Supplementary materials for: Consonant stability in Portuguese-based creoles

(05 January, 2023)

Contents

1 Overview

Supplementary materials for, "Consonant Stability in Portuguese-based creoles". In this report, we provide code in R (RStudio Team 2020) and we use these R libraries (Wickham et al. 2019; Xie 2021; Slowikowski 2022; Kuznetsova, Brockhoff, and Christensen 2017; Wood 2004):

```
library(tidyverse)
library(knitr)
library(ggrepel)
library(lmerTest)
library(mgcv)

# Set the theme for all figures
theme_set(theme_bw())
```

Load the data set.

```
database <- read_csv("database.csv")
```

We extend the database with some additional variables. First, duration of contact.

```
database$duration <- database$`EndOfInfluence` - database$`FirstMajorSettlement`
```

Next, a variable of global stability.

```
database <- mutate(database, GlobalStability = (PlaceStability + MannerStability) / 2)
```

Also, a categorical variable for duration.

```r
database <- database %>%
  mutate(duration_group = ifelse(duration <= 200, "short", "long"))
```

And a categorical variable for changes in manner and/or place. Stability in the database is ‘1’ (no change) and ‘0’ (change).

```r
database <- database %>%
  mutate(categorical_stability = ifelse(PlaceStability == 1 & MannerStability == 1,
                                        "no manner/no place", NA))

database <- database %>%
  mutate(categorical_stability = ifelse(PlaceStability == 1 & MannerStability == 0,
                                        "manner/no place", categorical_stability))

database <- database %>%
  mutate(categorical_stability = ifelse(PlaceStability == 0 & MannerStability == 1,
                                        "no manner/place", categorical_stability))

database <- database %>%
  mutate(categorical_stability = ifelse(PlaceStability == 0 & MannerStability == 0,
                                        "manner/place", categorical_stability))

table(database$categorical_stability)
```

```
##
##    manner/no place       manner/place no manner/no place    no manner/place
##                 43                 54                517                 24
```

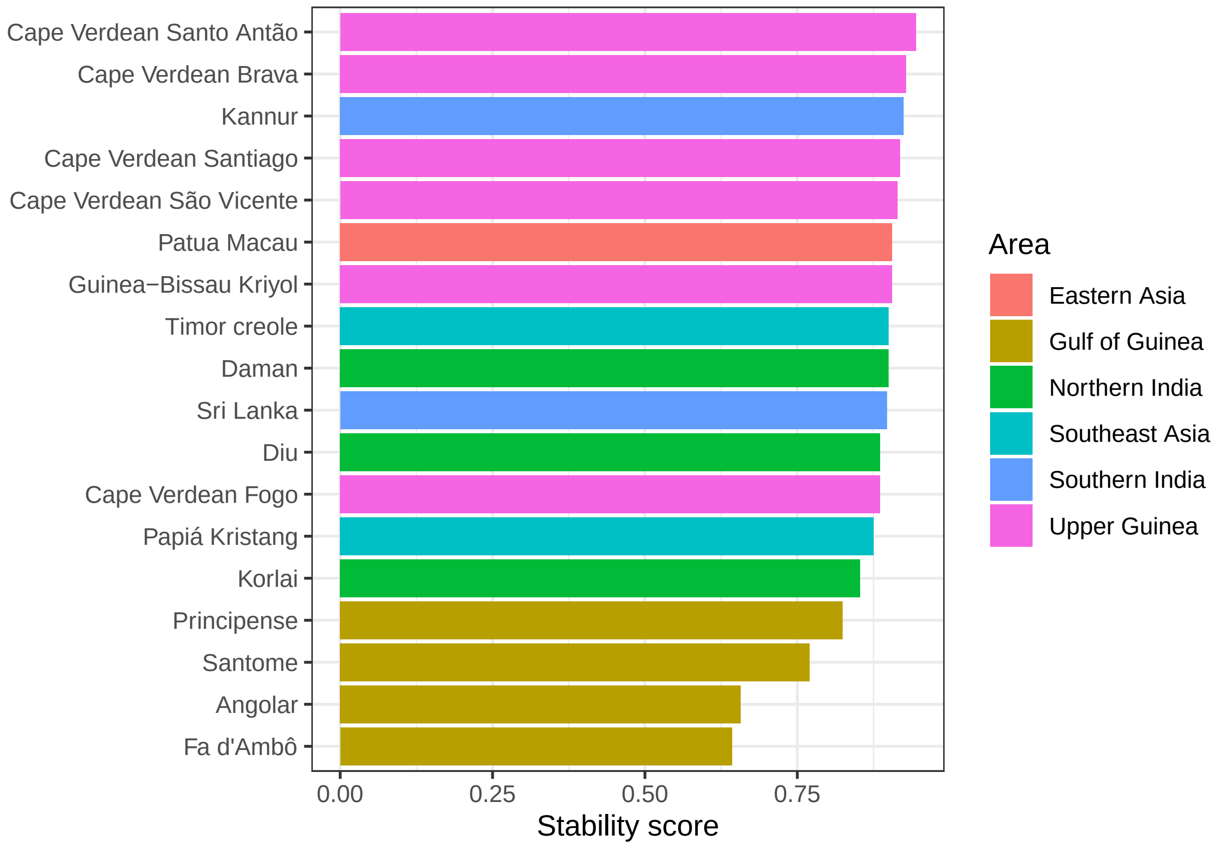
2 Creole stability

Which creoles in the sample are more or less stable overall?

```r
creole_stability <- database %>%
  group_by(Language, Area, duration, duration_group, ContactConditions) %>%
  summarize(MeanStability = mean(GlobalStability, na.rm = TRUE))
```

Plot it by area.

```r
ggplot(creole_stability) +
  geom_bar(aes(x = MeanStability, y = reorder(Language, MeanStability), fill = Area),
    stat = "identity", show.legend = TRUE) +
  theme(axis.title.y = element_blank()) +
  labs(x = "Stability score")
```

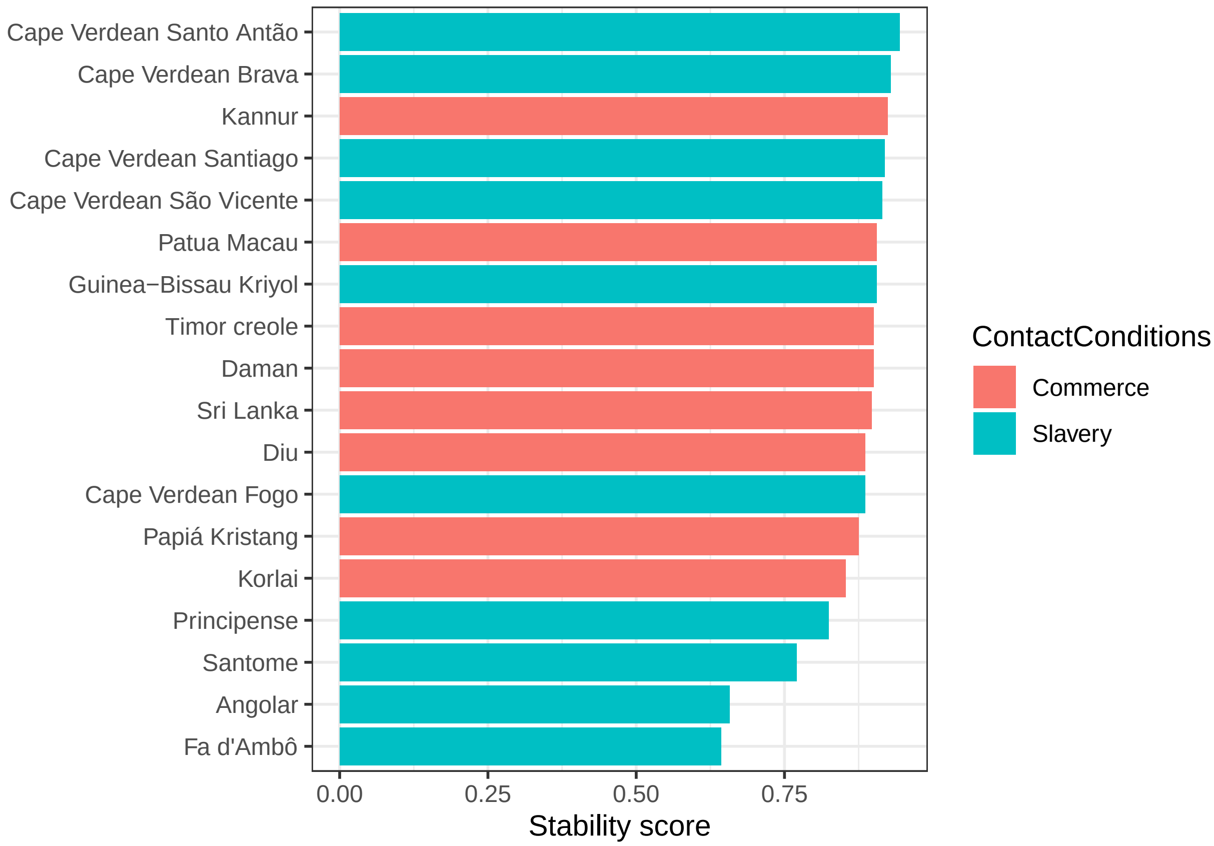



```
table(creole_stability$Area)
```

```
##
##    Eastern Asia Gulf of Guinea Northern India Southeast Asia Southern India
##               1              4              3              2              2
##    Upper Guinea
##               6
```

Plot it by conditions of contact.

```
ggplot(creole_stability) +
  geom_bar(aes(x = MeanStability, y = reorder(Language, MeanStability),
               fill = ContactConditions), stat = "identity", show.legend = TRUE
  ) +
  theme(axis.title.y = element_blank()) +
  labs(x = "Stability score")
```

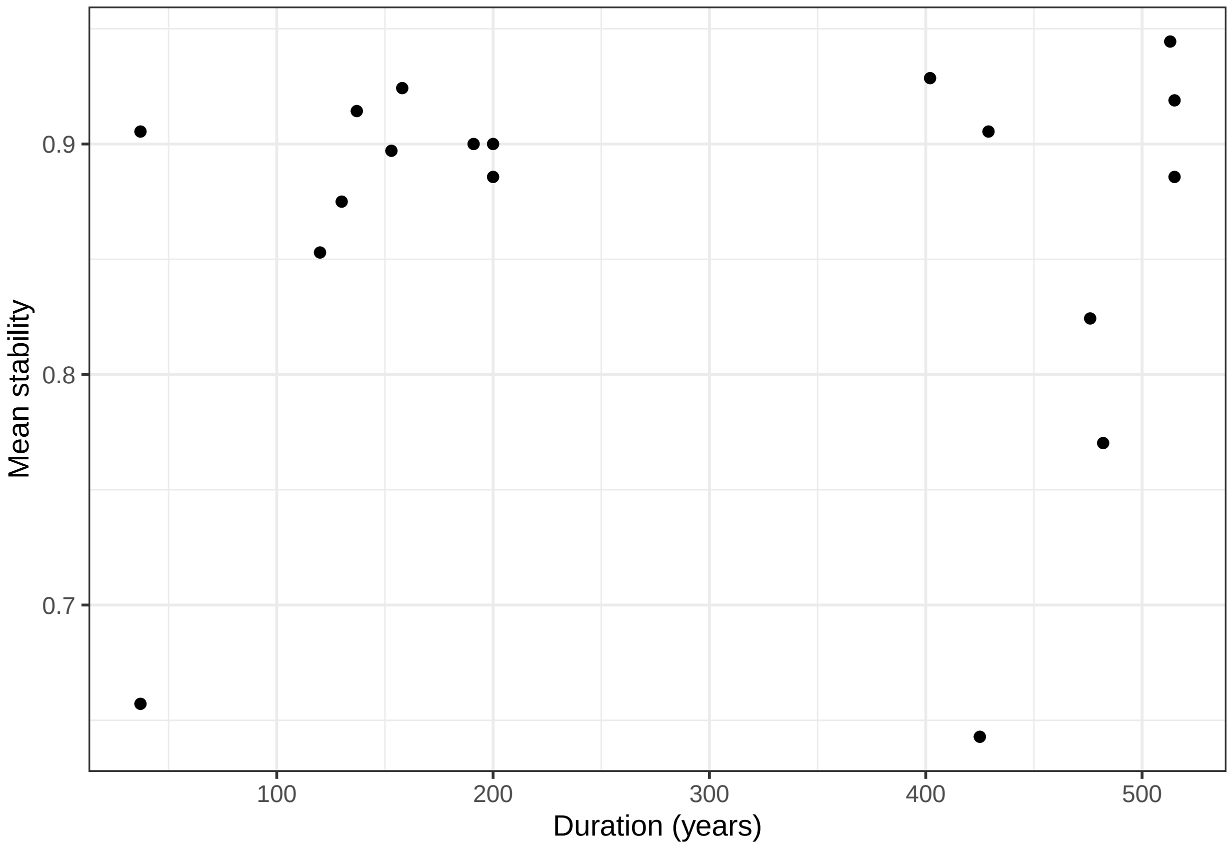


3 Duration

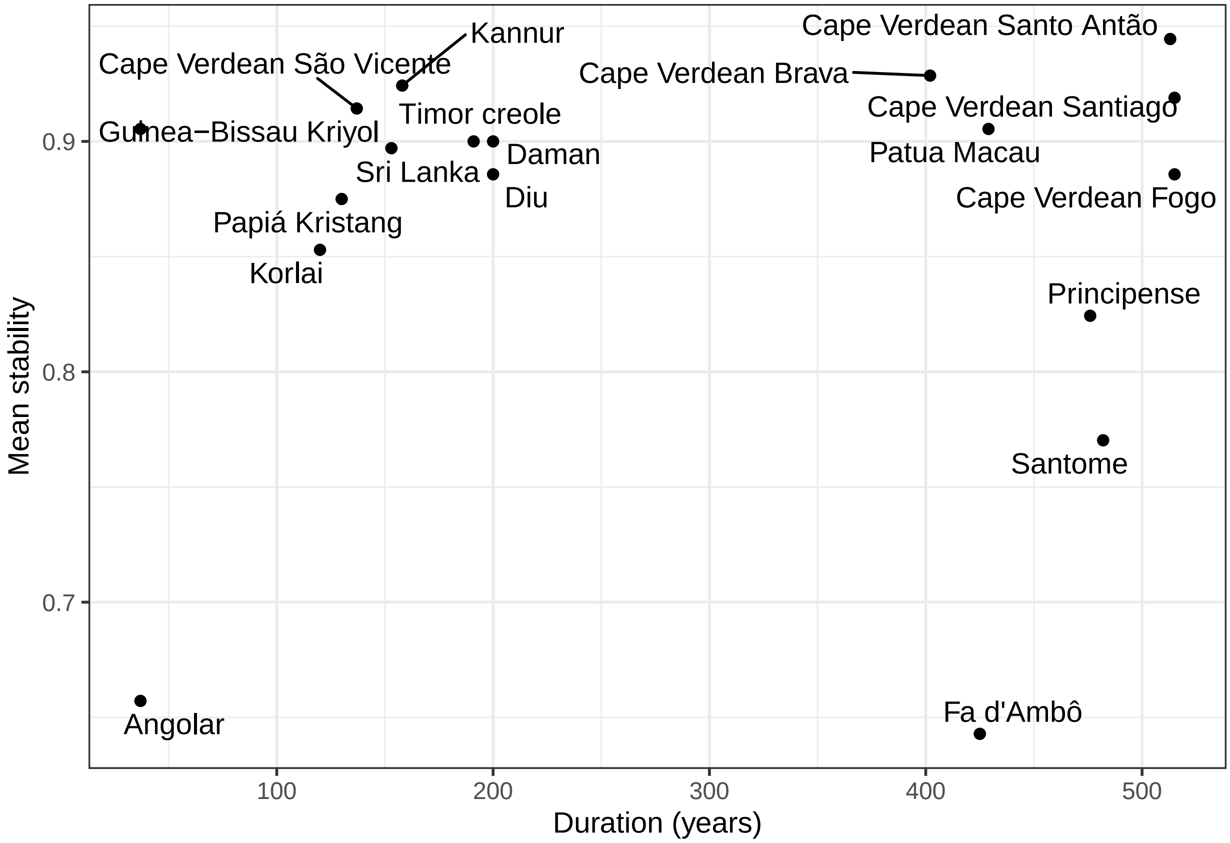
We have the overall stability values. What are these in relation to the duration of contact?

