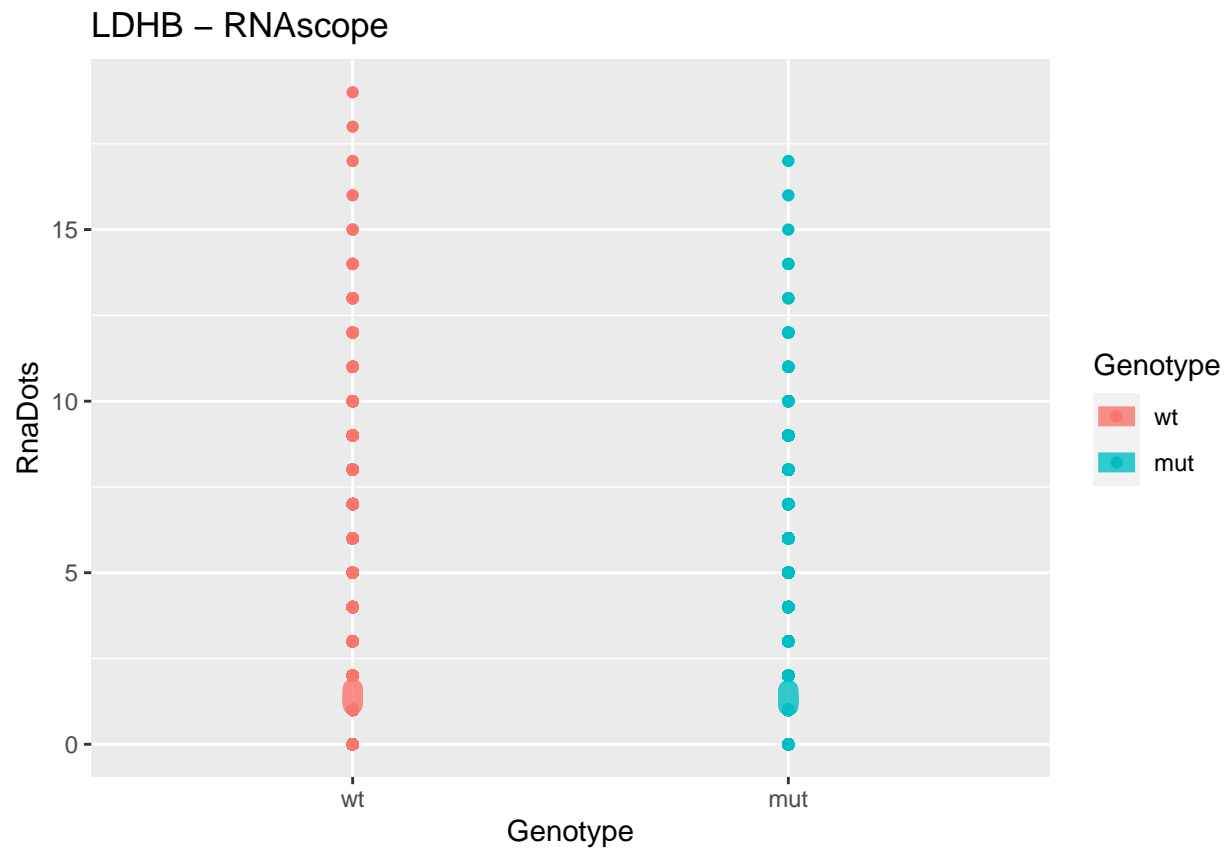


```
# Create a new dataset for predictions
prediction <- expand.grid(Genotype = unique(data$Genotype),
                        Animal = unique(data$Animal))

# Add predictions from the models
prediction$Pred_Model <- predict(model, newdata = prediction)

# Plot the data and the fitted models
ggplot(data, aes(x = Genotype, y = RnaDots, color = Genotype)) +
  geom_point() +
  geom_line(data = prediction, aes(x = Genotype, y = Pred_Model, color = Genotype), linetype = "solid",
