# Supplement

## 1 Read data

These chunks read the data and processes it for analysis.

The following reads `gestures.csv` and `utterances.csv` into `gesture_tot` and `utterances_tot`. `gestures_tot` has time series data of infant gestures and maternal Contingent Talks at 10, 11, and 12 months. `utterance_tot` has time series data of maternal utterances at 10, 11, and 12 months. Data is aggregated from the two experimental activities.

```
gestures <- read_csv("./data/gestures.csv")

gestures_tot <- gestures %>%
  group_by(dyad, background, months, gesture) %>%
  summarise(
    count = sum(count),
    ct = sum(ct)
  ) %>%
  ungroup() %>%
  mutate(
    gesture = factor(gesture, levels = c("reach", "point", "ho_gv"))
  ) %>%
  mutate_if(is.character, as.factor) %>%
  mutate(
    # Needed for GAMs
    back_o = ordered(background, levels = c("English", "Bengali", "Chinese"))
  )

# Needed for GAMs
contrasts(gestures_tot$back_o) <- "contr.treatment"

utterances <- read_csv("./data/utterances.csv")

utterances_tot <- utterances %>%
  group_by(dyad, background, months) %>%
  summarise(
    utterances = sum(utterances) # there are NAs that must be kept
  ) %>%
  ungroup() %>%
  mutate_if(is.character, as.factor) %>%
  mutate(
    # Needed for GAMs
    back_o = ordered(background, levels = c("English", "Bengali", "Chinese"))
  )

# Needed for GAMs
contrasts(utterances_tot$back_o) <- "contr.treatment"
```

Here we create individual datasets for HoGs, reaches, pointing, and a dataset with aggreagated gestures count and maternal contingent talks (`all_tot`).

```r
hg_tot <- filter(gestures_tot, gesture == "ho_gv")
reach_tot <- filter(gestures_tot, gesture == "reach")
point_tot <- filter(gestures_tot, gesture == "point")

# Count = all gestures count, CT is aggregated from all gestures types
all_tot <- gestures_tot %>%
  group_by(dyad, back_o, months) %>%
  summarise(count = sum(count), ct = sum(ct))
```

The following code creates datasets for the analysis of pointing as predicted by HoGs, reaches, maternal CTs, and maternal utterances. The datasets are constructed so that the count of pointing at 11 months is matched with the count of gesture/utterances at 10 months, and the pointing at 12 is matched with the count of gesture/utterances at 11 months. Pointing at 10 months is dropped (since there is no data at 9 months).

```r
hg_point_lead <- gestures_tot %>%
  dplyr::select(-ct) %>%
  spread(gesture, count) %>%
  dplyr::select(-reach) %>%
  group_by(dyad) %>%
  mutate(
    lead_point = lead(point)
  ) %>%
  filter(months != 12)

reach_point_lead <- gestures_tot %>%
  dplyr::select(-ct) %>%
  spread(gesture, count) %>%
  dplyr::select(-ho_gv) %>%
  group_by(dyad) %>%
  mutate(
    lead_point = lead(point)
  ) %>%
  filter(months != 12)

ct_point_lead <- gestures_tot %>%
  filter(gesture == "point") %>%
  dplyr::select(-gesture) %>%
  rename(point = count) %>%
  group_by(dyad) %>%
  mutate(
    lead_point = lead(point)
  ) %>%
  filter(months != 12)

utter_point_lead <- gestures_tot %>%
  filter(gesture == "point") %>%
  right_join(y = utterances_tot) %>%
  group_by(dyad) %>%
  mutate(
    lead_point = lead(count)
  ) %>%
  filter(months != 12)
```

```
## Joining, by = c("dyad", "background", "months", "back_o")
```

The following creates a dataset with the infants' vocabulary counts and total counts of all gestures, HoGs + point, reaches, maternal utterances and maternal contingent talks.

```
hgp_tot <- gestures_tot %>%
  filter(gesture != "reach") %>%
  group_by(dyad, background) %>%
  summarise(hgp_tot = sum(count))

reach_tot_2 <- gestures_tot %>%
  filter(gesture == "reach") %>%
  group_by(dyad, background) %>%
  summarise(reach_tot = sum(count))

vocab_gest <- gestures_tot %>%
  group_by(dyad, background) %>%
  summarise(count_tot = sum(count), ct_tot = sum(ct)) %>%
  ungroup() %>%
  full_join(y = hgp_tot) %>%
  full_join(y = reach_tot_2) %>%
  mutate_if(is.factor, as.character)
```

```
## Joining, by = c("dyad", "background")
## Joining, by = c("dyad", "background")
```

```
vocab_utt <- utterances_tot %>%
  group_by(dyad, background) %>%
  summarise(utt_tot = sum(utterances)) %>%
  ungroup() %>%
  mutate_if(is.factor, as.character)

vocab <- read_csv("./data/vocab.csv") %>%
  full_join(y = vocab_gest) %>%
  full_join(y = vocab_utt) %>%
  arrange(dyad, months) %>%
  mutate(
    months = as.factor(months),
    background = factor(background, levels = c("English", "Bengali", "Chinese"))
  ) %>%
  mutate_if(is.character, as.factor)
```

```
## Parsed with column specification:
## cols(
##   dyad = col_character(),
##   comprehension = col_double(),
##   production = col_double(),
##   months = col_double(),
##   background = col_character()
## )
## Joining, by = c("dyad", "background")
## Joining, by = c("dyad", "background")
```

# 2 Analysis 1a. The development of reaches, hold out and gives (HoGs), and points from 10-12 months.

For analysis 1a, we fitted a series of GAMMs using the negative binomial function. The choice of using the negative binomial rather than the Poisson distribution is justified by the overdispersion of the data (and the very long tail in the distribution). The negative binomial distribution requires the specification of the theta parameter. The parameter has been estimated from the data by fitting a generalised linear model with the negative binomial distribution using `MASS::glm.nb`.