There does not seem to be a relationship between overall duration and overall stability.

```
ggplot(creole_stability, aes(x = duration, y = MeanStability)) +
  geom_point() +
  xlab("Duration (years)") +
  ylab("Mean stability")
```




```
ggplot(creole_stability, aes(x = duration, y = MeanStability)) +
  geom_point() +
  geom_text_repel(aes(label = creole_stability$Language)) +
  xlab("Duration (years)") +
  ylab("Mean stability")
```



Results from the simple regression.

```
msd <- lm(MeanStability ~ duration, data = creole_stability)
summary(msd)
```

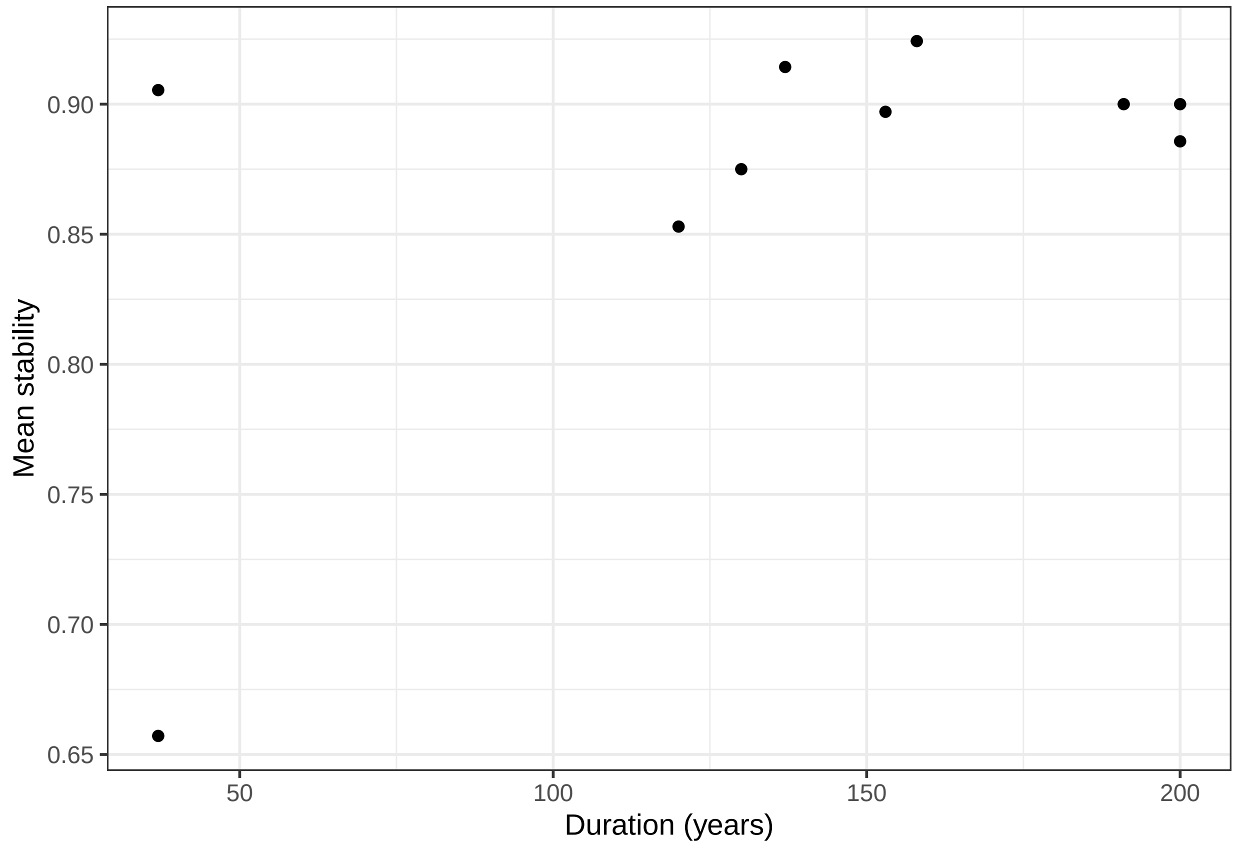
```
##
## Call:
## lm(formula = MeanStability ~ duration, data = creole_stability)
##
## Residuals:
##       Min        1Q    Median        3Q       Max
## -0.221577 -0.002688  0.036798  0.051036  0.079053
##
## Coefficients:
##              Estimate Std. Error t value Pr(>|t|)
## (Intercept) 8.598e-01  4.086e-02  21.042 4.37e-13 ***
## duration    1.088e-05  1.227e-04   0.089     0.93
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 0.09017 on 16 degrees of freedom
## Multiple R-squared:  0.0004911,  Adjusted R-squared:  -0.06198
## F-statistic: 0.007862 on 1 and 16 DF,  p-value: 0.9304
```

However, there does seem to be two groups of languages – ones that belong to "long duration" (>= 400 years) and those that below to "short duration" (<= 200 years).

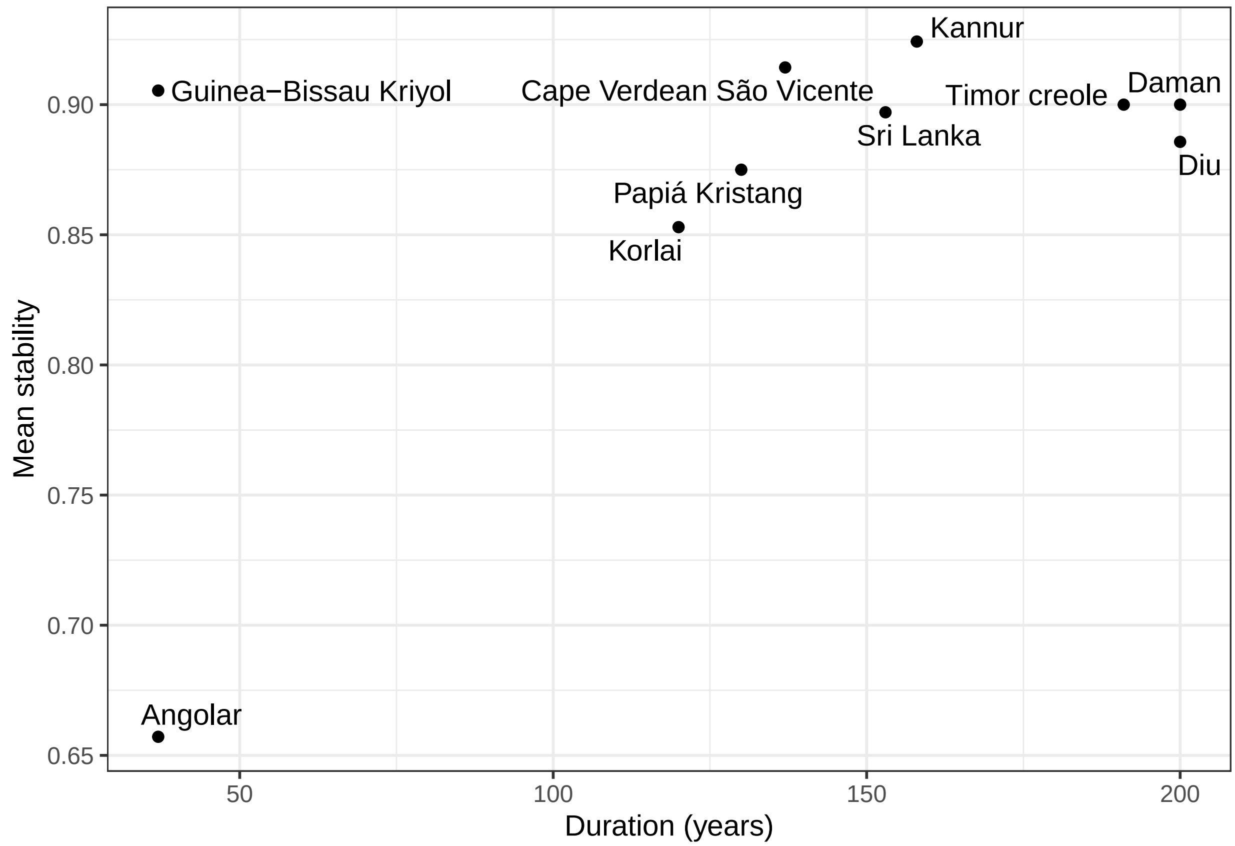
We can try to split the data and rerun the models, but we note that there are very few data points.

```r
tmp_short <- creole_stability %>% filter(duration <= 200)
tmp_long <- creole_stability %>% filter(duration > 200)
```

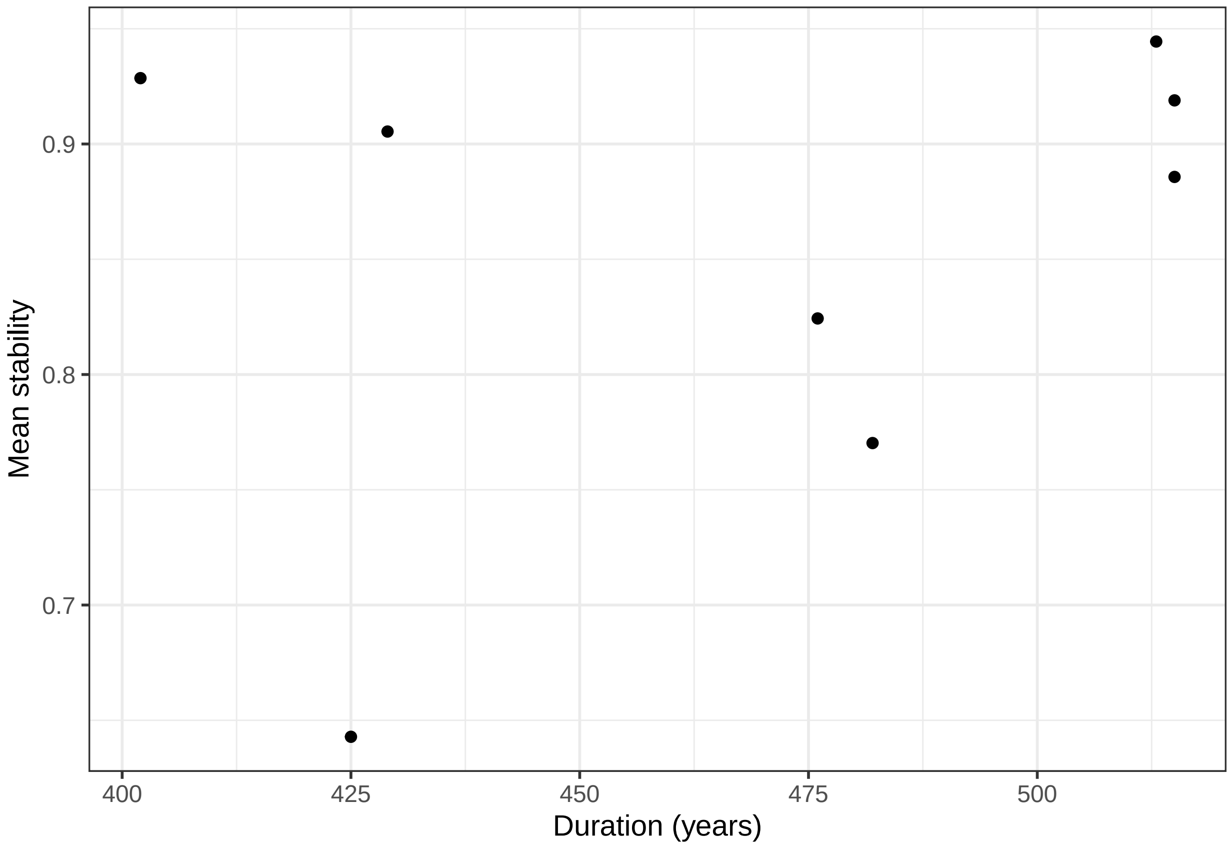
```r
ggplot(tmp_short, aes(x = duration, y = MeanStability)) +
  geom_point() +
  xlab("Duration (years)") +
  ylab("Mean stability")
```



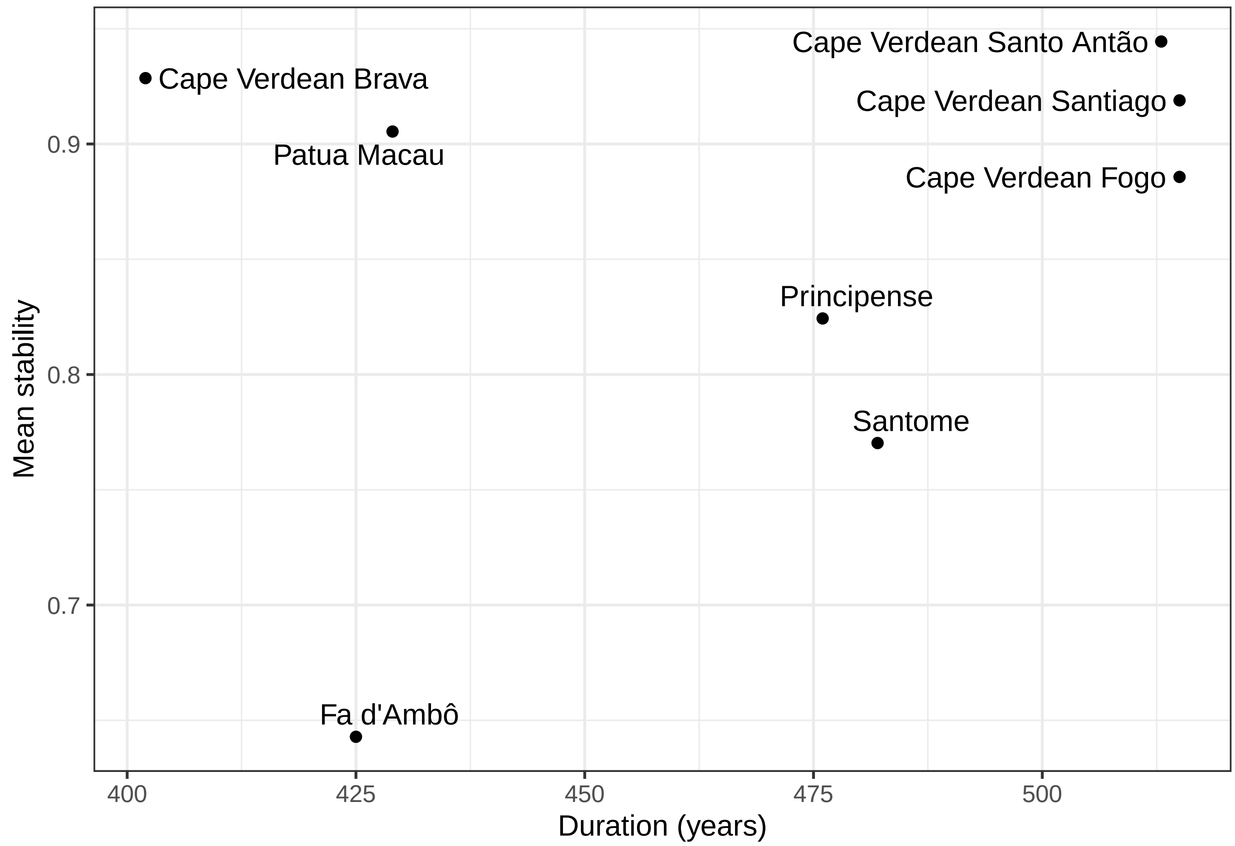

```r
ggplot(tmp_short, aes(x = duration, y = MeanStability)) +
  geom_point() +
  geom_text_repel(aes(label = tmp_short$Language)) +
  xlab("Duration (years)") +
  ylab("Mean stability")
```




```
ggplot(tmp_long, aes(x = duration, y = MeanStability)) +
  geom_point() +
  xlab("Duration (years)") +
  ylab("Mean stability")
```




```r
ggplot(tmp_long, aes(x = duration, y = MeanStability)) +
  geom_point() +
  geom_text_repel(aes(label = tmp_long$Language)) +
  xlab("Duration (years)") +
  ylab("Mean stability")
```