  labs(x = "Genotype", y = "RnaDots", color = "Genotype", title = "LDHB - RNAscope")
```

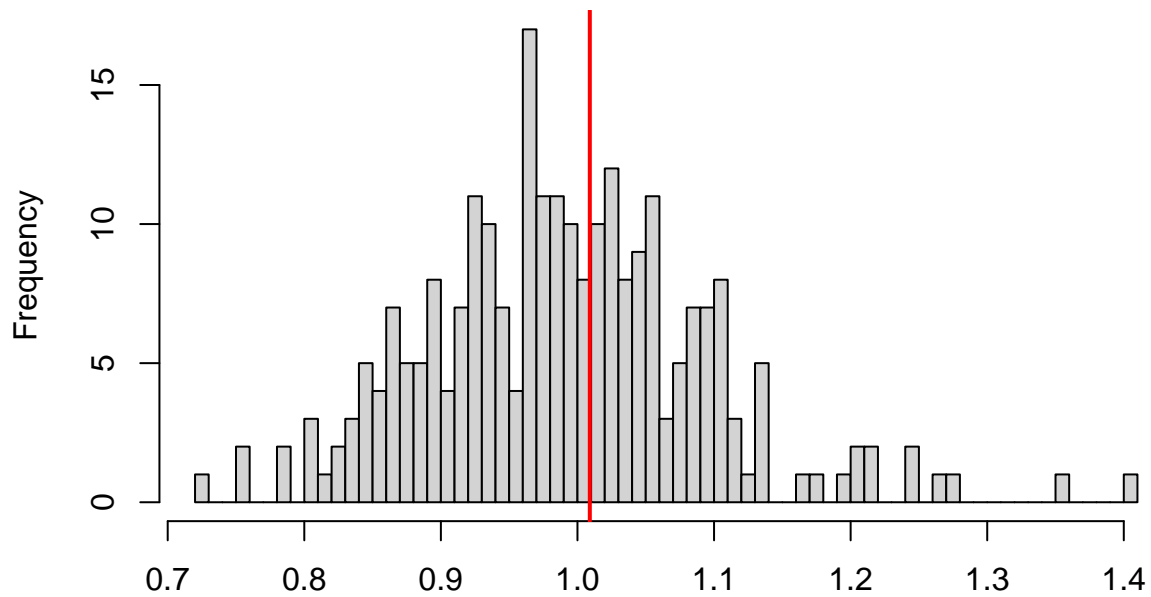
```
## Warning: Removed 1228 rows containing missing values ('geom_point()').
```



```
# Create simulated residuals
simulationOutput <- simulateResiduals(fittedModel = model)

# Check for dispersion
testDispersion(simulationOutput)
```

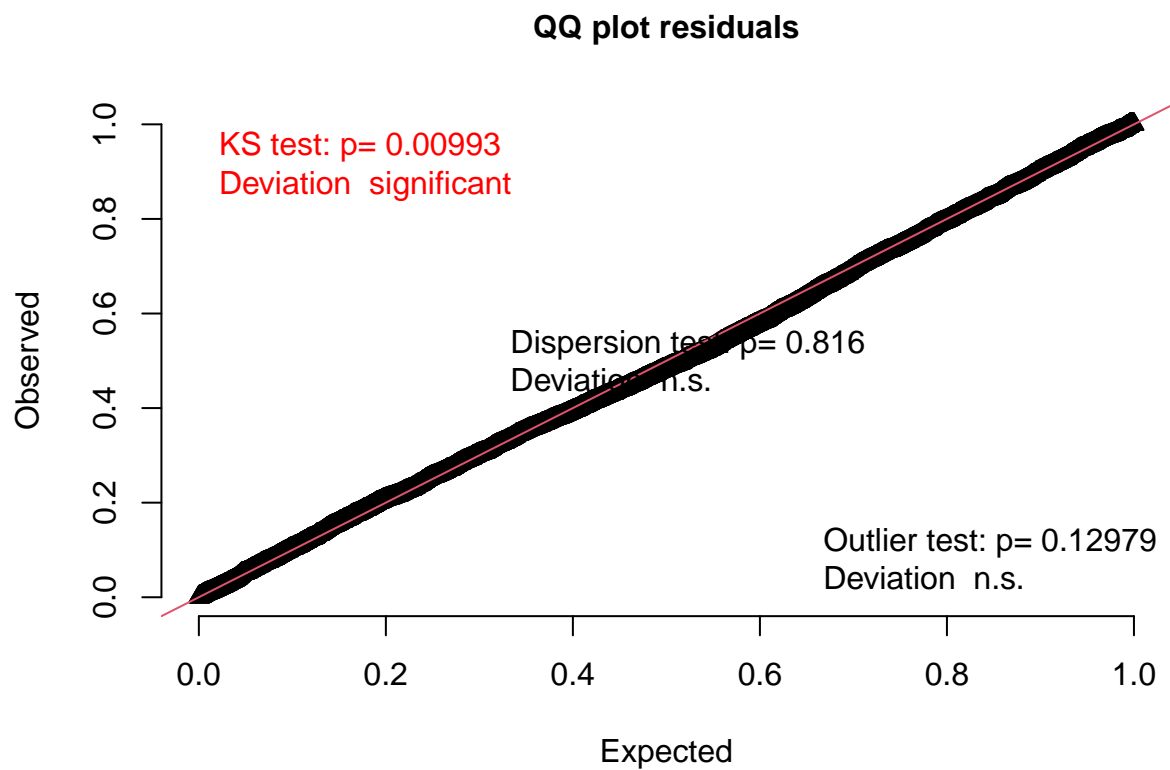
**DHARMA nonparametric dispersion test via sd of
residuals fitted vs. simulated**



Simulated values, red line = fitted model. p-value (two.sided) = 0.816