## 2.1 Reaches development

The following models test cultural group.

```
# Estimation of theta for the negbin() family
reach_nb <- glm.nb(count ~ months, data = reach_tot)
theta <- summary(reach_nb)[["theta"]]

reach_gam <- gam(
  count ~
    back_o +
    s(months, k = 3) +
    s(months, k = 3, by = back_o) +
    s(months, dyad, k = 2, bs = "fs", m = 1),
  data = reach_tot,
  method = "ML",
  family = negbin(theta)
)
```

```
## Warning in gam.side(sm, X, tol = .Machine$double.eps^0.5): model has
## repeated 1-d smooths of same variable.
```

```
summary(reach_gam)
```

```
##
## Family: Negative Binomial(0.986)
## Link function: log
##
## Formula:
## count ~ back_o + s(months, k = 3) + s(months, k = 3, by = back_o) +
##     s(months, dyad, k = 2, bs = "fs", m = 1)
##
## Parametric coefficients:
##                Estimate Std. Error z value Pr(>|z|)
## (Intercept)      0.6375     0.1920   3.321 0.000898 ***
## back_oBengali    0.5874     0.2601   2.258 0.023923 *
## back_oChinese    0.2403     0.2651   0.906 0.364704
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Approximate significance of smooth terms:
##                             edf  Ref.df Chi.sq p-value
## s(months)                 1.156   1.287  1.181  0.2853
```

```
## s(months):back_oBengali  1.000   1.000  0.437  0.5085
## s(months):back_oChinese  1.000   1.000  0.125  0.7238
## s(months,dyad)          14.522 112.000 20.065  0.0315 *
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## R-sq.(adj) =  0.165   Deviance explained = 21.4%
## -ML = 378.53  Scale est. = 1         n = 173
```

```
reach_gam_null <- gam(
  count ~
    # back_o +
    s(months, k = 3) +
    # s(months, k = 3, by = back_o) +
    s(months, dyad, k = 2, bs = "fs", m = 1),
  data = reach_tot,
  method = "ML",
  family = negbin(theta)
)
```

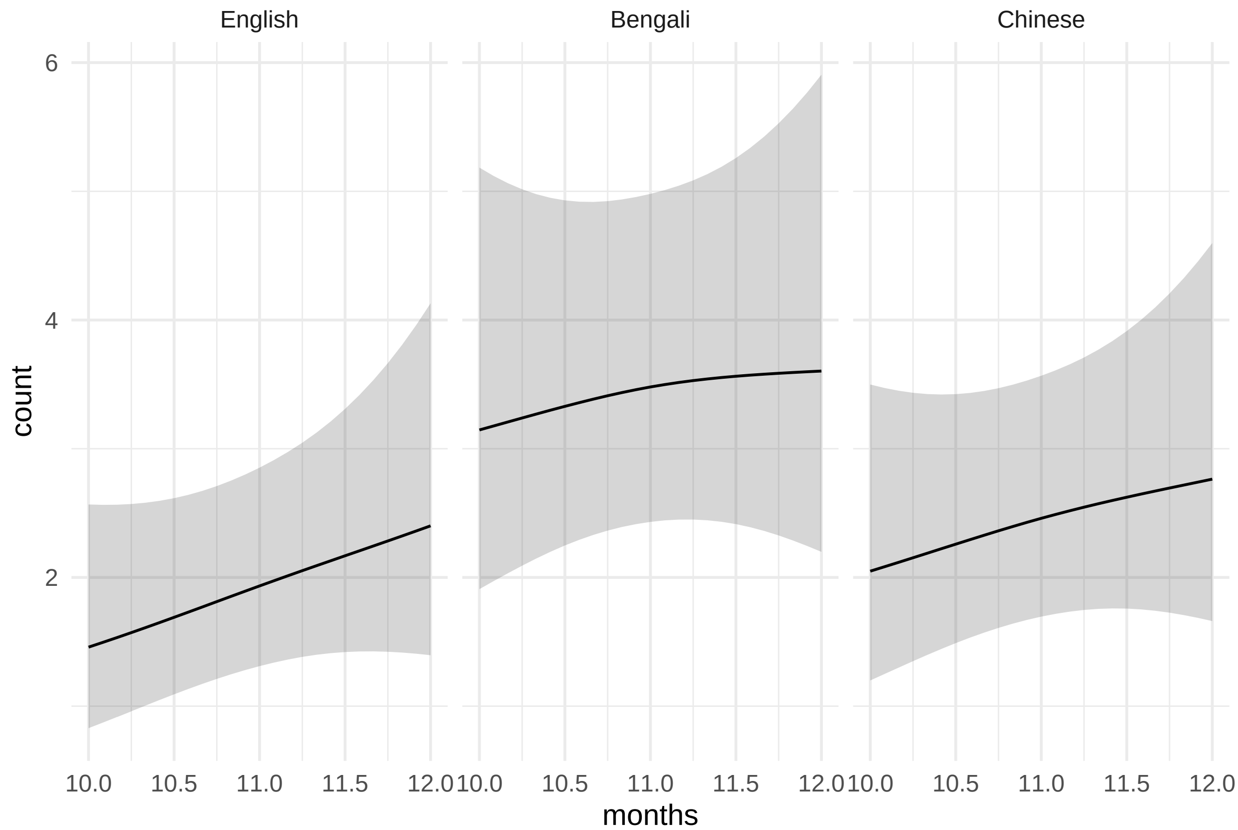
```
## Warning in gam.side(sm, X, tol = .Machine$double.eps^0.5): model has
## repeated 1-d smooths of same variable.
```

```
compareML(reach_gam_null, reach_gam)
```

```
## reach_gam_null: count ~ s(months, k = 3) + s(months, dyad, k = 2, bs = "fs",
##     m = 1)
##
## reach_gam: count ~ back_o + s(months, k = 3) + s(months, k = 3, by = back_o) +
##     s(months, dyad, k = 2, bs = "fs", m = 1)
##
## Chi-square test of ML scores
## -----
##            Model    Score Edf Difference    Df p.value Sig.
## 1 reach_gam_null 381.3235   5
## 2      reach_gam 378.5313  11      2.792 6.000   0.471
##
## AIC difference: -1.91, model reach_gam_null has lower AIC.
```

```
## Warning in compareML(reach_gam_null, reach_gam): Only small difference in ML...
```

```
plot_smooths(reach_gam, months, facet_terms = back_o, series_length = 25, transform = exp)
```




The following models test time sample.

```
reach_gam_2 <- gam(
  count ~
    s(months, k = 3) +
    s(months, dyad, k = 2, bs = "fs", m = 1),
  data = reach_tot,
  method = "ML",
  family = negbin(theta)
)
```