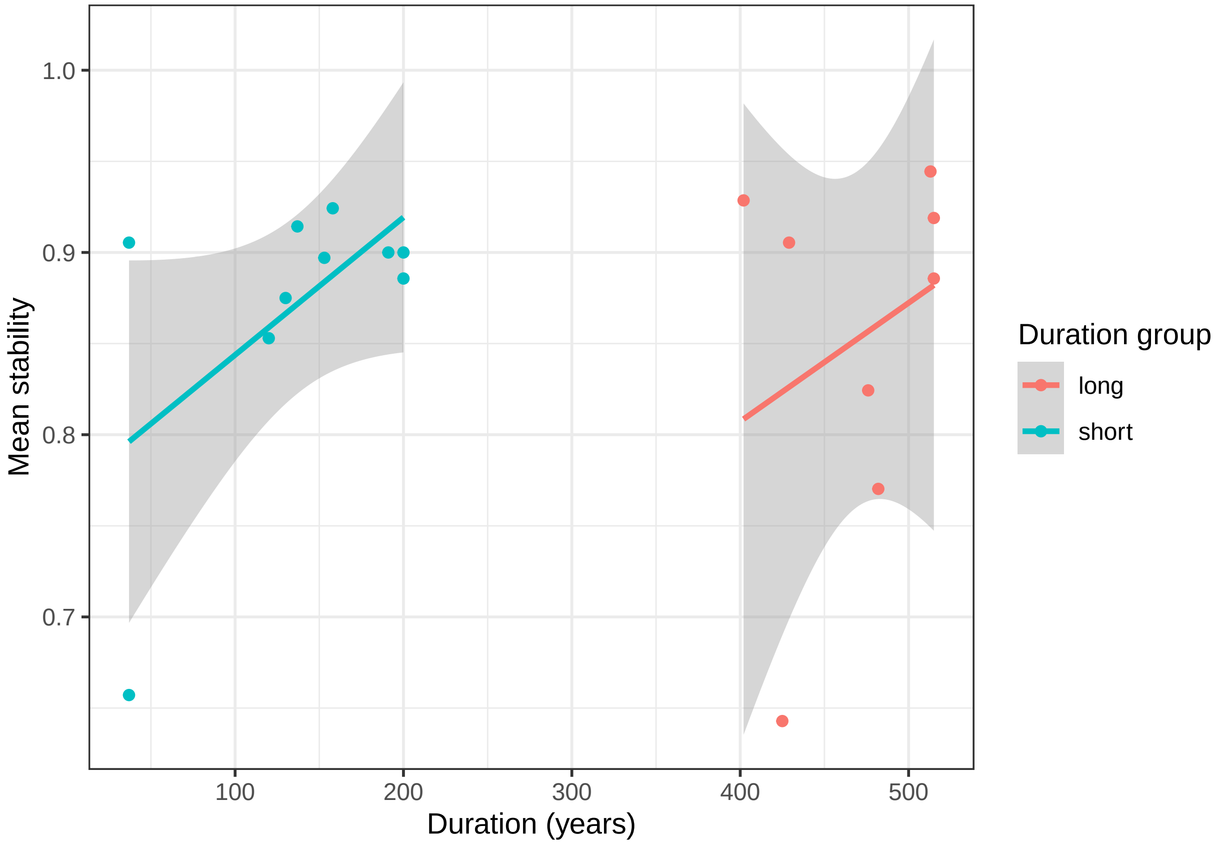
A single model with an interaction term MeanSim ~ duration, group * duration.

```
msd <- lm(MeanStability ~ duration + duration_group * duration, data = creole_stability)
summary(msd)
```

```
##
## Call:
## lm(formula = MeanStability ~ duration + duration_group * duration,
##     data = creole_stability)
##
## Residuals:
##       Min        1Q    Median        3Q       Max
## -0.180674 -0.029112  0.006105  0.041142  0.120003
##
## Coefficients:
##                               Estimate Std. Error t value Pr(>|t|)
## (Intercept)                  0.5470360  0.3391096   1.613    0.129
## duration                     0.0006506  0.0007192   0.905    0.381
## duration_groupshort          0.2212025  0.3465288   0.638    0.534
## duration:duration_groupshort 0.0001047  0.0008665   0.121    0.906
##
## Residual standard error: 0.08632 on 14 degrees of freedom
## Multiple R-squared:  0.1984, Adjusted R-squared:  0.02667
## F-statistic: 1.155 on 3 and 14 DF,  p-value: 0.3615
```

```
ggplot(creole_stability, aes(x = duration, y = MeanStability, color = duration_group)) +
  geom_smooth(method = "lm") +
  geom_point() +
```

```r
  xlab("Duration (years)") +
  ylab("Mean stability") +
  labs(color = "Duration group")
```



The variability in the two groups is very different. The direction of the effect is interesting: shorter durations yield more stability more consistently. Over time, the variability in mean stability increases. Time is "destabillizing the pattern of stability".

But it looks like you might have something tastier on your hands. The creoles appear to be bouncing back toward the lexifier over time (based on the duration findings; but perhaps I misunderstand).

And we can also increase the number of observations by running the analysis at the segment level, rather than on mean stability.

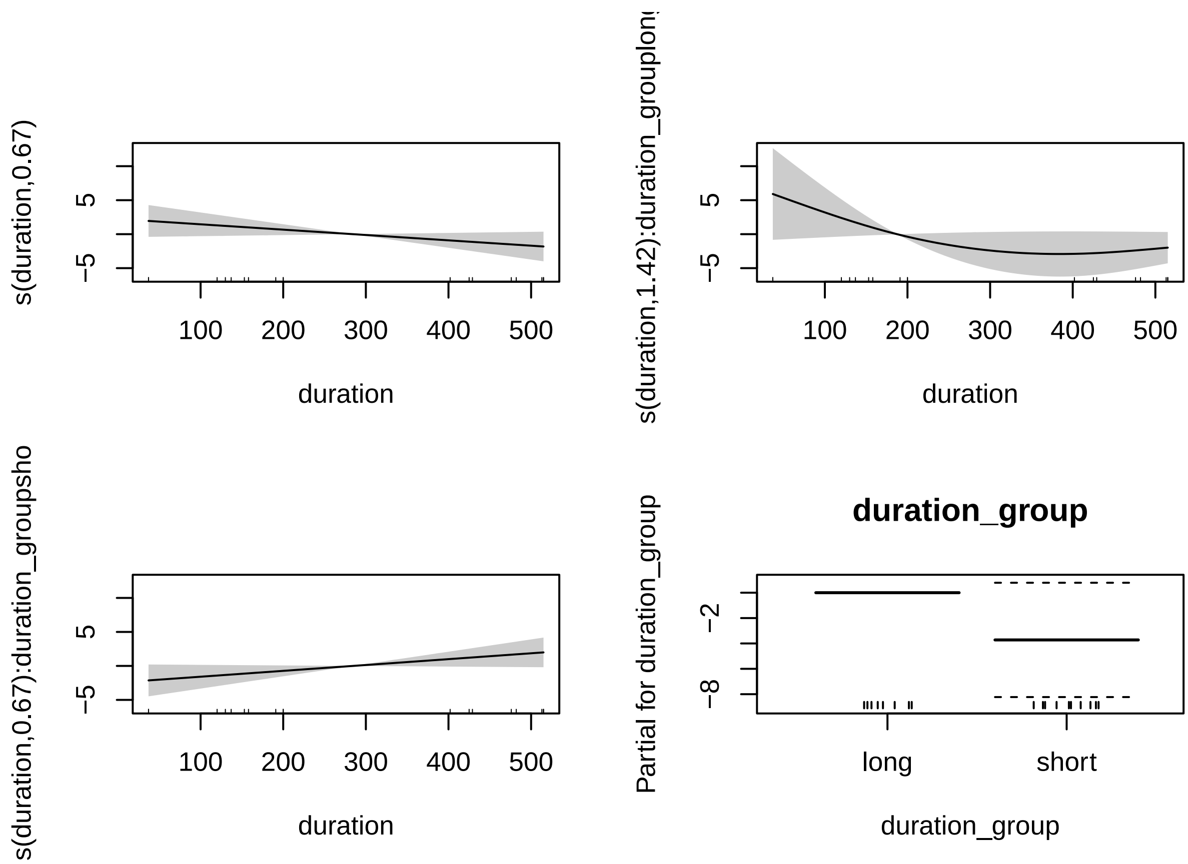
Exploratory analysis with a generalized additive model (GAM).

```r
# Factorize duration_group
creole_stability$duration_group <- as.factor(creole_stability$duration_group)

# Model with an interaction between duration_group and duration
# (with maximum of cubic-spline fit)
msd.gam <- gam(MeanStability ~ duration_group + s(duration, k = 3) +
                 s(duration, by = duration_group, k = 3), data = creole_stability)

summary(msd.gam)
```

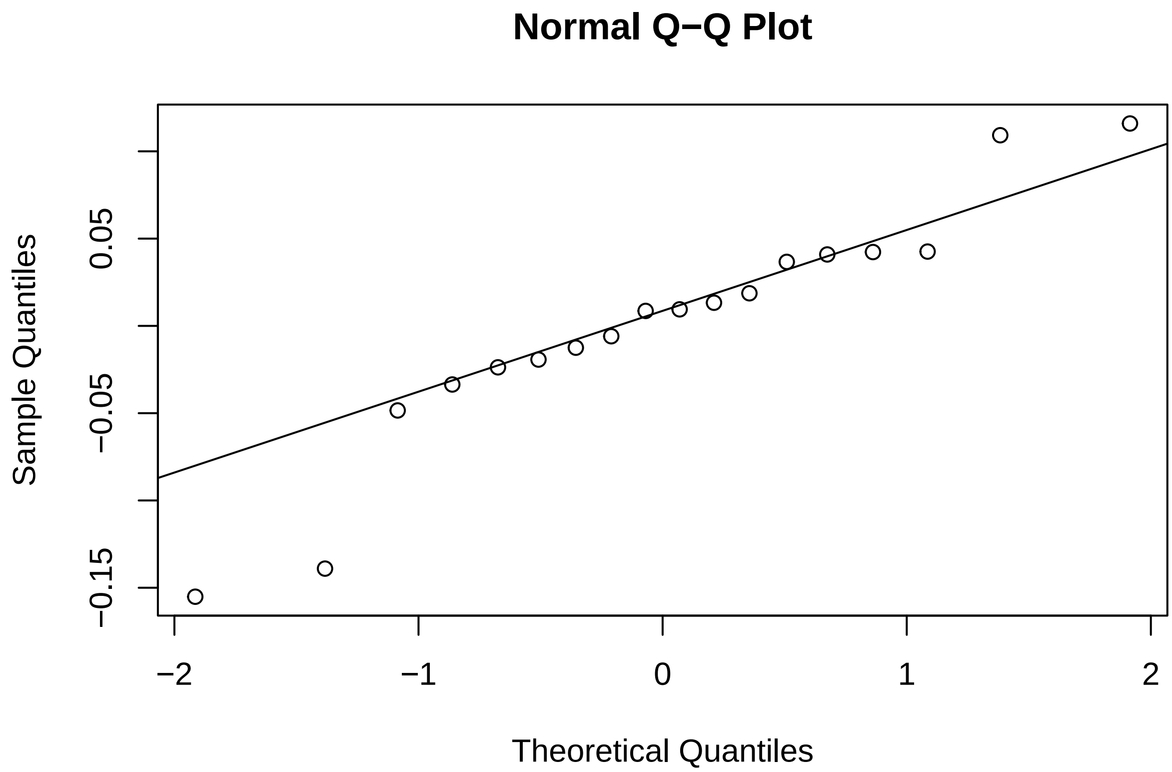
```
##
## Family: gaussian
## Link function: identity
```

```
##
## Formula:
## MeanStability ~ duration_group + s(duration, k = 3) + s(duration,
##     by = duration_group, k = 3)
##
## Parametric coefficients:
##                     Estimate Std. Error t value Pr(>|t|)
## (Intercept)            4.705      2.252   2.090   0.0565 .
## duration_groupshort   -3.722      2.253  -1.652   0.1219
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Approximate significance of smooth terms:
##                                  edf Ref.df     F p-value
## s(duration)                   0.6667 0.6667 4.160  0.1197
## s(duration):duration_grouplong  1.4242 1.6079 1.606  0.1825
## s(duration):duration_groupshort 0.6667 0.6667 4.984  0.0914 .
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Rank: 7/8
## R-sq.(adj) =  0.204   Deviance explained =   38%
## GCV = 0.008281  Scale est. = 0.0060923  n = 18
```

```r
plot(msd.gam, all.terms = T, shade = T, pages = 1)
```



```
qqnorm(resid(msd.gam))
qqline(resid(msd.gam))
```