```
##
## DHARMA nonparametric dispersion test via sd of residuals fitted vs.
## simulated
##
## data:  simulationOutput
## dispersion = 1.0191, p-value = 0.816
## alternative hypothesis: two.sided

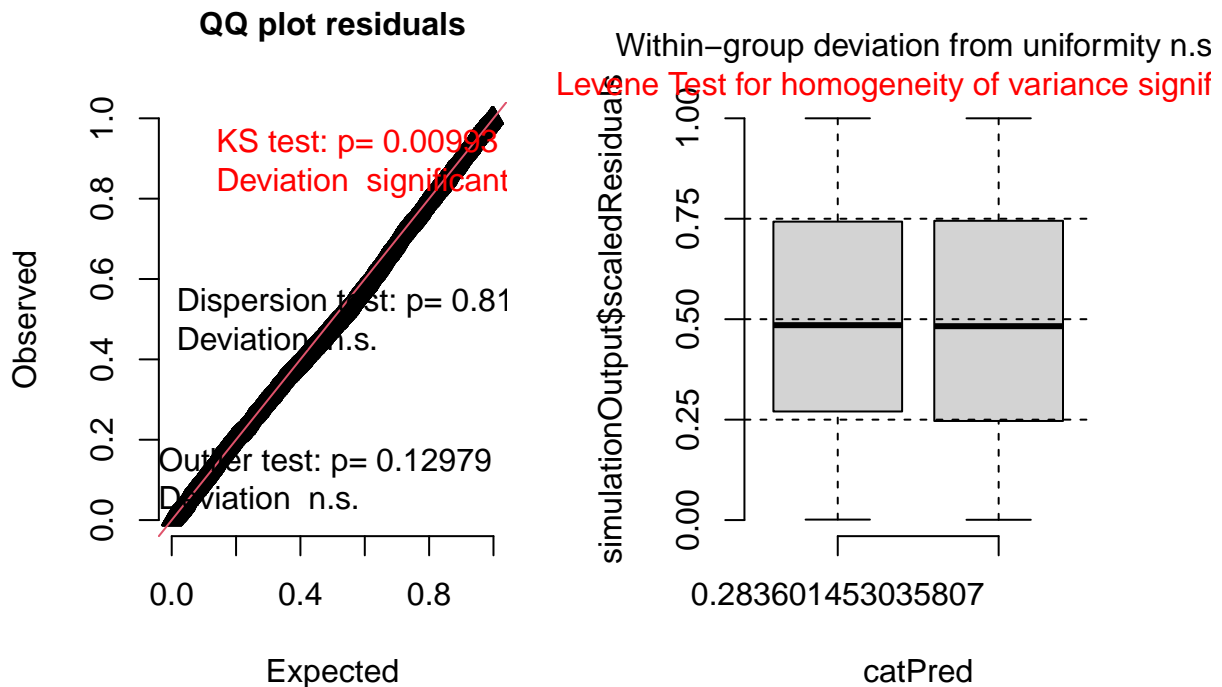
# Check for uniformity of residuals
testUniformity(simulationOutput)
```



```
##  
## One-sample Kolmogorov-Smirnov test  
##  
## data: simulationOutput$scaledResiduals  
## D = 0.021918, p-value = 0.009929  
## alternative hypothesis: two-sided
```

```
# Create diagnostic plots  
plot(simulationOutput)
```


DHARMA residual



```
#Imports excel file
LDHAB_ON_CA2_file <- "LDHAB_EM_ON_CAII_Quantification.xlsx"
ldha_OL_CA2 <- read_excel(path = here::here(LDHAB_ON_CA2_file), sheet = "LDHA") %>%
  mutate(Staining = "LDHA")

#ldh_OL_CA2 <- dplyr::bind_rows(ldha_OL_CA2, ldhb_OL_CA2)

model <- lmer(goldDotsPerArea ~ Genotype + (1|Mouse) + (1|Mouse:Genotype), data = ldha_OL_CA2)
summary(model)

## Linear mixed model fit by REML. t-tests use Satterthwaite's method [
## lmerModLmerTest]
## Formula: goldDotsPerArea ~ Genotype + (1 | Mouse) + (1 | Mouse:Genotype)
## Data: ldha_OL_CA2
##
## REML criterion at convergence: 67.8
##
## Scaled residuals:
##   Min       1Q   Median       3Q      Max
## -1.9909 -0.4807  0.1087  0.5286  2.5549
##
## Random effects:
##   Groups             Name               Variance Std.Dev.
##   Mouse              (Intercept)    0.01867   0.1366
##   Mouse:Genotype      (Intercept)    0.02137   0.1462
##   Residual                                0.33664   0.5802
```

```