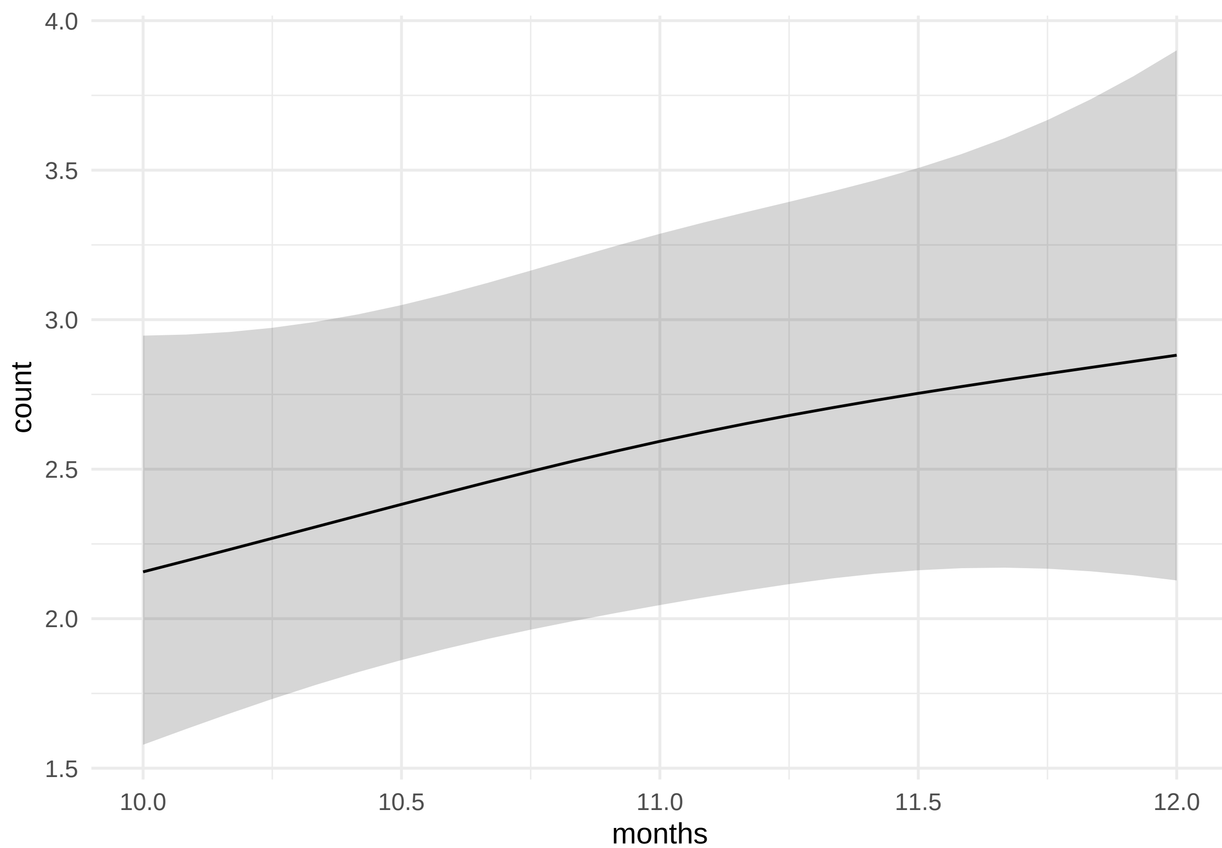
```
## Warning in gam.side(sm, X, tol = .Machine$double.eps^0.5): model has
## repeated 1-d smooths of same variable.
```

```
reach_gam_2_null <- gam(
  count ~
    # s(months, k = 3) +
    s(months, dyad, k = 2, bs = "fs", m = 1),
  data = reach_tot,
  method = "ML",
  family = negbin(theta)
)
compareML(reach_gam_2_null, reach_gam_2)
```

```
## reach_gam_2_null: count ~ s(months, dyad, k = 2, bs = "fs", m = 1)
```

```
##
## reach_gam_2: count ~ s(months, k = 3) + s(months, dyad, k = 2, bs = "fs",
##     m = 1)
##
## Chi-square test of ML scores
## -----
##              Model    Score Edf Difference    Df p.value Sig.
## 1 reach_gam_2_null 382.1529   3
## 2      reach_gam_2 381.3235   5      0.829 2.000   0.436
##
## AIC difference: -3.95, model reach_gam_2_null has lower AIC.

## Warning in compareML(reach_gam_2_null, reach_gam_2): Only small difference in ML...
```

```
plot_smooths(reach_gam_2, months, series_length = 25, transform = exp)
```




## 2.2 HGs development

The following models test cultural group.

```
hg_nb <- glm.nb(count ~ months, data = hg_tot)
theta_2 <- summary(hg_nb)[["theta"]]

hg_gam <- gam(
```

```r
  count ~
    back_o +
    s(months, k = 3) +
    s(months, k = 3, by = back_o) +
    s(months, dyad, k = 2, bs = "fs", m = 1),
  data = hg_tot,
  method = "ML",
  family = negbin(theta_2)
)
```

```
## Warning in gam.side(sm, X, tol = .Machine$double.eps^0.5): model has
## repeated 1-d smooths of same variable.
```

```r
summary(hg_gam)
```

```
##
## Family: Negative Binomial(0.643)
## Link function: log
##
## Formula:
## count ~ back_o + s(months, k = 3) + s(months, k = 3, by = back_o) +
##     s(months, dyad, k = 2, bs = "fs", m = 1)
##
## Parametric coefficients:
##                Estimate Std. Error z value Pr(>|z|)
## (Intercept)      0.7491     0.2316   3.234  0.00122 **
## back_oBengali    0.9117     0.3143   2.901  0.00372 **
## back_oChinese    0.7257     0.3163   2.295  0.02176 *
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Approximate significance of smooth terms:
##                             edf Ref.df Chi.sq p-value
## s(months)                  1.00      1  9.708 0.00184 **
## s(months):back_oBengali    1.00      1  0.025 0.87559
## s(months):back_oChinese    1.00      1  0.426 0.51391
## s(months,dyad)            17.71    112 26.332 0.01074 *
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## R-sq.(adj) =  0.335   Deviance explained = 38.5%
## -ML = 451.06  Scale est. = 1         n = 173
```

```r
hg_gam_null <- gam(
  count ~
    # back_o +
    s(months, k = 3) +
    # s(months, k = 3, by = back_o) +
    s(months, dyad, k = 2, bs = "fs", m = 1),
  data = hg_tot,
  method = "ML",
  family = negbin(theta_2)
)
```