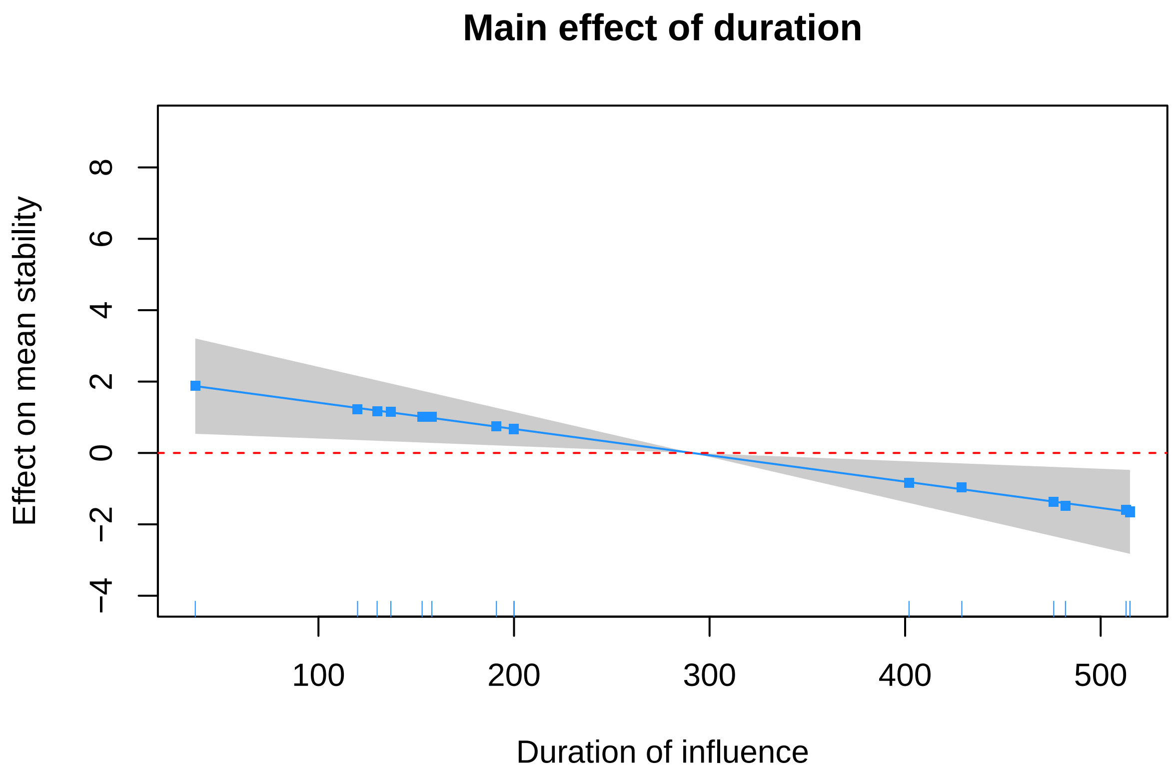



```
msd.gam.trimmed <- gam(MeanStability ~ duration_group + s(duration, k = 3)
                       + s(duration, by = duration_group, k = 3),
                       data = creole_stability %>% filter(MeanStability > 0.7))

summary(msd.gam.trimmed)
```

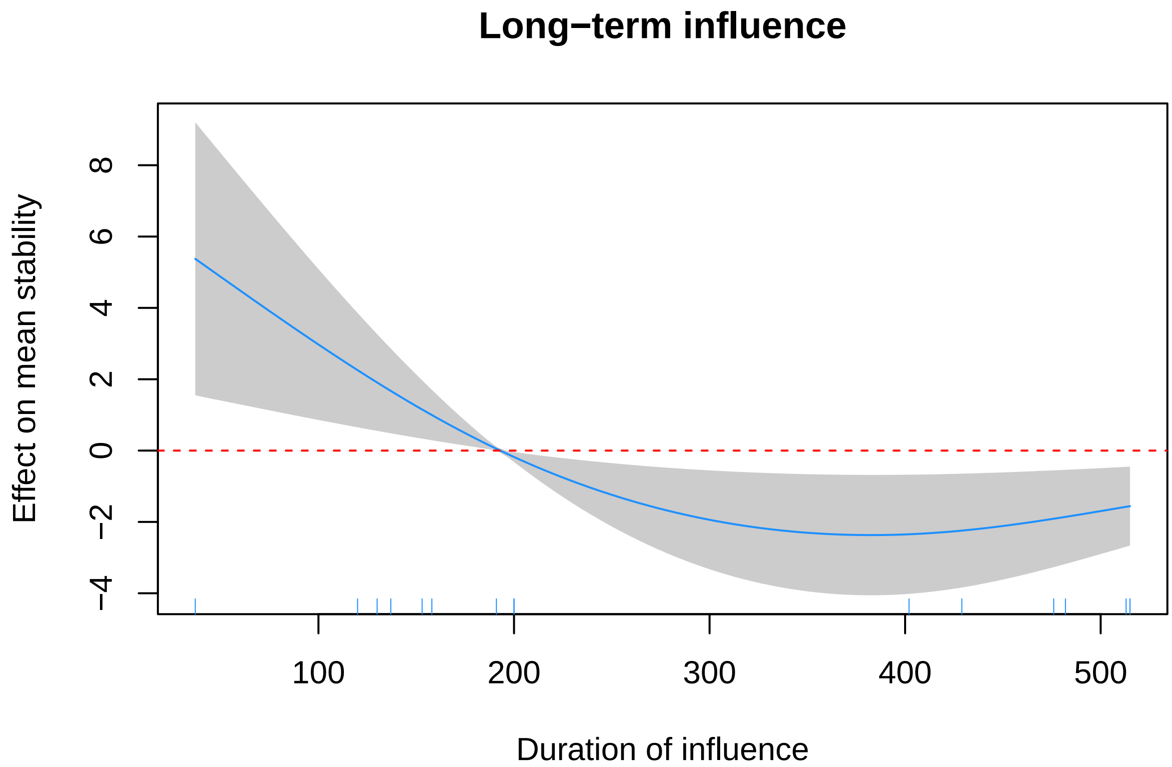
```
##
## Family: gaussian
## Link function: identity
##
## Formula:
## MeanStability ~ duration_group + s(duration, k = 3) + s(duration,
##     by = duration_group, k = 3)
##
## Parametric coefficients:
##                      Estimate Std. Error t value Pr(>|t|)
## (Intercept)             4.110      1.147   3.583  0.00423 **
## duration_groupshort    -3.212      1.148  -2.799  0.01716 *
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Approximate significance of smooth terms:
##                                 edf Ref.df      F p-value
## s(duration)                  0.6667 0.6667 11.824  0.0170 *
## s(duration):duration_grouplong  1.5535 1.6538  4.984  0.0362 *
## s(duration):duration_groupshort 0.6667 0.6667 11.858  0.0169 *
```

```
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Rank: 7/8
## R-sq.(adj) =  0.265   Deviance explained = 45.5%
## GCV = 0.00198  Scale est. = 0.0013752  n = 16
```

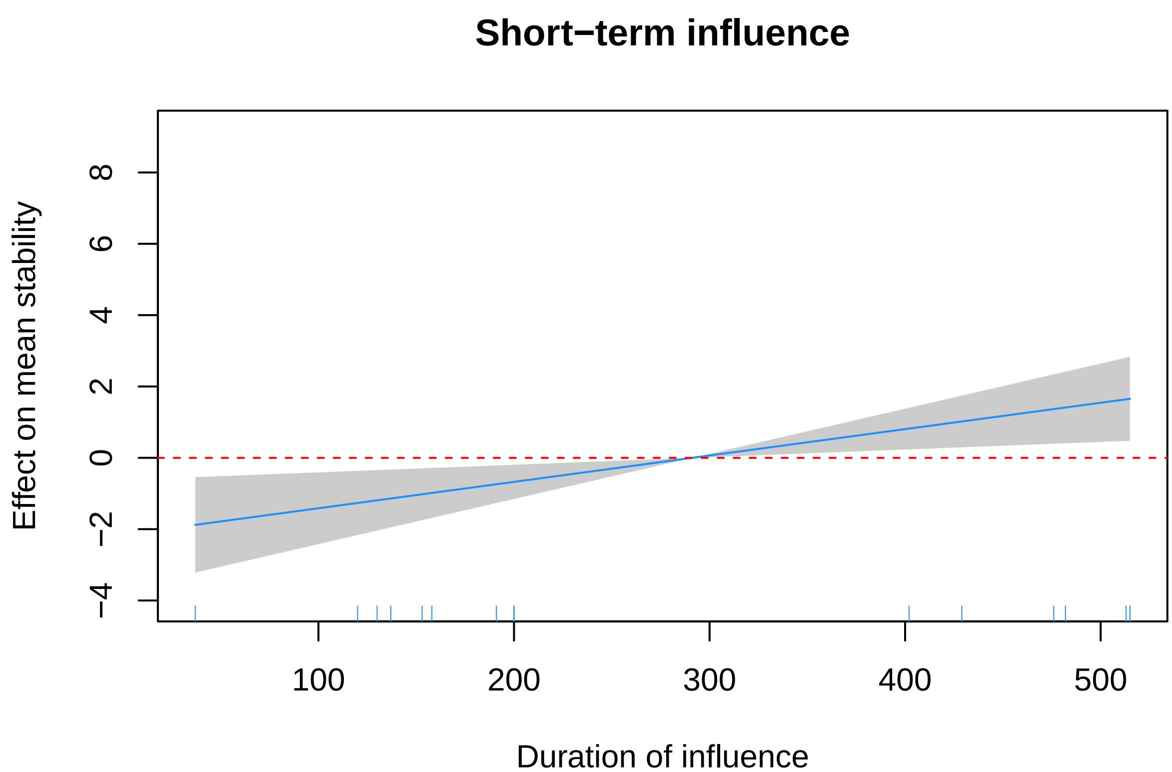
```
plot(msd.gam.trimmed, sel = 1, shade = T, ylab = "Effect on mean stability",
     xlab = "Duration of influence", residuals = T, main = "Main effect of duration",
     cex = 5, pch = ".", col = "dodgerblue")
abline(h = 0, lty = 2, col = "red")
```



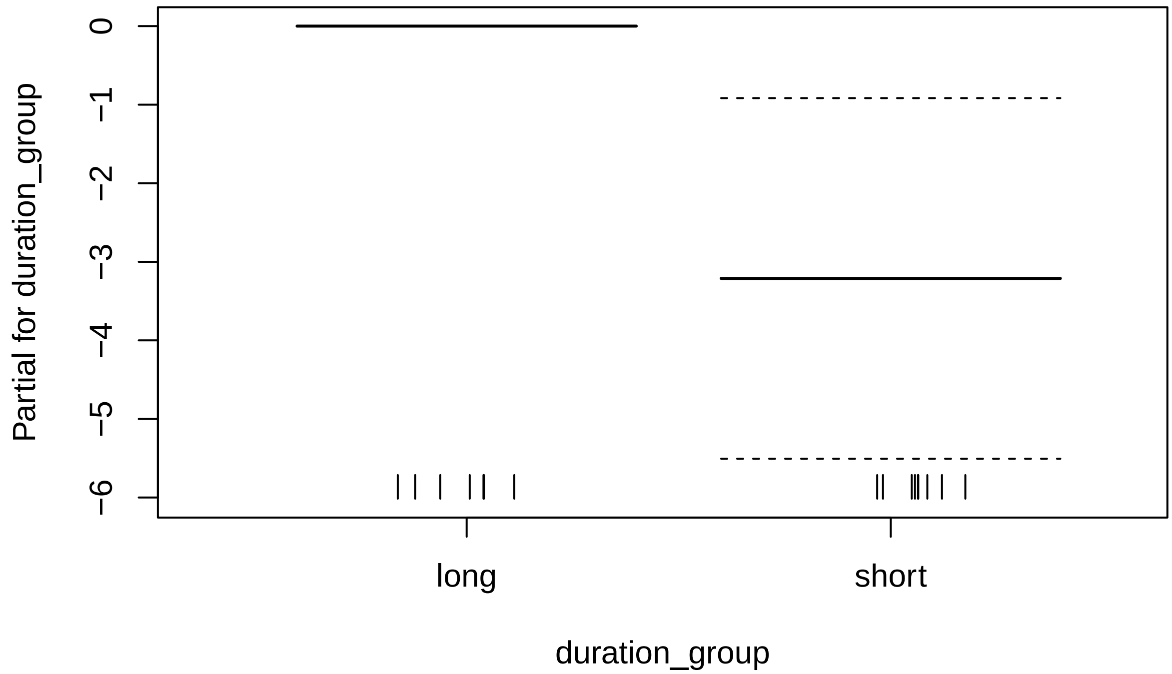

```
plot(msd.gam.trimmed, sel = 2, shade = T, ylab = "Effect on mean stability",
     xlab = "Duration of influence", main = "Long-term influence", col = "dodgerblue")
abline(h = 0, lty = 2, col = "red")
```



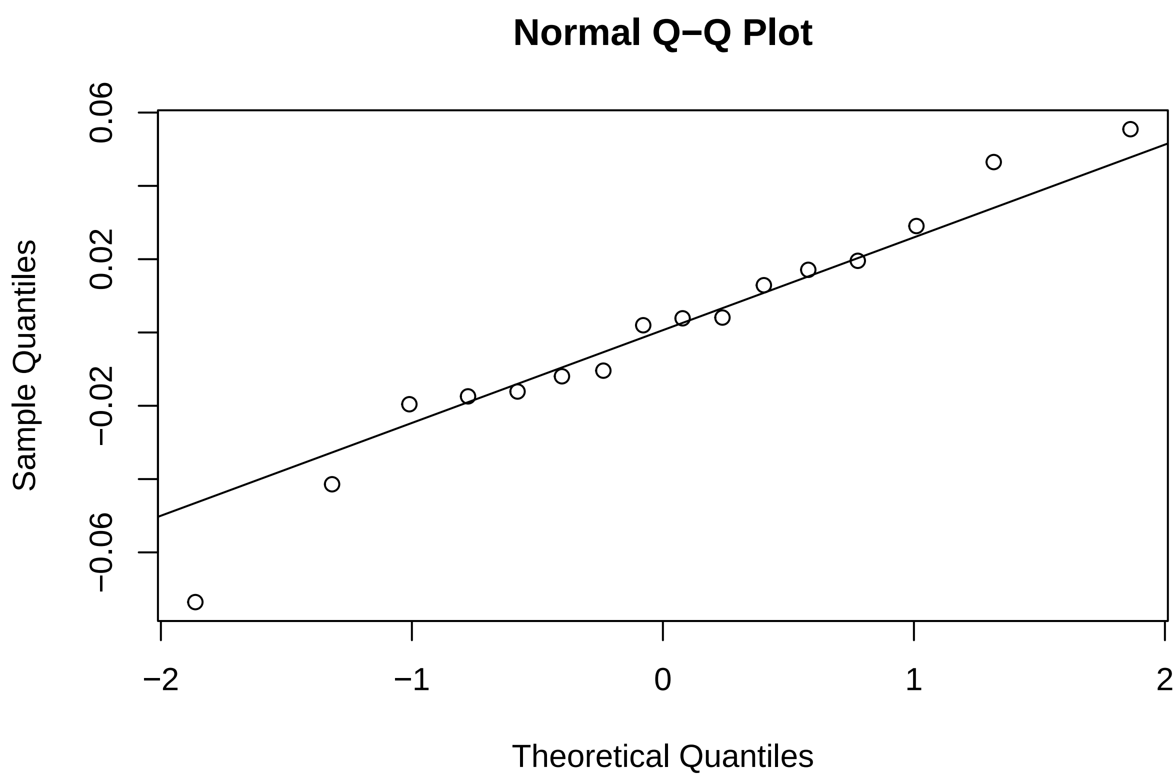

```
plot(msd.gam.trimmed, sel = 3, shade = T, ylab = "Effect on mean stability",
     xlab = "Duration of influence", main = "Short-term influence", col = "dodgerblue")
abline(h = 0, lty = 2, col = "red")
```



```r
# (dotted lines indicate error)
plot(msd.gam.trimmed, all.terms = T, sel = 4, ylab = "Effect on mean stability",
     xlab = "Duration group", main = "Main effect of duration group")
```




```r
# checking out the model performance
qqnorm(resid(msd.gam.trimmed))
qqline(resid(msd.gam.trimmed)) # meh
```