## Number of obs: 36, groups: Mouse, 8; Mouse:Genotype, 8
##
## Fixed effects:
##           Estimate Std. Error    df t value Pr(>|t|)
## (Intercept)  1.1647      0.1667  5.2524   6.987 0.000755 ***
## Genotypemut   0.1140      0.2409  5.5974   0.473 0.653948
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Correlation of Fixed Effects:
##           (Intr)
## Genotypemut -0.692
```

```
anova(model)
```

```
## Type III Analysis of Variance Table with Satterthwaite's method
##           Sum Sq Mean Sq NumDF DenDF F value Pr(>F)
## Genotype 0.075384 0.075384     1 5.5974  0.2239 0.6539
```

```
# Pairwise comparison
emm <- emmeans(model, ~ Genotype)
pairs(emm)
```

```
## contrast estimate SE df t.ratio p.value
## ctr - mut -0.114 0.242 5.85 -0.470 0.6552
##
## Degrees-of-freedom method: kenward-roger
```

```
data <- ldha_OL_CA2
# Create a new dataset for predictions
prediction <- data %>%
  dplyr::select(Genotype, Mouse, Area) %>%
  distinct()

# Add predictions from the models
prediction$Pred_Model <- predict(model, newdata = prediction) /prediction$Area

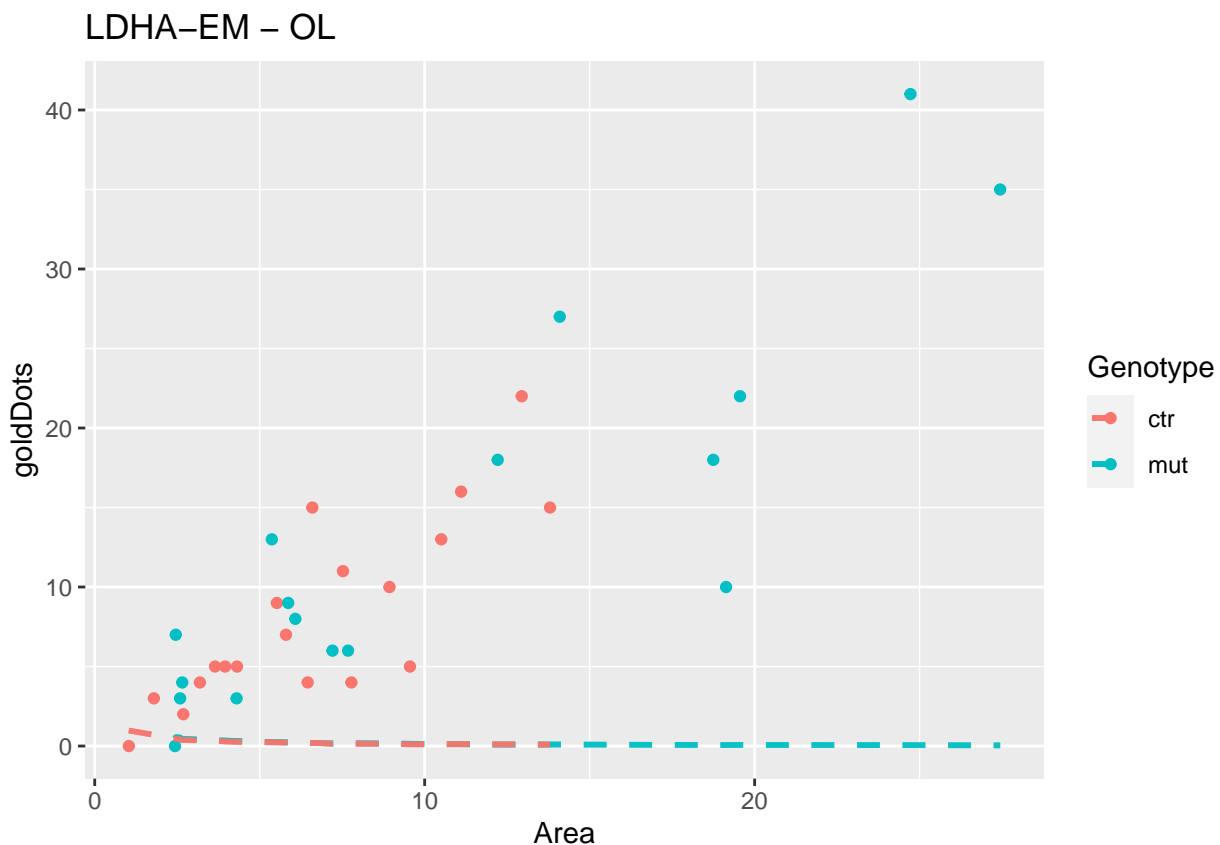
lowerLimit_mut <- prediction %>%
  dplyr::filter(Genotype == "mut") %>%
  dplyr::group_by(Area) %>%
  dplyr::filter(Pred_Model == min(Pred_Model))
upperLimit_mut <- prediction %>%
  dplyr::filter(Genotype == "mut") %>%
  dplyr::group_by(Area) %>%
  dplyr::filter(Pred_Model == max(Pred_Model))
lowerLimit_ctr <- prediction %>%
  dplyr::filter(Genotype != "mut") %>%
  dplyr::group_by(Area) %>%
  dplyr::filter(Pred_Model == min(Pred_Model))
upperLimit_ctr <- prediction %>%
  dplyr::filter(Genotype != "mut") %>%
  dplyr::group_by(Area) %>%
```

```
dplyr::filter(Pred_Model == max(Pred_Model))