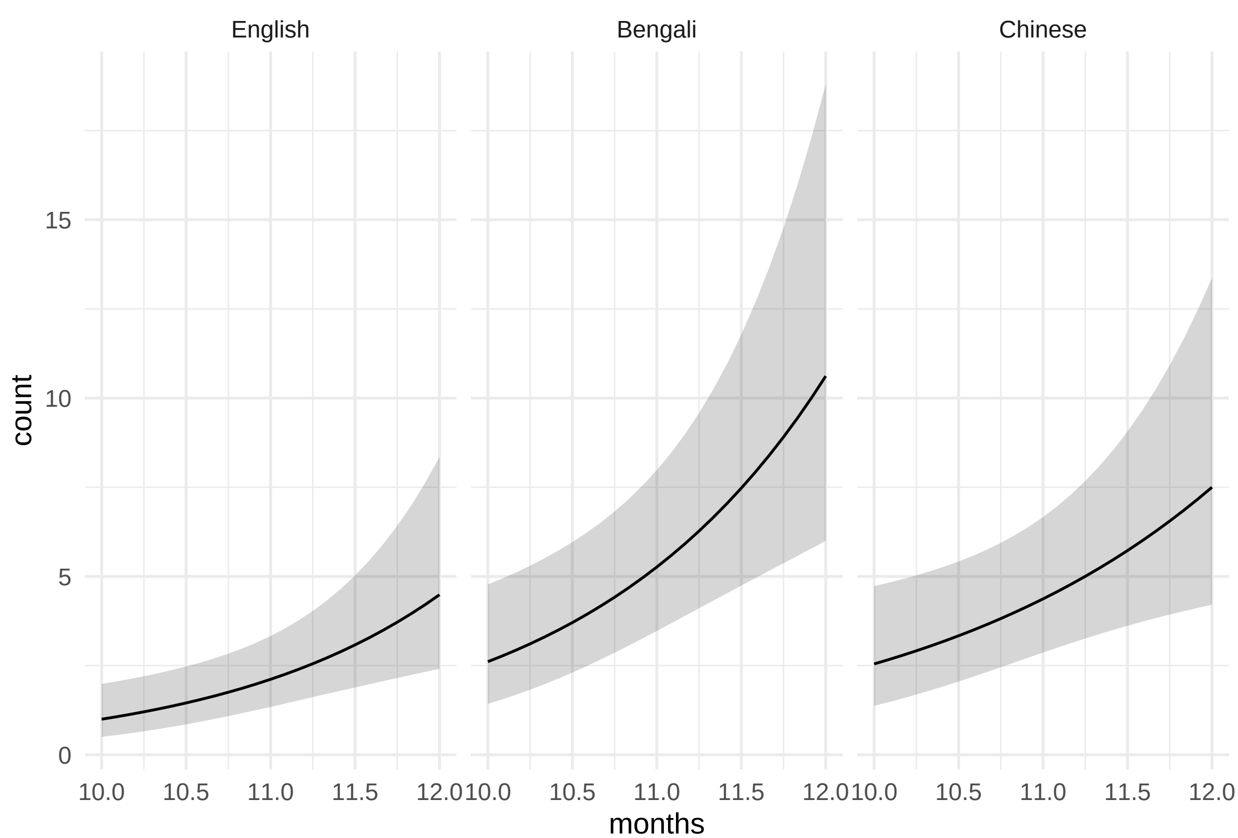
```
## Warning in gam.side(sm, X, tol = .Machine$double.eps^0.5): model has
## repeated 1-d smooths of same variable.
```

```r
compareML(hg_gam_null, hg_gam)
```

```
## hg_gam_null: count ~ s(months, k = 3) + s(months, dyad, k = 2, bs = "fs",
##     m = 1)
##
## hg_gam: count ~ back_o + s(months, k = 3) + s(months, k = 3, by = back_o) +
##     s(months, dyad, k = 2, bs = "fs", m = 1)
##
## Chi-square test of ML scores
## -----
##         Model    Score Edf Difference    Df p.value Sig.
## 1 hg_gam_null 455.3692   5
## 2      hg_gam 451.0596  11      4.310 6.000   0.196
##
## AIC difference: -2.20, model hg_gam_null has lower AIC.
```

```
## Warning in compareML(hg_gam_null, hg_gam): Only small difference in ML...
```

```r
plot_smooths(hg_gam, months, facet_terms = back_o, series_length = 25, transform = exp)
```




The following models test time sample.

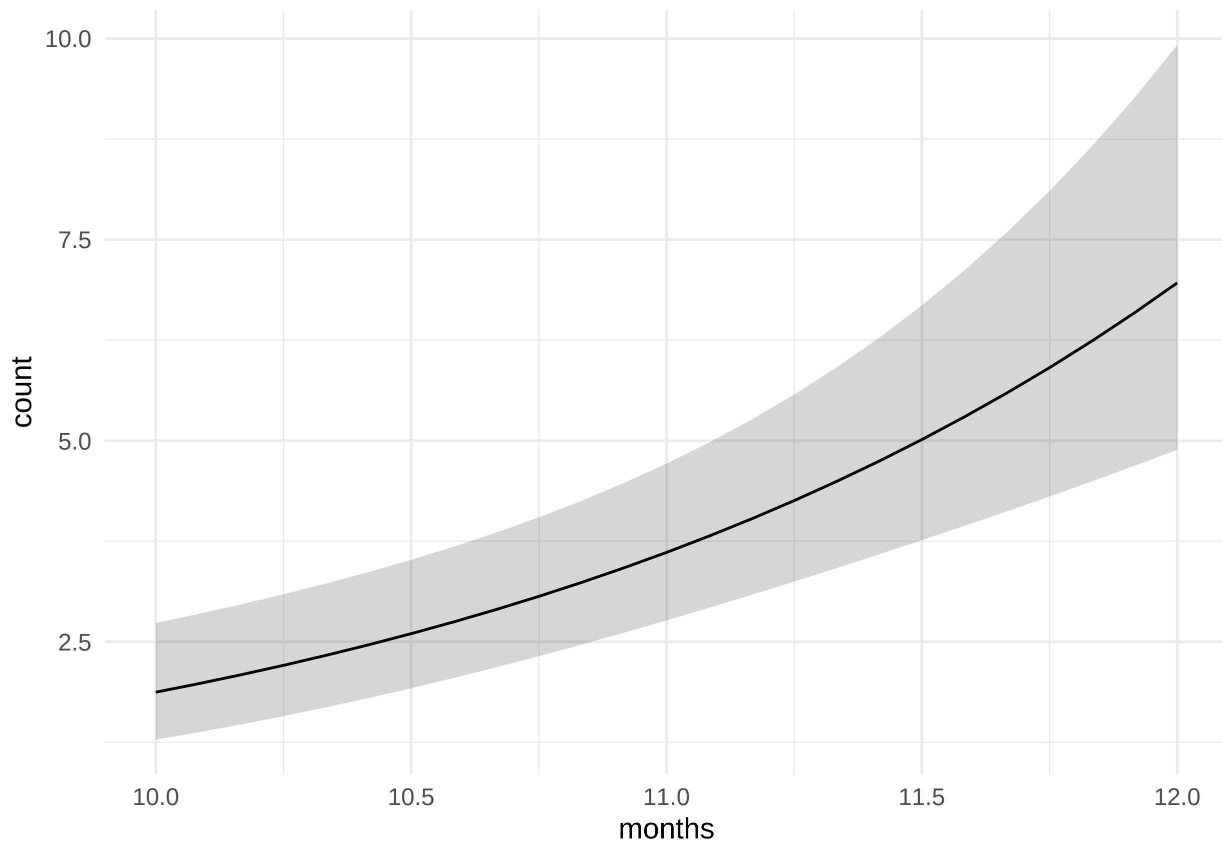
```r
hg_gam_2 <- gam(
  count ~
    s(months, k = 3) +
    s(months, dyad, k = 2, bs = "fs", m = 1),
  data = hg_tot,
  method = "ML",
  family = negbin(theta_2)
)
```

```
## Warning in gam.side(sm, X, tol = .Machine$double.eps^0.5): model has
## repeated 1-d smooths of same variable.
```

```r
hg_gam_2_null <- gam(
  count ~
    # s(months, k = 3) +
    s(months, dyad, k = 2, bs = "fs", m = 1),
  data = hg_tot,
  method = "ML",
  family = negbin(theta_2)
)
compareML(hg_gam_2_null, hg_gam_2)
```

```
## hg_gam_2_null: count ~ s(months, dyad, k = 2, bs = "fs", m = 1)
##
## hg_gam_2: count ~ s(months, k = 3) + s(months, dyad, k = 2, bs = "fs",
##     m = 1)
##
## Chi-square test of ML scores
## -----
##           Model    Score Edf Difference    Df   p.value Sig.
## 1 hg_gam_2_null 467.6971   3
## 2      hg_gam_2 455.3692   5     12.328 2.000 4.427e-06  ***
##
## AIC difference: 29.27, model hg_gam_2 has lower AIC.
```

```r
plot_smooths(hg_gam_2, months, series_length = 25, transform = exp)
```