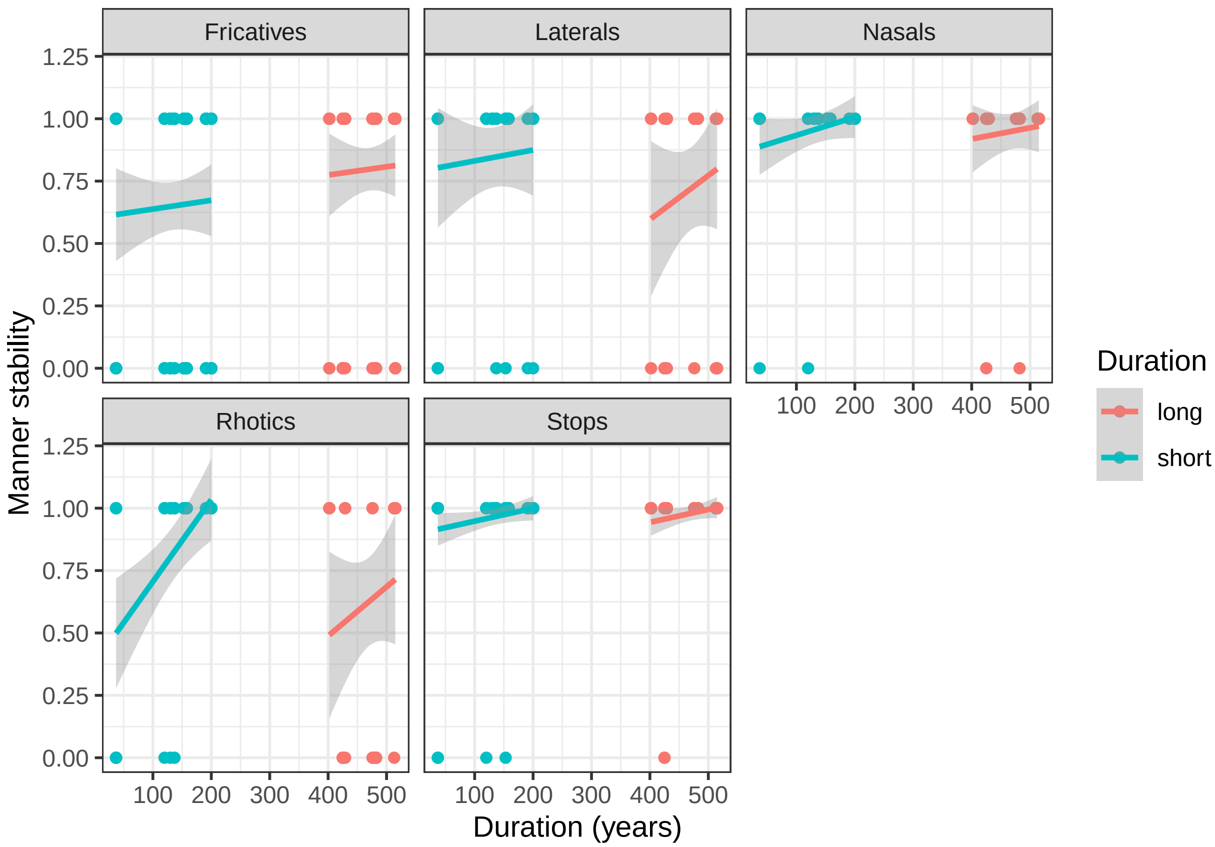


Removing the two creoles with the lowest scores produces significant effects. This doesn't seem very reliable though, especially given the small sample size. Also, the pattern is strange: a negative trend of duration for long-term influence and a positive one for short-term influence? Note that the model detected a mean difference between duration groups, with the short group having (slightly) lower mean stability. This appears to be the case – but again – we have so few observations.

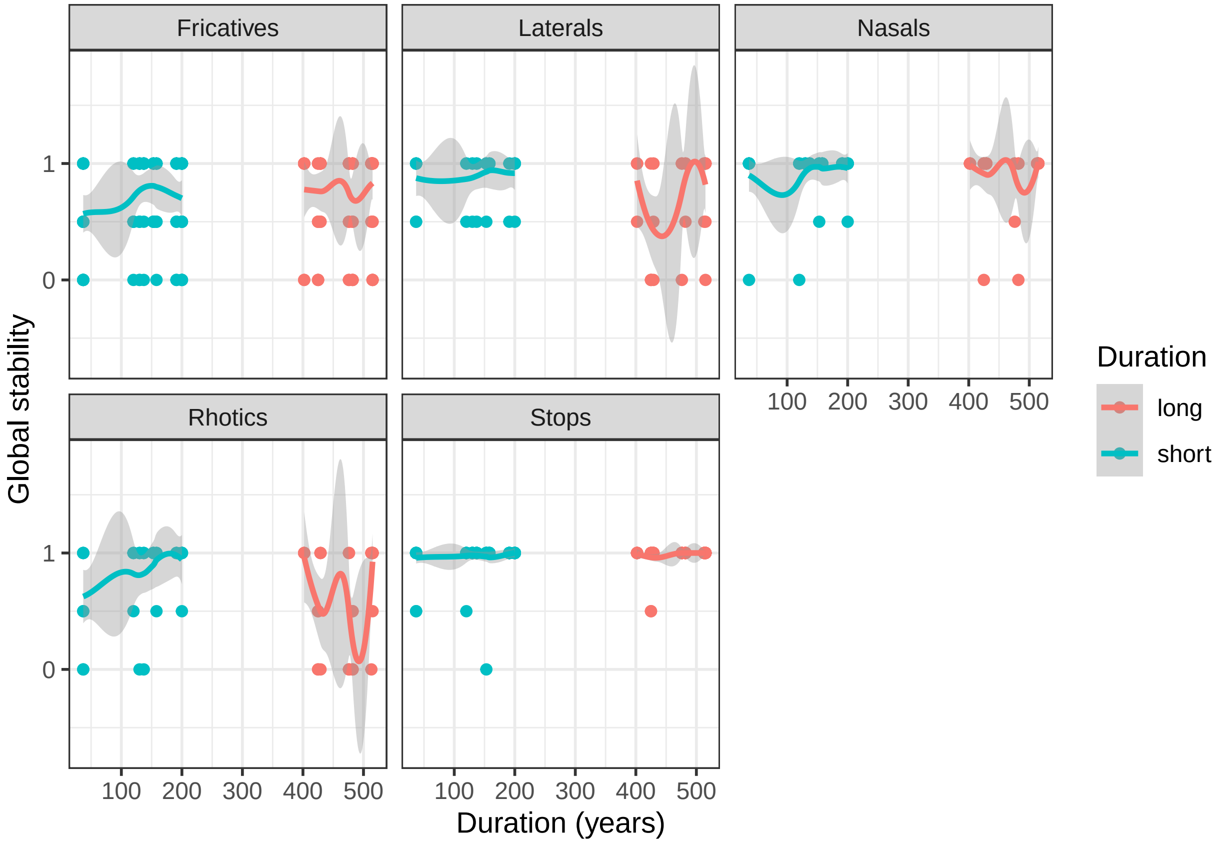
4 Duration effects on the segment level

Does duration affect the stability values of specific segments or segment classes?

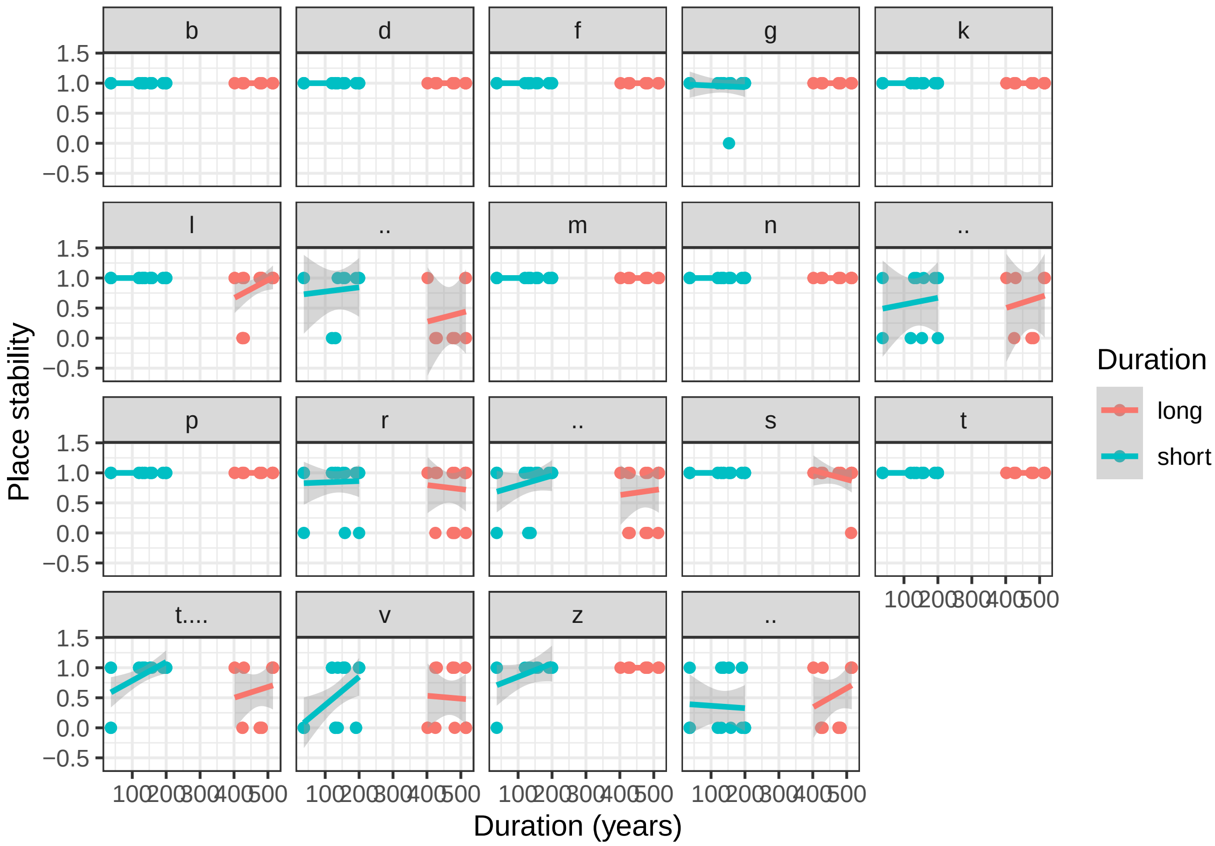
```
ggplot(database, aes(duration, MannerStability, colour = duration_group)) +
  geom_point() +
  geom_smooth(method = "lm") +
  facet_wrap(~Class) +
  xlab("Duration (years)") +
  ylab("Manner stability") +
  labs(color = "Duration")
```



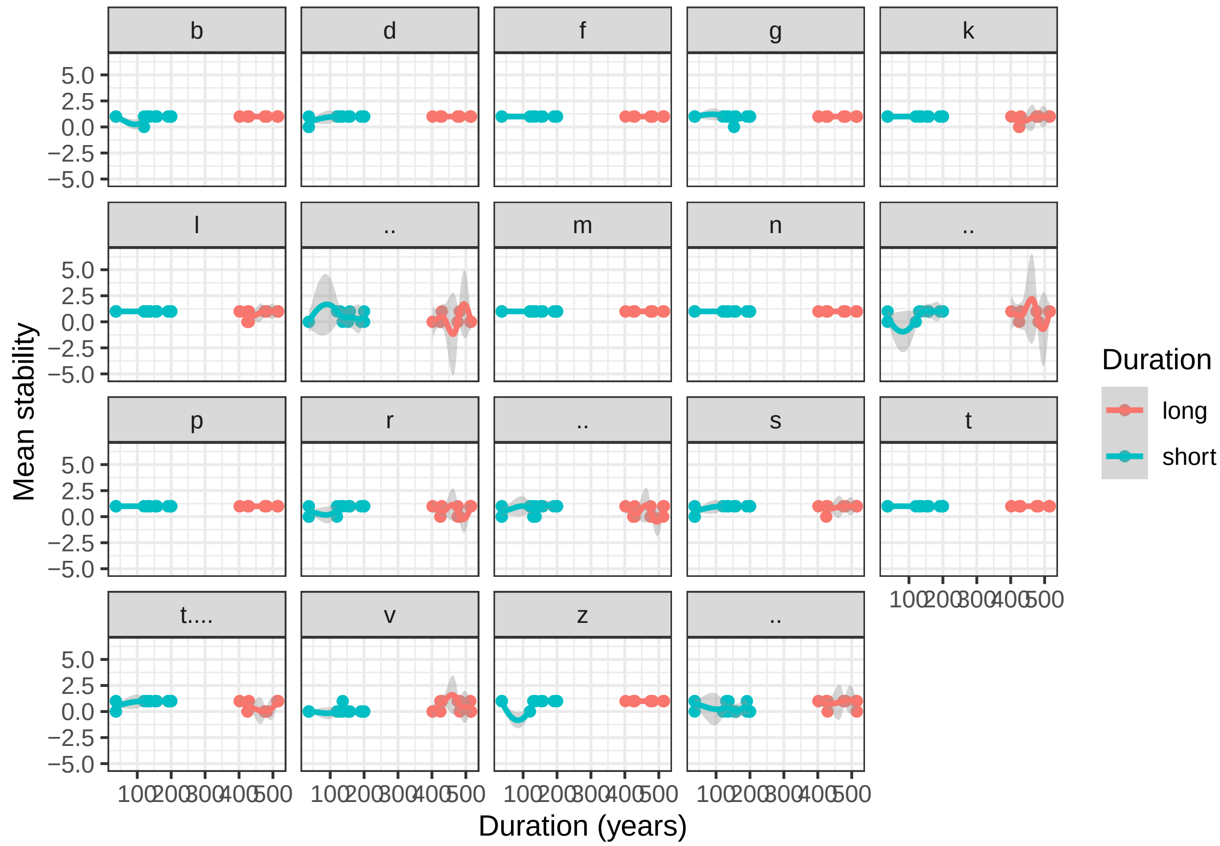

```
ggplot(database, aes(duration, GlobalStability, colour = duration_group)) +
  geom_point() +
  geom_smooth() +
  facet_wrap(~Class) +
  xlab("Duration (years)") +
  ylab("Global stability") +
  labs(color = "Duration")
```