prediction$Pred_Model[seq(from = 1, to = length(prediction$Pred_Model), by = 2)]
```

```
##          1          3          5          7          9          11          13
## 0.25862646 0.05615674 0.09850340 0.10562320 0.97604419 0.19418655 0.14030380
##          15          17          19          21          23          25          27
## 0.19003550 0.06294636 0.11351896 0.09739720 0.09134825 0.35614714 0.10809188
##          29          31          33          35
## 0.55622940 0.23309835 0.16029896 0.47457450
```

```
# Plot the data and the fitted models
ggplot(data, aes(x = Area, y = goldDots, color = Genotype)) +
  geom_point() +
  geom_line(data = lowerLimit_mut, aes(x = Area, y = Pred_Model, color = Genotype), linetype = "dashed")
  geom_line(data = upperLimit_mut, aes(x = Area, y = Pred_Model, color = Genotype), linetype = "dashed")
  geom_line(data = upperLimit_ctr, aes(x = Area, y = Pred_Model, color = Genotype), linetype = "dashed")
  geom_line(data = lowerLimit_ctr, aes(x = Area, y = Pred_Model, color = Genotype), linetype = "dashed")
  labs(x = "Area", y = "goldDots", color = "Genotype", title = "LDHA-EM - OL")
```



```
#Imports excel file
ldhb_OL_CA2 <- read_excel(path = here::here(LDHAB_ON_CA2_file), sheet = "LDHB") %>%
  mutate(goldDotsPerArea = goldDots / Area) %>%
  na.omit
```

```

dependentVar <- "goldDotsPerArea"
fixedEffect <- "Genotype"
groupingVars <- (c("Mouse", "Genotype"))
analysisName <- "LDHB_OLs+CA2"
formula <- goldDotsPerArea ~ Genotype + (1|Mouse) + (1|Mouse:Genotype)
Interaction <- NULL

model <- lmer(goldDotsPerArea ~ Genotype + (1|Mouse) + (1|Mouse:Genotype), data = ldhb_OL_CA2)
summary(model)