### 2.3 Points development

The following models test cultural group.

```
point_nb <- glm.nb(count ~ months, data = point_tot)
theta_3 <- summary(point_nb)[["theta"]]

point_gam <- gam(
  count ~
    back_o +
    s(months, k = 3) +
    s(months, k = 3, by = back_o) +
    s(months, dyad, k = 2, bs = "fs", m = 1),
  data = point_tot,
  method = "ML",
  family = negbin(theta_3)
)
```

```
## Warning in gam.side(sm, X, tol = .Machine$double.eps^0.5): model has
## repeated 1-d smooths of same variable.
```

```
summary(point_gam)
```

```
##
```

```
## Family: Negative Binomial(0.195)
## Link function: log
##
## Formula:
## count ~ back_o + s(months, k = 3) + s(months, k = 3, by = back_o) +
##     s(months, dyad, k = 2, bs = "fs", m = 1)
##
## Parametric coefficients:
##                Estimate Std. Error z value Pr(>|z|)
## (Intercept)      0.6919     0.3953   1.750   0.0801 .
## back_oBengali   -0.4994     0.5588  -0.894   0.3715
## back_oChinese   -0.5735     0.5675  -1.011   0.3122
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Approximate significance of smooth terms:
##                            edf  Ref.df Chi.sq p-value
## s(months)                1.000   1.000  1.068  0.3014
## s(months):back_oBengali  1.538   1.786  0.726  0.5737
## s(months):back_oChinese  1.000   1.000  2.118  0.1456
## s(months,dyad)          18.368 112.000 25.998  0.0225 *
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## R-sq.(adj) =  0.332   Deviance explained =   41%
## -ML = 326.24  Scale est. = 1         n = 173
```

```
point_gam_null <- gam(
  count ~
    # back_o +
    s(months, k = 3) +
    # s(months, k = 3, by = back_o) +
    s(months, dyad, k = 2, bs = "fs", m = 1),
  data = point_tot,
  method = "ML",
  family = negbin(theta_3)
)
```

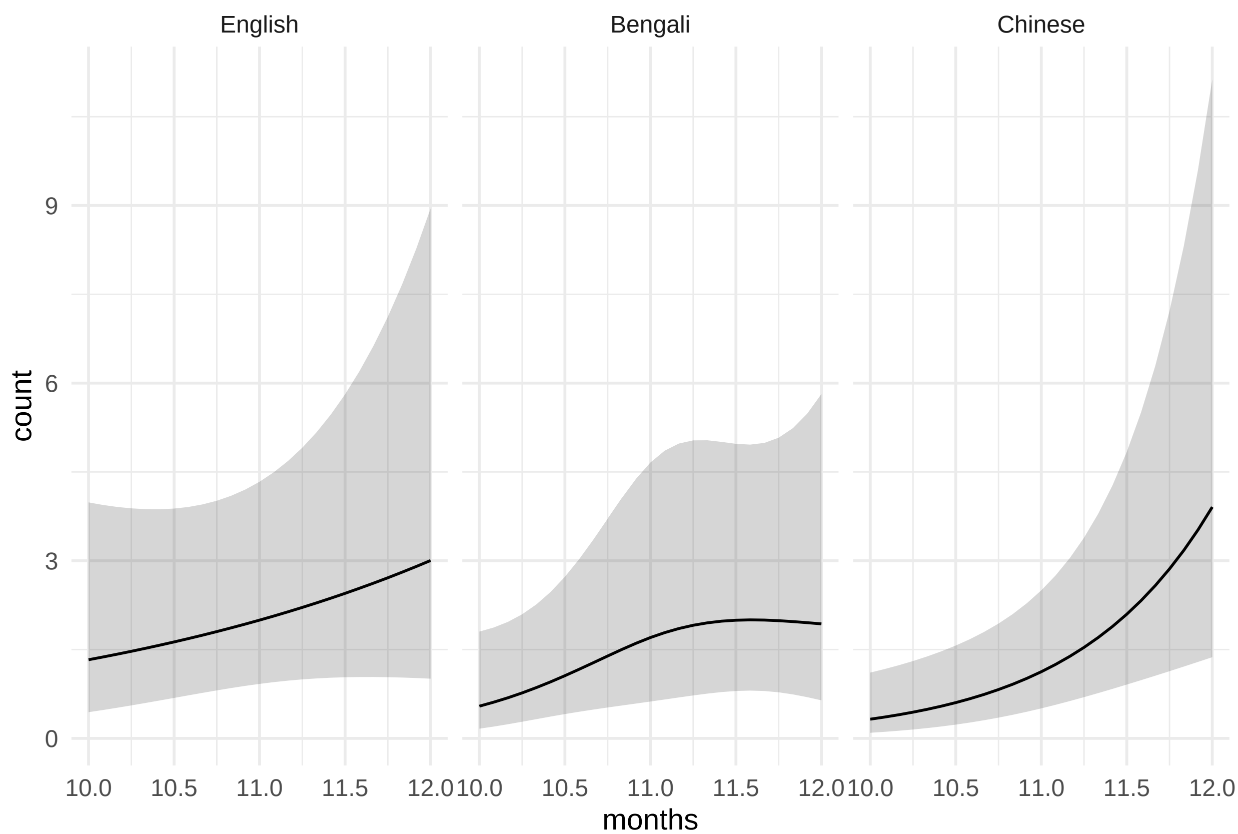
```
## Warning in gam.side(sm, X, tol = .Machine$double.eps^0.5): model has
## repeated 1-d smooths of same variable.
```

```
compareML(point_gam_null, point_gam)
```

```
## point_gam_null: count ~ s(months, k = 3) + s(months, dyad, k = 2, bs = "fs",
##     m = 1)
##
## point_gam: count ~ back_o + s(months, k = 3) + s(months, k = 3, by = back_o) +
##     s(months, dyad, k = 2, bs = "fs", m = 1)
##
## Chi-square test of ML scores
## -----
##            Model    Score Edf Difference    Df p.value Sig.
## 1 point_gam_null 327.9371   5
```

```
## 2      point_gam 326.2371  11      1.700 6.000   0.757
##
## AIC difference: -7.40, model point_gam_null has lower AIC.

## Warning in compareML(point_gam_null, point_gam): Only small difference in ML...
```

```
plot_smooths(point_gam, months, facet_terms = back_o, series_length = 25, transform = exp)
```