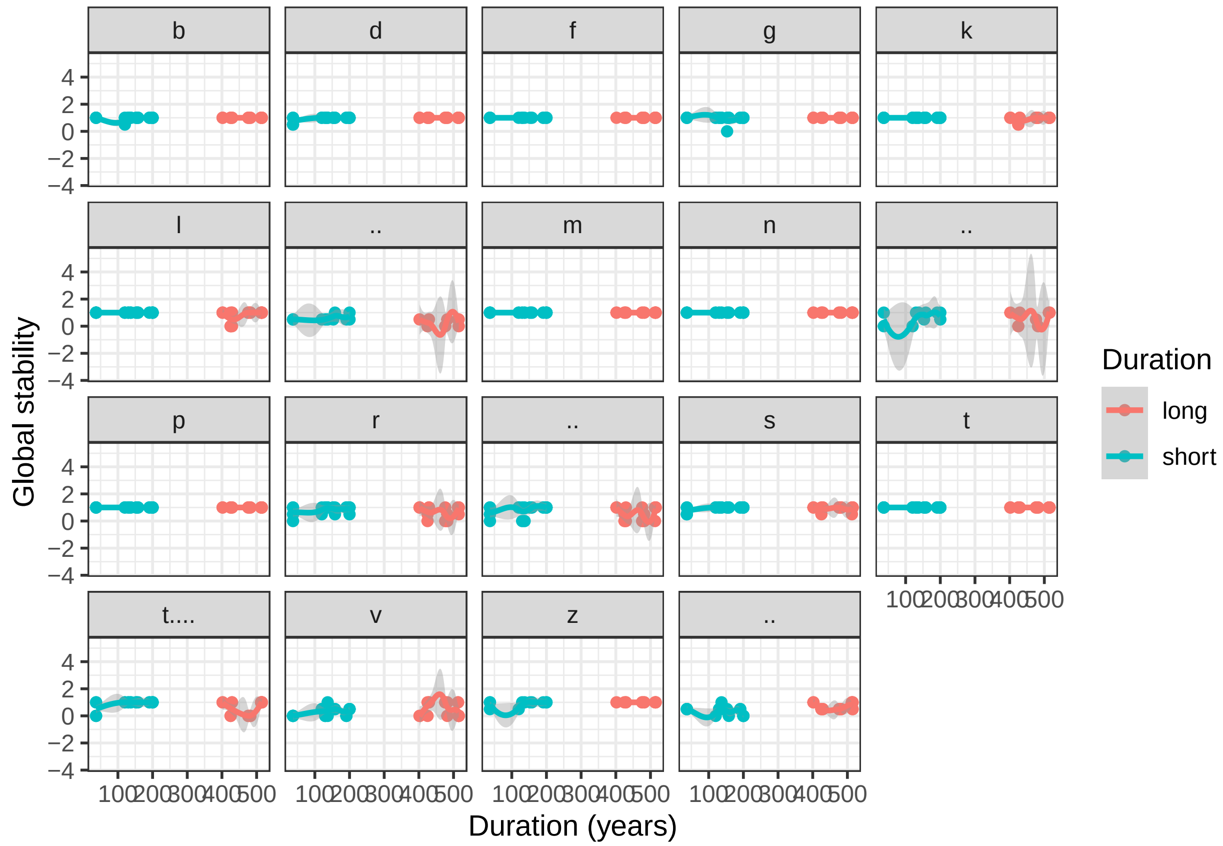

```
ggplot(database, aes(duration, PlaceStability, colour = duration_group)) +
  geom_point() +
  geom_smooth(method = "lm") +
  facet_wrap(~LexifierPhoneme) +
  xlab("Duration (years)") +
  ylab("Place stability") +
  labs(color = "Duration")
```




```r
ggplot(database, aes(duration, MannerStability, colour = duration_group)) +
  geom_point() +
  geom_smooth() +
  facet_wrap(~LexifierPhoneme) +
  xlab("Duration (years)") +
  ylab("Mean stability") +
  labs(color = "Duration")
```




```r
ggplot(database, aes(duration, GlobalStability, colour = duration_group)) +
  geom_point() +
  geom_smooth() +
  facet_wrap(~LexifierPhoneme) +
  xlab("Duration (years)") +
  ylab("Global stability") +
  labs(color = "Duration")
```



5 Segment stability

Which segments are the most stable across creoles in the language sample?

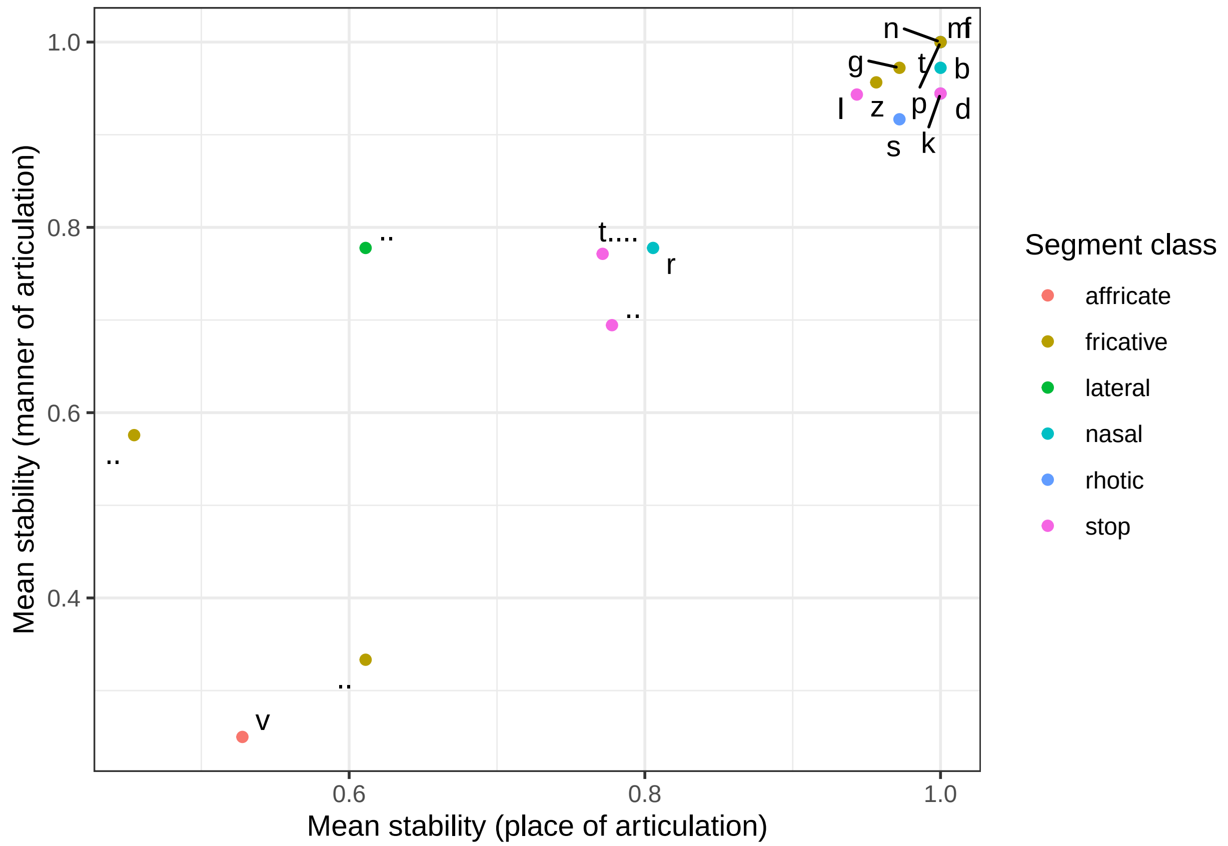
We calculate stability of place and manner for each phoneme.

```
place_results <- database %>%
  group_by(LexifierPhoneme) %>%
  summarize(mplace = mean(PlaceStability, na.rm = TRUE))
manner_results <- database %>%
  group_by(LexifierPhoneme) %>%
  summarize(mmanner = mean(MannerStability, na.rm = TRUE))

consonant_stability <- left_join(place_results, manner_results, by = "LexifierPhoneme")

class <- c("nasal", "rhotic", "lateral", "fricative", "stop", "stop", "fricative",
           "stop", "stop", "lateral", "nasal", "nasal", "stop", "rhotic",
           "fricative", "stop", "affricate", "fricative", "fricative")

consonant_stability_class <- cbind(consonant_stability, class)
```

Next, we plot the results.

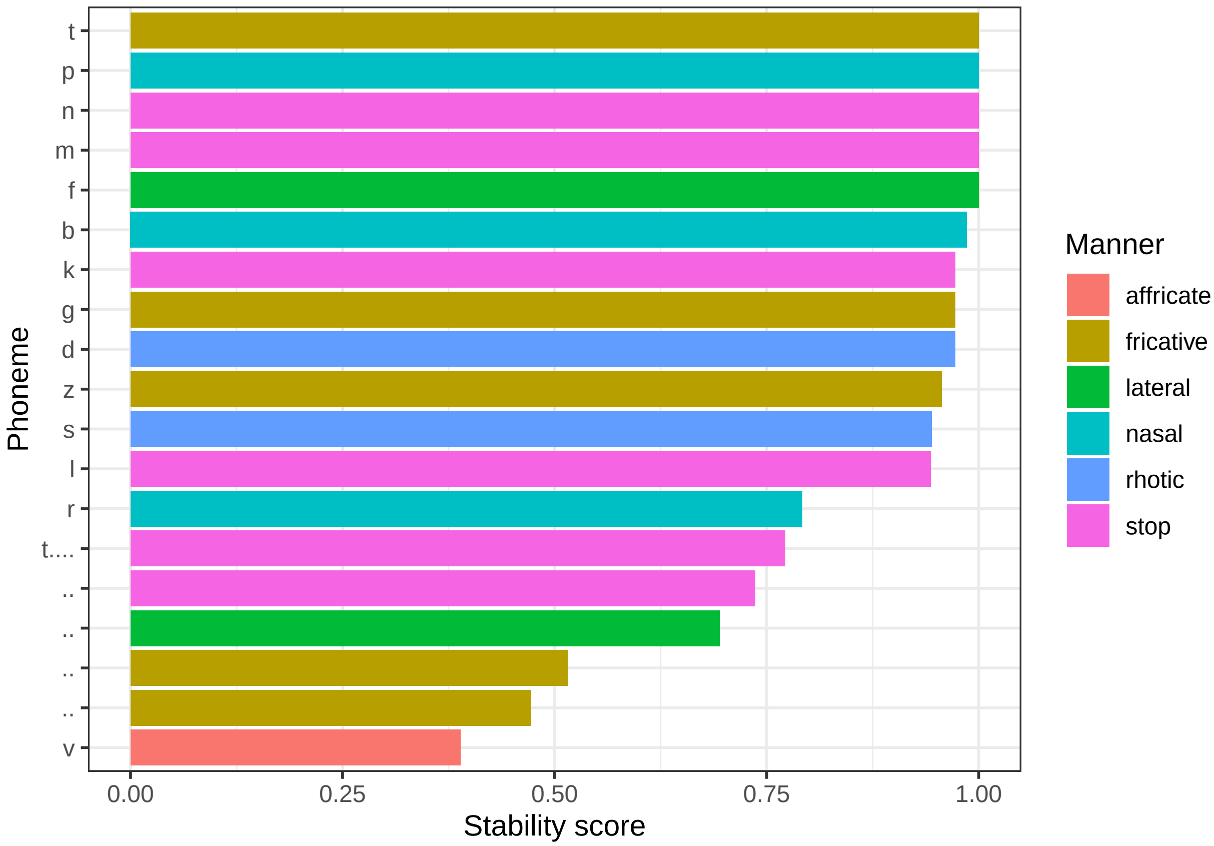
```
ggplot(consonant_stability, aes(y = mmanner, x = mplace)) +
  geom_point(position = "dodge", aes(color = class)) +
  geom_text_repel(aes(label = LexifierPhoneme), size = 4) +
  xlab("Mean stability (place of articulation)") +
```

```
  ylab("Mean stability (manner of articulation)") +
  labs(color = "Segment class")
```



Here is an alternative view for the global results.

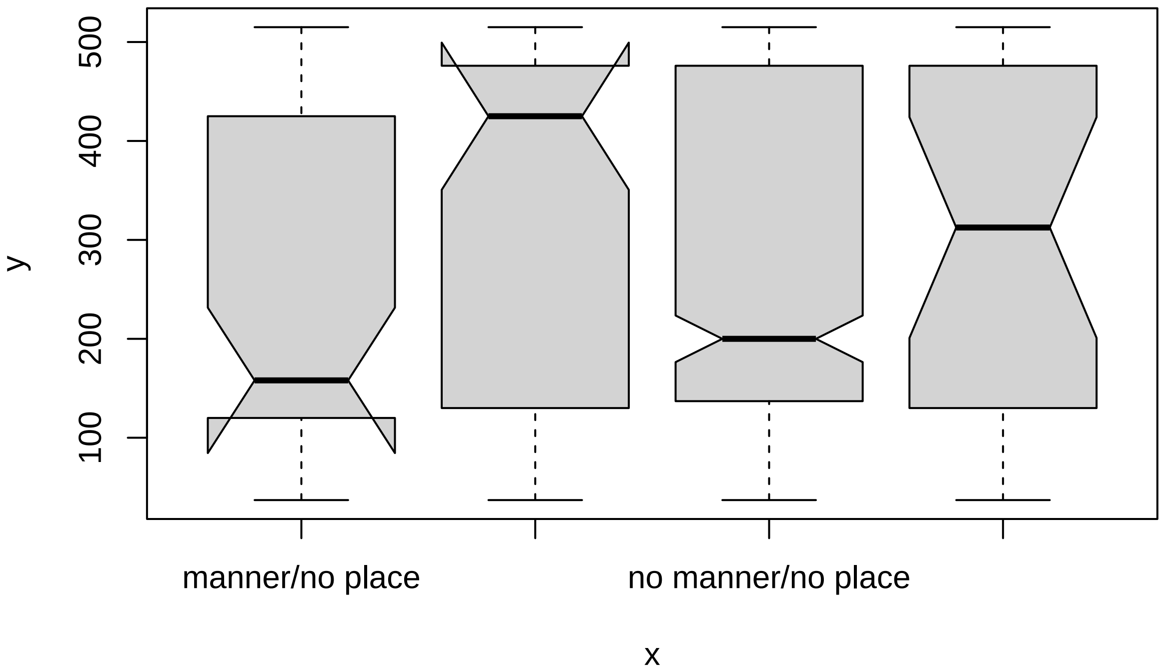
```
consonant_global_stability <- mutate(consonant_stability_class,
                                     mglobal = (mmanner + mplace) / 2)

ggplot(consonant_global_stability) +
  geom_bar(aes(
    x = mglobal,
    y = reorder(LexifierPhoneme, mglobal),
    fill = class
  ), stat = "identity", show.legend = TRUE) +
  labs(x = "Stability score", y = "Phoneme", fill = "Manner")
```



And we can also increase the number of observations in duration regression by running the analysis at the segment level, rather than on mean stability.

```
# Factorizing
mod.db <- database %>%
  as.data.frame() %>%
  mutate(
    categorical_stability = as.factor(categorical_stability),
    Lexifier = as.factor(Lexifier),
    CreolePhoneme = as.factor(CreolePhoneme),
    Language = as.factor(Language)
  )

# Remove singletons/doubletons
# goodies = names(table(mod.db$CreolePhoneme)>2)

# mod.db = mod.db %>%
#         filter(CreolePhoneme %in% goodies)
```

```
plot(mod.db$categorical_stability, mod.db$duration, notch = T)
```