## Linear mixed model fit by REML. t-tests use Satterthwaite's method [
## lmerModLmerTest]
## Formula: goldDotsPerArea ~ Genotype + (1 | Mouse) + (1 | Mouse:Genotype)
## Data: ldhb_OL_CA2
##
## REML criterion at convergence: 45.2
##
## Scaled residuals:
##      Min       1Q   Median       3Q      Max
## -1.27929 -0.66144 -0.00569  0.65069  2.31729
##
## Random effects:
## Groups           Name          Variance Std.Dev.
## Mouse            (Intercept)  0.00460  0.06783
## Mouse:Genotype    (Intercept)  0.05205  0.22814
## Residual                  0.17883  0.42288
## Number of obs: 33, groups: Mouse, 8; Mouse:Genotype, 8
##
## Fixed effects:
##              Estimate Std. Error    df t value Pr(>|t|)
## (Intercept)  0.47059    0.15790 6.04026   2.980   0.0244 *
## Genotypemut  0.07138    0.22466 6.19787   0.318   0.7611
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Correlation of Fixed Effects:
##              (Intr)
## Genotypemut -0.703

anova(model)

## Type III Analysis of Variance Table with Satterthwaite's method
##              Sum Sq Mean Sq NumDF DenDF F value Pr(>F)
## Genotype 0.018051 0.018051     1 6.1979  0.1009 0.7611

emm <- emmeans(model, ~ Genotype)
pairs(emm)

## contrast estimate    SE    df t.ratio p.value
## ctr - mut  -0.0714 0.225 5.92  -0.317  0.7623
##
## Degrees-of-freedom method: kenward-roger

```

```

data <- ldhb_OL_CA2
# Create a new dataset for predictions
prediction <- data %>%
  dplyr::select(Genotype, Mouse, Area) %>%
  distinct()

# Add predictions from the models
prediction$Pred_Model <- predict(model, newdata = prediction) /prediction$Area

lowerLimit_mut <- prediction %>%
  dplyr::filter(Genotype == "mut") %>%
  dplyr::group_by(Area) %>%
  dplyr::filter(Pred_Model == min(Pred_Model))
upperLimit_mut <- prediction %>%
  dplyr::filter(Genotype == "mut") %>%
  dplyr::group_by(Area) %>%
  dplyr::filter(Pred_Model == max(Pred_Model))
lowerLimit_ctr <- prediction %>%
  dplyr::filter(Genotype != "mut") %>%
  dplyr::group_by(Area) %>%
  dplyr::filter(Pred_Model == min(Pred_Model))
upperLimit_ctr <- prediction %>%
  dplyr::filter(Genotype != "mut") %>%
  dplyr::group_by(Area) %>%
  dplyr::filter(Pred_Model == max(Pred_Model))

# Plot the data and the fitted models
ggplot(data, aes(x = Area, y = goldDots, color = Genotype)) +
  geom_point() +
  geom_line(data = prediction, aes(x = Area, y = Pred_Model, color = Genotype), linetype = "dashed", si
  geom_line(data = lowerLimit_mut, aes(x = Area, y = Pred_Model, color = Genotype), linetype = "dashed"
  geom_line(data = upperLimit_mut, aes(x = Area, y = Pred_Model, color = Genotype), linetype = "dashed"
  geom_line(data = upperLimit_ctr, aes(x = Area, y = Pred_Model, color = Genotype), linetype = "dashed"
  geom_line(data = lowerLimit_ctr, aes(x = Area, y = Pred_Model, color = Genotype), linetype = "dashed"
  labs(x = "Area", y = "goldDots", color = "Genotype", title = "LDHB-EM - OL")

```

LDHB-EM – OL