The following models test time sample.

```
point_gam_2 <- gam(
  count ~
    s(months, k = 3) +
    s(months, dyad, k = 2, bs = "fs", m = 1),
  data = point_tot,
  method = "ML",
  family = negbin(theta_3)
)
```

```
## Warning in gam.side(sm, X, tol = .Machine$double.eps^0.5): model has
## repeated 1-d smooths of same variable.
```

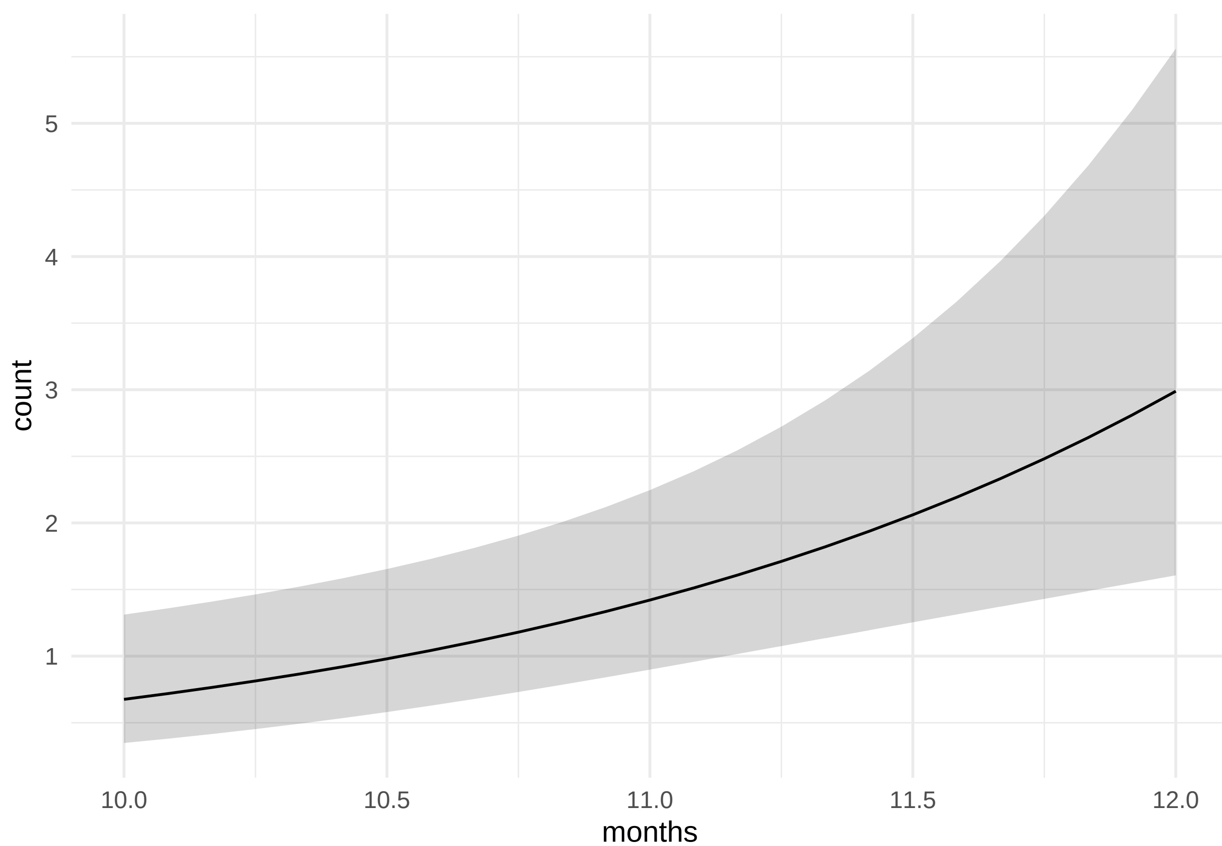
```
point_gam_2_null <- gam(
  count ~
    # s(months, k = 3) +
```

```
    s(months, dyad, k = 2, bs = "fs", m = 1),
  data = point_tot,
  method = "ML",
  family = negbin(theta_3)
)
compareML(point_gam_2_null, point_gam_2)
```

```
## point_gam_2_null: count ~ s(months, dyad, k = 2, bs = "fs", m = 1)
##
## point_gam_2: count ~ s(months, k = 3) + s(months, dyad, k = 2, bs = "fs",
##     m = 1)
##
## Chi-square test of ML scores
## -----
##              Model    Score Edf Difference    Df p.value Sig.
## 1 point_gam_2_null 332.5523   3
## 2      point_gam_2 327.9371   5      4.615 2.000   0.010  **
##
## AIC difference: 10.13, model point_gam_2 has lower AIC.
```

```
## Warning in compareML(point_gam_2_null, point_gam_2): Only small difference in ML...
```

```
plot_smooths(point_gam_2, months, series_length = 25, transform = exp)
```



# 3 Analysis 1b. Frequency of maternal utterances and contingent talk to infants aged 10-12 months.

For maternal utterances we used a normal distribution, since the distribution of the data was almost normal. For maternal contingent talks instead we used again the negative binomial distribution for the same reasons as above.