Hugely skewed in favor of no manner/place (10x as frequent as the next most frequent level; this could cause problems for the models).

```
table(mod.db$categorical_stability)
```

```
##
##    manner/no place       manner/place no manner/no place    no manner/place
##                 43                 54                517                 24
```

```
# Place stability
cat.mod.place <- glmer(PlaceStability ~ log(duration) + (1 | CreolePhoneme),
                       data = mod.db, family = "binomial")

summary(cat.mod.place)
```

```
## Generalized linear mixed model fit by maximum likelihood (Laplace
##   Approximation) [glmerMod]
##  Family: binomial  ( logit )
## Formula: PlaceStability ~ log(duration) + (1 | CreolePhoneme)
##    Data: mod.db
##
##      AIC      BIC   logLik deviance df.resid
##    296.8    310.2   -145.4    290.8      635
##
## Scaled residuals:
##     Min      1Q  Median      3Q     Max
## -6.2517  0.0388  0.0432  0.1725  2.1540
##
## Random effects:
##  Groups        Name        Variance Std.Dev.
##  CreolePhoneme (Intercept) 31.32    5.597
## Number of obs: 638, groups:  CreolePhoneme, 34
##
## Fixed effects:
```

```
##                Estimate Std. Error z value Pr(>|z|)
## (Intercept)      5.3041     2.5433   2.086    0.037 *
## log(duration)  -0.1279     0.2215  -0.577    0.564
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Correlation of Fixed Effects:
##             (Intr)
## log(duratn) -0.511
```

```
# Manner stability
cat.mod.manner <- glmer(MannerStability ~ log(duration) + (1 | CreolePhoneme),
                        data = mod.db, family = "binomial")

summary(cat.mod.manner)
```

```
## Generalized linear mixed model fit by maximum likelihood (Laplace
##   Approximation) [glmerMod]
##  Family: binomial  ( logit )
## Formula: MannerStability ~ log(duration) + (1 | CreolePhoneme)
##    Data: mod.db
##
##      AIC      BIC   logLik deviance df.resid
##    251.1    264.4   -122.5    245.1      635
##
## Scaled residuals:
##     Min      1Q  Median      3Q     Max
## -6.2224  0.0043  0.0046  0.1928  0.7464
##
## Random effects:
##  Groups        Name        Variance Std.Dev.
##  CreolePhoneme (Intercept) 396.3    19.91
## Number of obs: 638, groups:  CreolePhoneme, 34
##
## Fixed effects:
##                Estimate Std. Error z value Pr(>|z|)
## (Intercept)    10.11364    2.42778   4.166  3.1e-05 ***
## log(duration)  0.08086    0.22973   0.352    0.725
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Correlation of Fixed Effects:
##             (Intr)
## log(duratn) -0.517
```

```
# Duration group
cat.mod.group <- glmer(as.factor(duration_group) ~ PlaceStability +
                         MannerStability + (1 | CreolePhoneme),
                       data = mod.db, family = "binomial", nAGQ = 0)
```

```
## boundary (singular) fit: see help('isSingular')
```

```
summary(cat.mod.group)
```

```
## Generalized linear mixed model fit by maximum likelihood (Adaptive
##   Gauss-Hermite Quadrature, nAGQ = 0) [glmerMod]
```

```
##  Family: binomial  ( logit )
## Formula: as.factor(duration_group) ~ PlaceStability + MannerStability +
##     (1 | CreolePhoneme)
##    Data: mod.db
##
##      AIC      BIC   logLik deviance df.resid
##    882.3    900.2   -437.2    874.3      634
##
## Scaled residuals:
##     Min      1Q  Median      3Q     Max
## -1.3362 -1.1102  0.8246  0.9007  1.2288
##
## Random effects:
##  Groups        Name        Variance Std.Dev.
##  CreolePhoneme (Intercept) 0        0
## Number of obs: 638, groups:  CreolePhoneme, 34
##
## Fixed effects:
##                 Estimate Std. Error z value Pr(>|z|)
## (Intercept)     -0.04164    0.24231  -0.172   0.8636
## PlaceStability   0.62124    0.29861   2.080   0.0375 *
## MannerStability -0.37043    0.27504  -1.347   0.1780
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Correlation of Fixed Effects:
##             (Intr) PlcStb
## PlaceStblty -0.521
## MannrStblty -0.339 -0.580
## optimizer (bobyqa) convergence code: 0 (OK)
## boundary (singular) fit: see help('isSingular')
```

Some indication that place stability is more often associated with shorter periods of influence.

Numerically, the manner/place category has 50% of its observations in the longest duration from the sample. At the same time, no manner/no place is associated with the shortest duration.

6 Word position

Next we ask, does word position influence stability?

First, data preparation.

```
data_by_position <- database %>%
  select(Position, LexifierPhoneme, PlaceStability, MannerStability) %>%
  mutate(Position = tolower(Position))

data_by_position$PlaceStability <- as.numeric(data_by_position$PlaceStability)

data_by_position$MannerStability <- as.numeric(data_by_position$MannerStability)
```

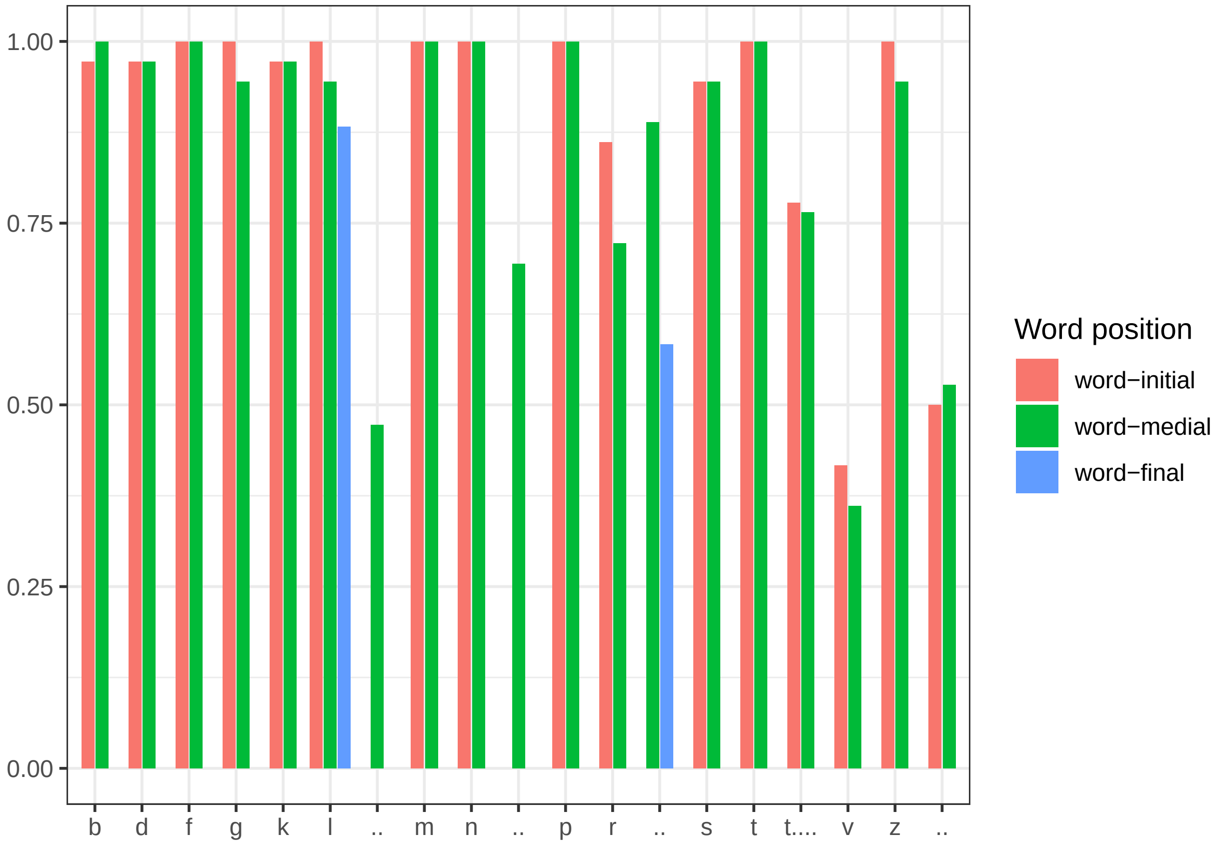
Next, calculate stability for each segment according to its word position.

```
position_stability <- mutate(data_by_position, GlobalStability =
                              (PlaceStability + MannerStability) / 2)
```

```
position_results <- position_stability %>%
  group_by(LexifierPhoneme, Position) %>%
  summarize(m = mean(GlobalStability, na.rm = TRUE))
```

And plot the results for all segments.

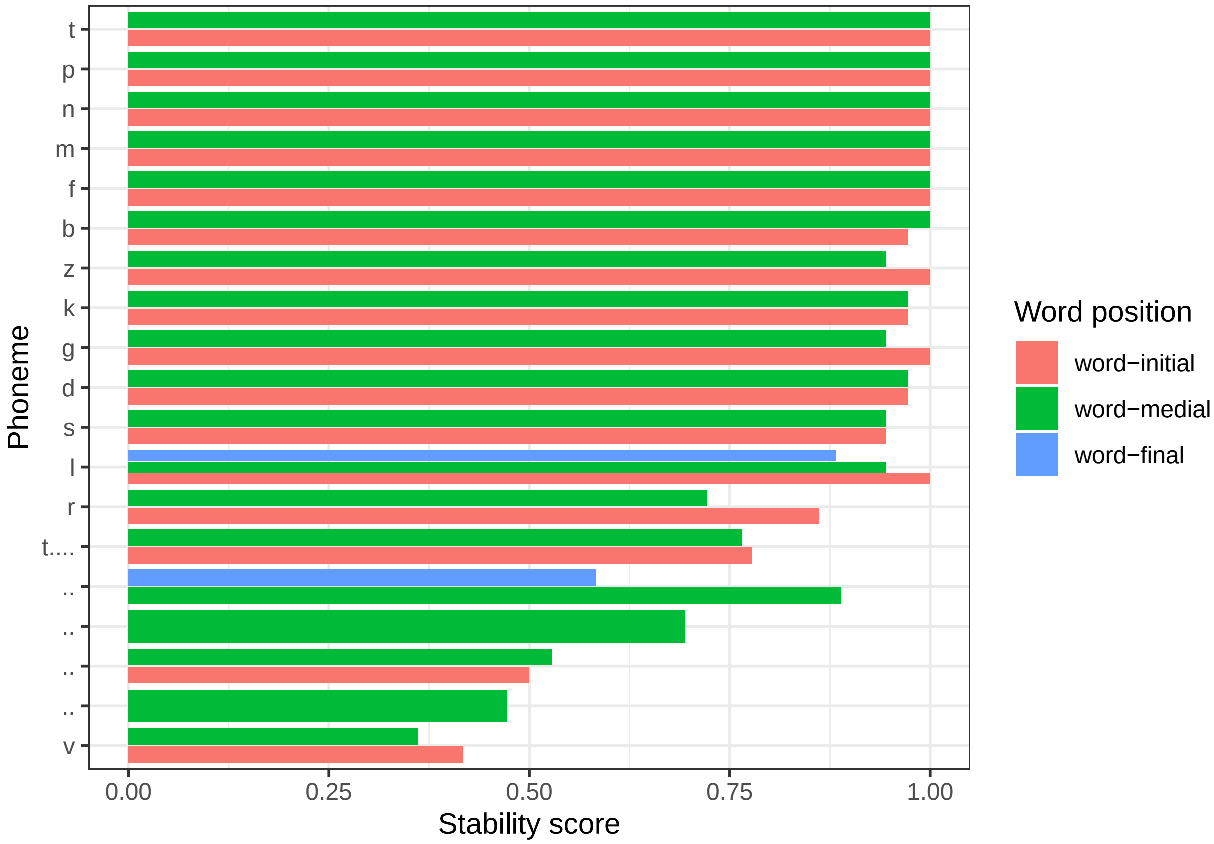
```
position_results$Position <- factor(position_results$Position,
                                    levels = c("word-initial",
                                               "word-medial",
                                               "word-final"))

ggplot(position_results, aes(x = LexifierPhoneme, y = m, fill = Position)) +
  geom_col(position = position_dodge2(width = 0.9, preserve = "single")) +
  theme(
    axis.title.x = element_blank(),
    axis.title.y = element_blank()
  ) +
  labs(x = "Lexifier phoneme", y = "Mean stability", fill = "Word position")
```



Flip horizontally.

```
ggplot(position_results) +
  geom_bar(
    aes(
      x = m,
      y = reorder(LexifierPhoneme, m),
      fill = Position
    ),
```

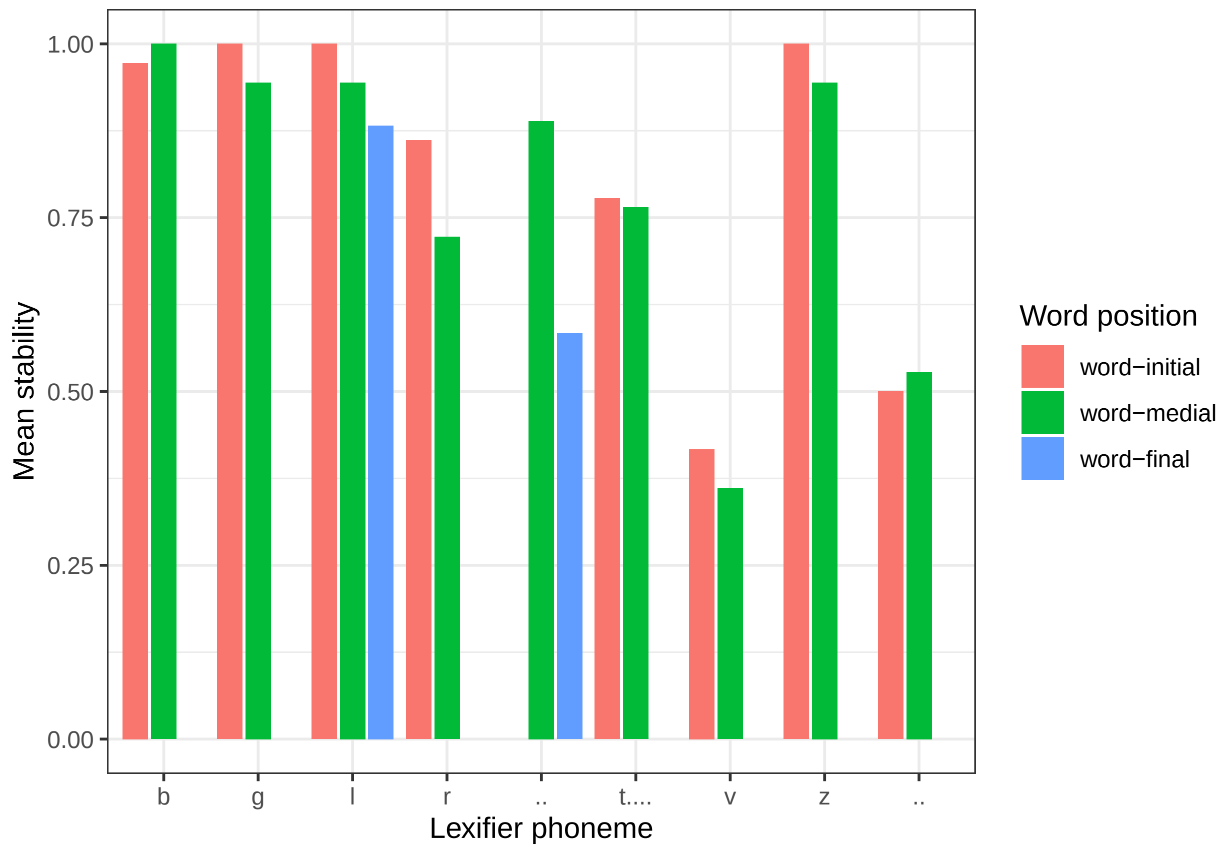
```
    stat = "identity",
    show.legend = TRUE,
    position = "dodge2"
  ) +
  labs(x = "Stability score", y = "Phoneme", fill = "Word position")
```



Plot the results for segments that show differences.