## 3.1 Maternal utterances development

The following models test cultural group.

```
utter_gam <- gam(
  utterances ~
    back_o +
    s(months, k = 3) +
    s(months, k = 3, by = back_o) +
    s(months, dyad, k = 2, bs = "fs", m = 1),
  data = utterances_tot,
  method = "ML"
)
```

```
## Warning in gam.side(sm, X, tol = .Machine$double.eps^0.5): model has
## repeated 1-d smooths of same variable.
```

```
summary(utter_gam)
```

```
##
## Family: gaussian
## Link function: identity
##
## Formula:
## utterances ~ back_o + s(months, k = 3) + s(months, k = 3, by = back_o) +
##     s(months, dyad, k = 2, bs = "fs", m = 1)
##
## Parametric coefficients:
##                 Estimate Std. Error t value Pr(>|t|)
## (Intercept)       284.44      27.10  10.494   <2e-16 ***
## back_oBengali     -65.59      37.82  -1.734   0.0865 .
## back_oChinese     -37.80      37.74  -1.002   0.3193
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Approximate significance of smooth terms:
##                             edf  Ref.df     F p-value
## s(months)                 1.693   1.880 0.966   0.333
## s(months):back_oBengali   1.001   1.001 1.065   0.305
## s(months):back_oChinese   1.334   1.533 1.924   0.107
## s(months,dyad)           73.930 111.000 7.087  <2e-16 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## R-sq.(adj) =  0.837   Deviance explained = 91.6%
## -ML = 991.97  Scale est. = 2827.4    n = 167
```

```r
utter_gam_null <- gam(
  utterances ~
    # back_o +
    s(months, k = 3) +
    # s(months, k = 3, by = back_o) +
    s(months, dyad, k = 2, bs = "fs", m = 1),
  data = utterances_tot,
  method = "ML"
)
```

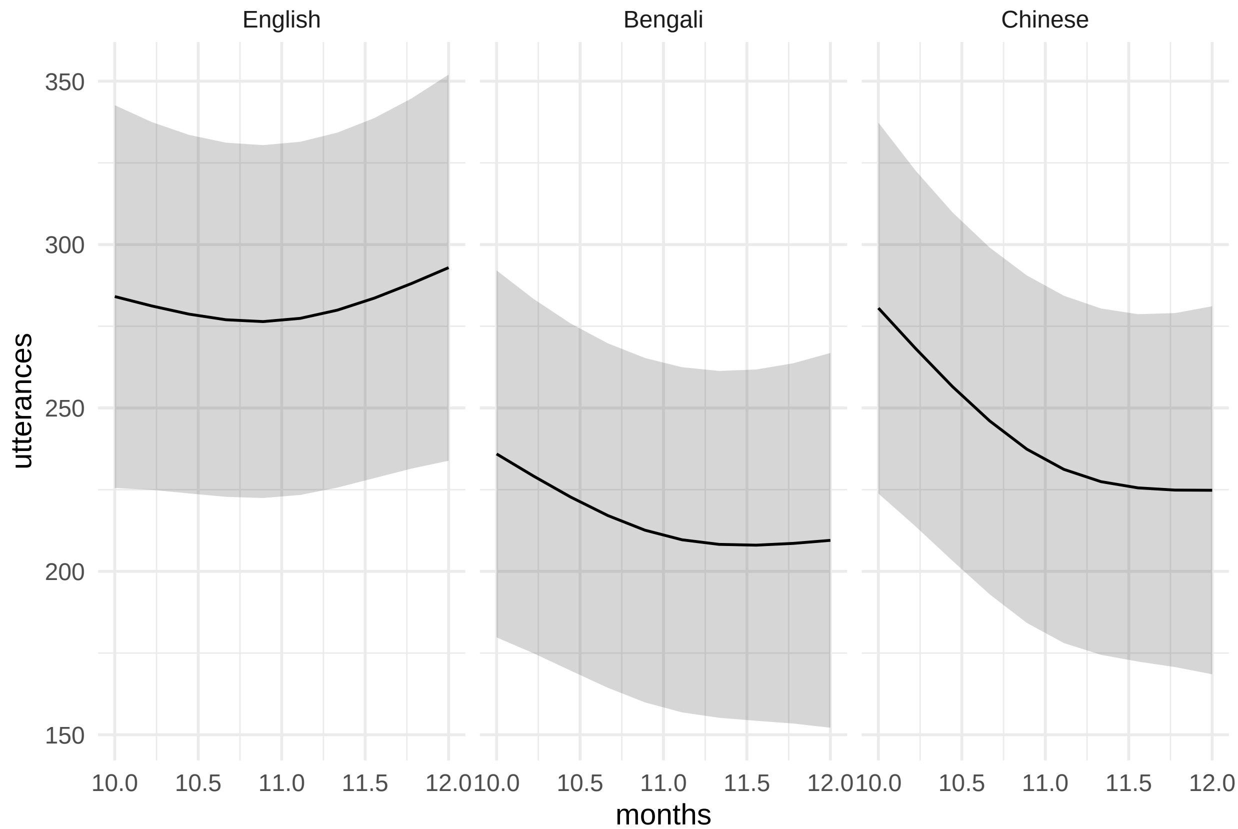
```
## Warning in gam.side(sm, X, tol = .Machine$double.eps^0.5): model has
## repeated 1-d smooths of same variable.
```

```r
compareML(utter_gam_null, utter_gam)
```

```
## utter_gam_null: utterances ~ s(months, k = 3) + s(months, dyad, k = 2, bs = "fs",
##     m = 1)
##
## utter_gam: utterances ~ back_o + s(months, k = 3) + s(months, k = 3, by = back_o) +
##     s(months, dyad, k = 2, bs = "fs", m = 1)
##
## Chi-square test of ML scores
## -----
##            Model    Score Edf Difference    Df p.value Sig.
## 1 utter_gam_null 995.3291   5
## 2      utter_gam 991.9724  11      3.357 6.000   0.348
##
## AIC difference: -3.68, model utter_gam_null has lower AIC.
```

```
## Warning in compareML(utter_gam_null, utter_gam): Only small difference in ML...
```

```r
plot_smooths(utter_gam, months, facet_terms = back_o, series_length = 10)
```




The following models test time sample.

```
utter_gam_2 <- gam(
  utterances ~
    s(months, k = 3) +
    s(months, dyad, k = 2, bs = "fs", m = 1),
  data = utterances_tot,
  method = "ML"
)
```

```
## Warning in gam.side(sm, X, tol = .Machine$double.eps^0.5): model has
## repeated 1-d smooths of same variable.
```

```
utter_gam_2_null <- gam(
  utterances ~
    # s(months, k = 3) +
    s(months, dyad, k = 2, bs = "fs", m = 1),
  data = utterances_tot,
  method = "ML"
)

compareML(utter_gam_2_null, utter_gam_2)
```

```
## utter_gam_2_null: utterances ~ s(months, dyad, k = 2, bs = "fs", m = 1)
##
```

```
## utter_gam_2: utterances ~ s(months, k = 3) + s(months, dyad, k = 2, bs = "fs",
##     m = 1)
##
## Chi-square test of ML scores
## -----
##              Model    Score Edf Difference    Df p.value Sig.
## 1 utter_gam_2_null 997.9664   3
## 2      utter_gam_2 995.3291   5      2.637 2.000   0.072
##
## AIC difference: 6.07, model utter_gam_2 has lower AIC.

## Warning in compareML(utter_gam_2_null, utter_gam_2): Only small difference in ML...
```