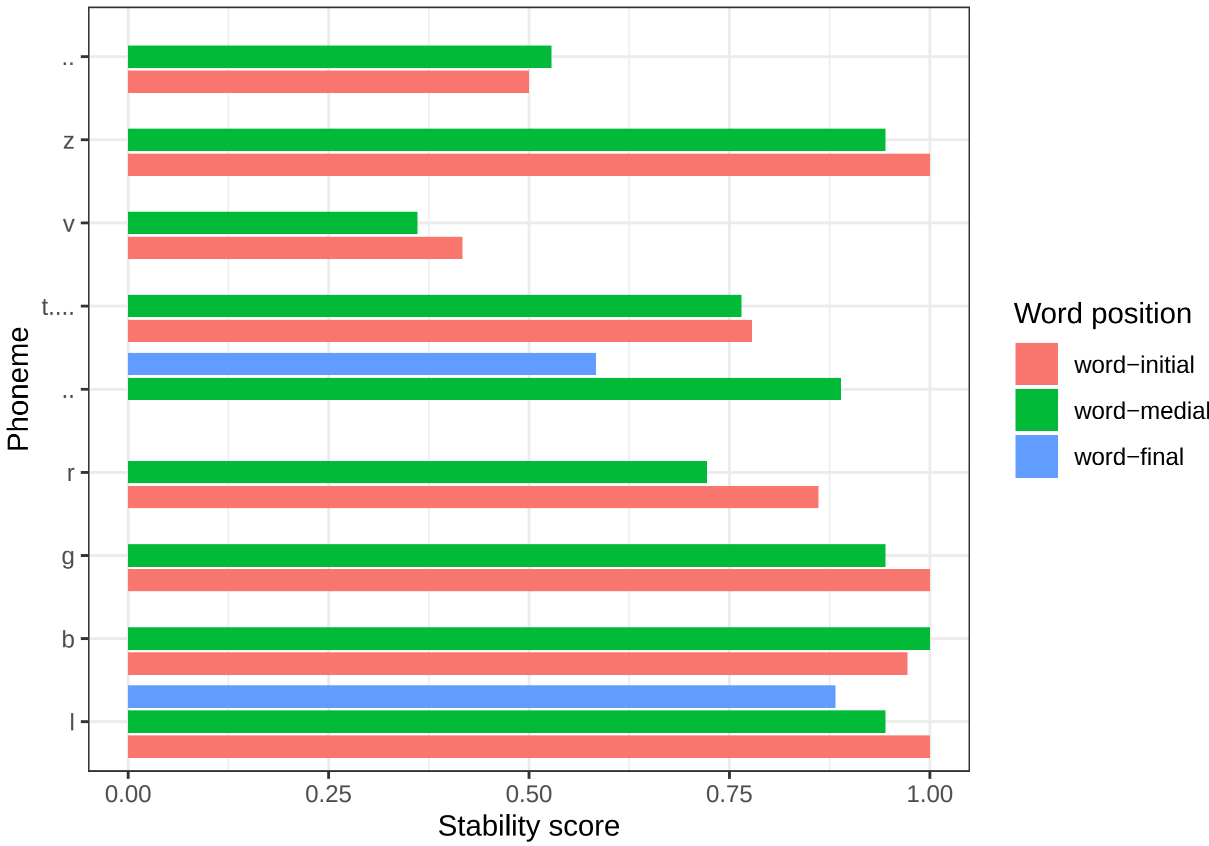
```
position_results1 <- position_results %>%
  pivot_wider(names_from = Position, values_from = m)

different_position <- subset(position_results1, position_results1$`word-initial`
                             != position_results1$`word-medial` |
                               position_results1$`word-final`
                             != position_results1$`word-medial`)

different_position_results <- different_position %>%
  pivot_longer(c(`word-initial`, `word-medial`, `word-final`),
               names_to = "Position", values_to = "m")

different_position_results$Position <- factor(different_position_results$Position,
                                               levels = c("word-initial",
                                                          "word-medial",
                                                          "word-final"))

ggplot(
  different_position_results,
```

```
  aes(x = LexifierPhoneme, y = m, fill = Position)
) +
  geom_col(position = position_dodge2(width = 0.9, preserve = "single")) +
  labs(x = "Lexifier phoneme", y = "Mean stability", fill = "Word position")
```



Flip horizontally.

```
ggplot(different_position_results) +
  geom_bar(
    aes(
      x = m,
      y = reorder(LexifierPhoneme, m),
      fill = Position
    ),
    stat = "identity",
    show.legend = TRUE,
    position = "dodge2"
  ) +
  labs(x = "Stability score", y = "Phoneme", fill = "Word position")
```



7 Conditions of contact

The finding that "slavery has a negative impact on stability" was mainly observational and also literature-based (e.g. Faraclas et al. (2007); Carvalho and Lucchesi (2016); Upper Guinea light creoles = slavery but with lighter contact conditions versus Gulf of Guinea hard creole = slavery and harder contact conditions).

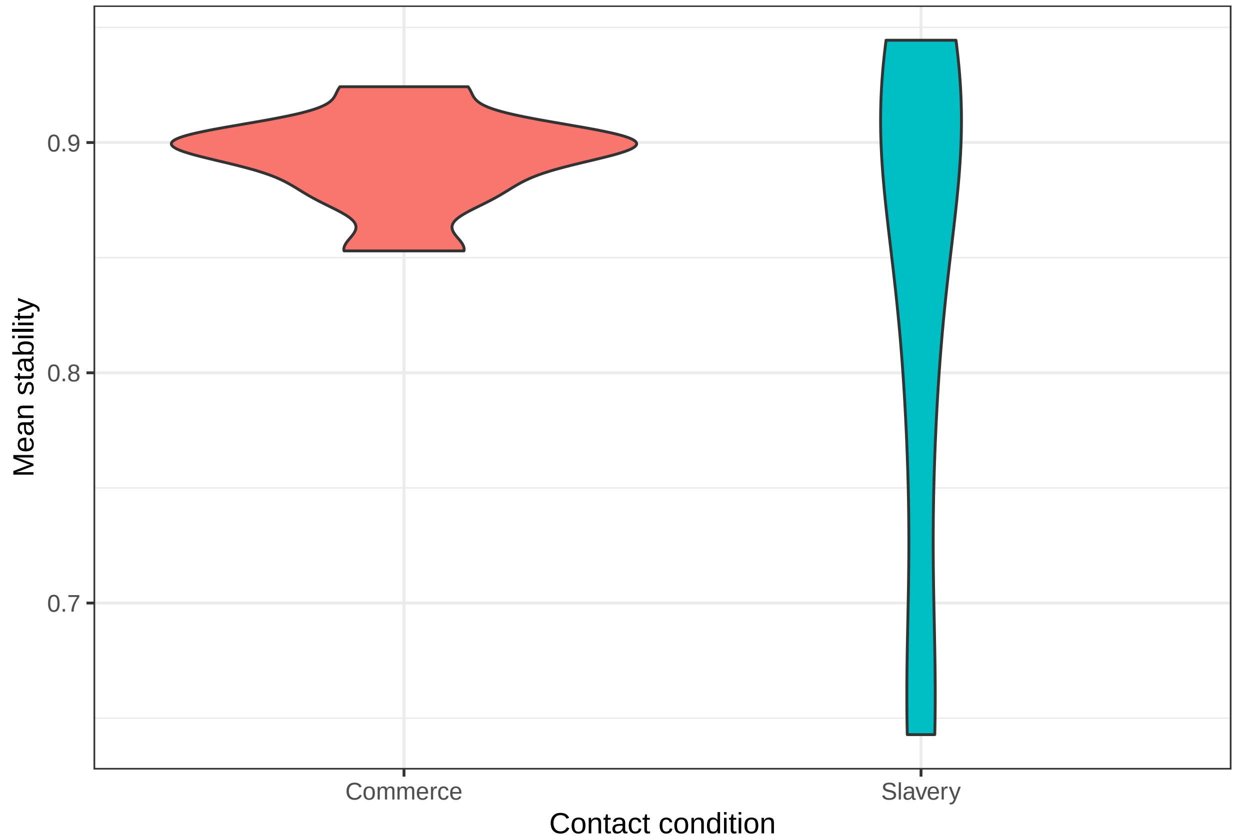
Test whether there's a relation between type of contact situation and overall mean stability.

```
m <- lm(MeanStability ~ ContactConditions, data = creole_stability)
summary(m)
```

```
##
## Call:
## lm(formula = MeanStability ~ ContactConditions, data = creole_stability)
##
## Residuals:
##       Min        1Q    Median        3Q       Max
## -0.196336 -0.016876  0.007455  0.061289  0.105251
##
## Coefficients:
##                            Estimate Std. Error t value Pr(>|t|)
## (Intercept)                 0.89255    0.03030  29.459 2.28e-15 ***
## ContactConditionsSlavery -0.05335    0.04065  -1.313    0.208
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 0.08569 on 16 degrees of freedom
```

```
## Multiple R-squared:  0.0972, Adjusted R-squared:  0.04078
## F-statistic: 1.723 on 1 and 16 DF,  p-value: 0.2079
```

```
ggplot(creole_stability, aes(x = ContactConditions, y = MeanStability,
                             fill = ContactConditions)) +
  geom_smooth(method = "lm") +
  geom_violin() +
  xlab("Contact condition") +
  ylab("Mean stability") +
  guides(fill = "none")
```

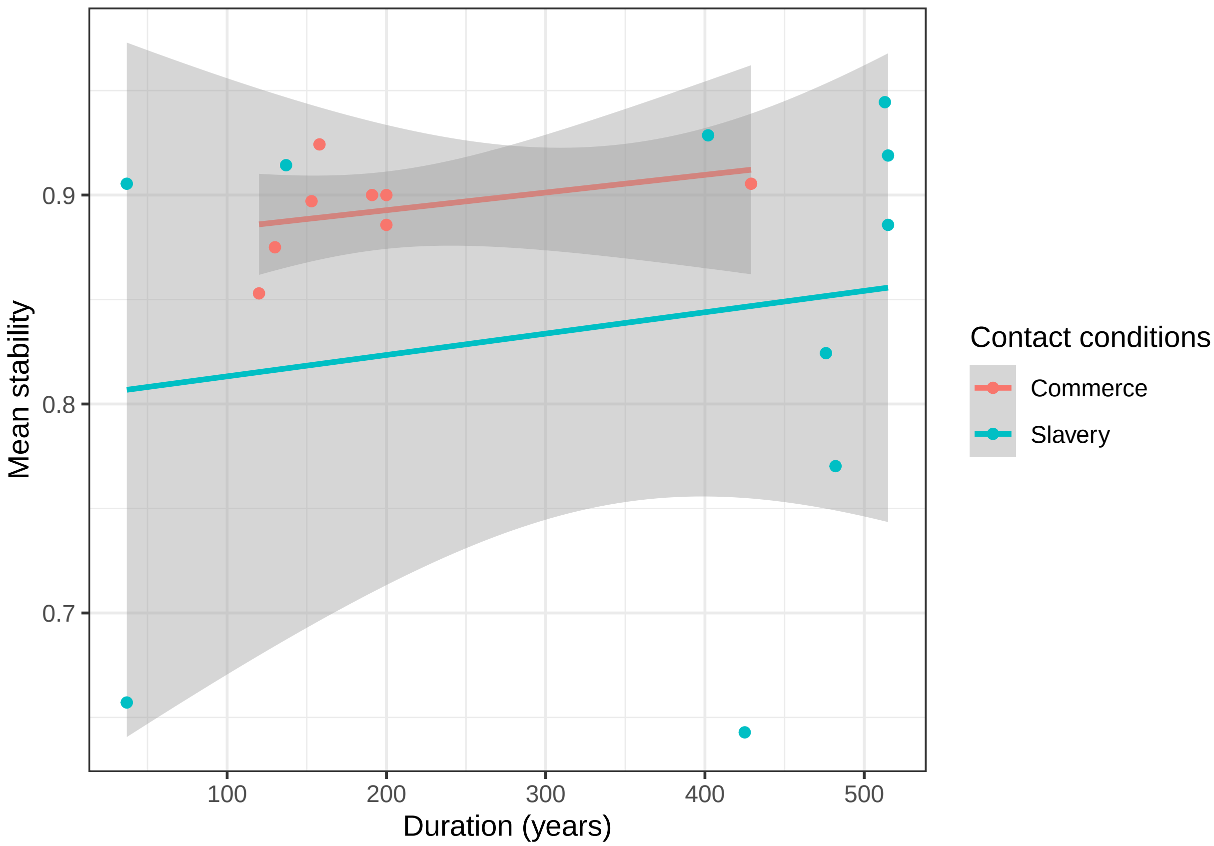



```
m <- lm(MeanStability ~ duration + ContactConditions * duration,
        data = creole_stability)
summary(m)
```

```
##
## Call:
## lm(formula = MeanStability ~ duration + ContactConditions * duration,
##     data = creole_stability)
##
## Residuals:
##       Min        1Q    Median        3Q       Max
## -0.203607 -0.023472  0.007634  0.056201  0.098616
##
## Coefficients:
##                                        Estimate Std. Error t value Pr(>|t|)
## (Intercept)                           8.758e-01  7.531e-02  11.629  1.4e-08 ***
## duration                              8.459e-05  3.455e-04   0.245    0.810
```

```
## ContactConditionsSlavery          -7.282e-02  9.625e-02  -0.757    0.462
## duration:ContactConditionsSlavery  1.766e-05  3.763e-04   0.047    0.963
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 0.08992 on 14 degrees of freedom
## Multiple R-squared:  0.1302, Adjusted R-squared:  -0.05624
## F-statistic: 0.6983 on 3 and 14 DF,  p-value: 0.5685
```

```
ggplot(creole_stability, aes(x = duration, y = MeanStability,
                             color = ContactConditions)) +
  geom_smooth(method = "lm") +
  geom_point() +
  xlab("Duration (years)") +
  ylab("Mean stability") +
  labs(color = "Contact conditions")
```



References

Carvalho, Ana Maria, and Dante Lucchesi. 2016. "Portuguese in Contact." In *The Handbook of Portuguese Linguistics*, 41–55. Wiley Blackwell. https://doi.org/10.1002/9781118791844.ch3.

Faraclas, Nicholas, Don Walicek, Mervyn Alleyne, Wilfredo Geigel, and Luis Ortiz. 2007. "The Complexity That Really Matters: The Role of Political Economy in Creole Genesis." In *Deconstructing Creole: New Horizons in Language Creation*, edited by U. Ansaldo, S. J. Matthews, and L. Lim, 227–64. John Benjamins. https://doi.org/10.1075/tsl.73.12far.

Kuznetsova, Alexandra, Per B. Brockhoff, and Rune H. B. Christensen. 2017. "lmerTest Package: Tests in Linear Mixed Effects Models." *Journal of Statistical Software* 82 (13): 1–26. https://doi.org/10.18637/j ss.v082.i13.

RStudio Team. 2020. *RStudio: Integrated Development Environment for r.* Boston, MA: RStudio, PBC. http://www.rstudio.com/.

Slowikowski, Kamil. 2022. *Ggrepel: Automatically Position Non-Overlapping Text Labels with 'Ggplot2'.* https://CRAN.R-project.org/package=ggrepel.

Wickham, Hadley, Mara Averick, Jennifer Bryan, Winston Chang, Lucy D'Agostino McGowan, Romain François, Garrett Grolemund, et al. 2019. "Welcome to the tidyverse." *Journal of Open Source Software* 4 (43): 1686. https://doi.org/10.21105/joss.01686.

Wood, S. N. 2004. "Stable and Efficient Multiple Smoothing Parameter Estimation for Generalized Additive Models." *Journal of the American Statistical Association* 99 (467): 673–86.

Xie, Yihui. 2021. *Knitr: A General-Purpose Package for Dynamic Report Generation in r.* https://yihui.org/knitr/.