### 3.2 Contingent talks development

The following models test cultural group.

```r
ct_nb <- glm.nb(ct ~ months, data = all_tot)
theta_4 <- summary(ct_nb)[["theta"]]

ct_gam <- gam(
  ct ~
    back_o +
    s(months, k = 3) +
    s(months, k = 3, by = back_o) +
    s(months, dyad, k = 2, bs = "fs", m = 1),
  data = all_tot,
  method = "ML",
  family = negbin(theta_4)
)
```

```
## Warning in gam.side(sm, X, tol = .Machine$double.eps^0.5): model has
## repeated 1-d smooths of same variable.
```

```r
summary(ct_gam)
```

```
##
## Family: Negative Binomial(0.385)
## Link function: log
##
## Formula:
## ct ~ back_o + s(months, k = 3) + s(months, k = 3, by = back_o) +
##     s(months, dyad, k = 2, bs = "fs", m = 1)
##
## Parametric coefficients:
##                Estimate Std. Error z value Pr(>|z|)
## (Intercept)      0.6527     0.2977   2.192   0.0283 *
## back_oBengali   -0.9863     0.4347  -2.269   0.0233 *
## back_oChinese   -0.2083     0.4226  -0.493   0.6222
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
```

```
## Approximate significance of smooth terms:
##                             edf  Ref.df Chi.sq p-value
## s(months)                  1.00   1.000  3.039 0.08129 .
## s(months):back_oBengali  1.75   1.937  3.064 0.24022
## s(months):back_oChinese  1.00   1.000  0.391 0.53191
## s(months,dyad)          18.38 112.000 27.602 0.00937 **
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## R-sq.(adj) =  0.394   Deviance explained = 43.7%
## -ML = 315.49  Scale est. = 1         n = 172
```

```r
ct_gam_null <- gam(
  ct ~
    # back_o +
    s(months, k = 3) +
    # s(months, k = 3, by = back_o) +
    s(months, dyad, k = 2, bs = "fs", m = 1),
  data = all_tot,
  method = "ML",
  family = negbin(theta_4)
)
```

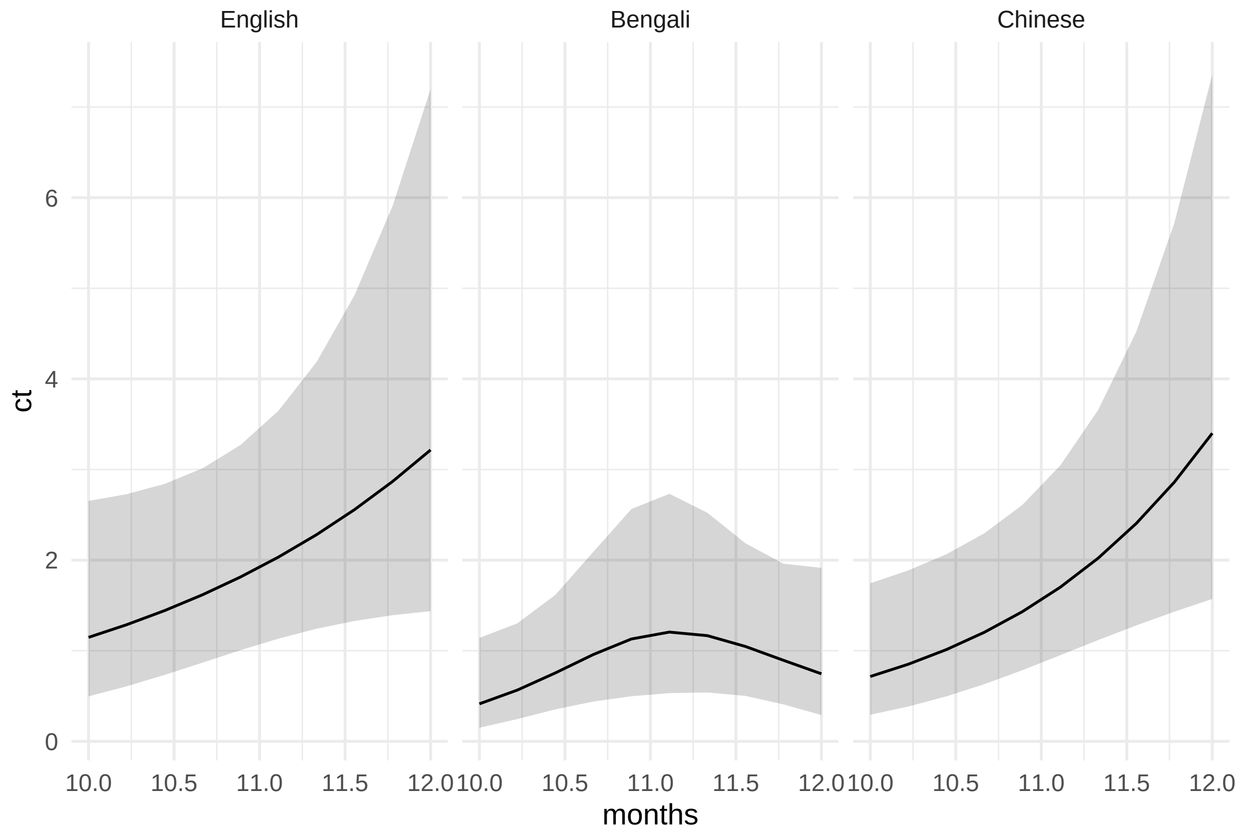
```
## Warning in gam.side(sm, X, tol = .Machine$double.eps^0.5): model has
## repeated 1-d smooths of same variable.
```

```r
compareML(ct_gam_null, ct_gam)
```

```
## ct_gam_null: ct ~ s(months, k = 3) + s(months, dyad, k = 2, bs = "fs", m = 1)
##
## ct_gam: ct ~ back_o + s(months, k = 3) + s(months, k = 3, by = back_o) +
##     s(months, dyad, k = 2, bs = "fs", m = 1)
##
## Chi-square test of ML scores
## -----
##         Model    Score Edf Difference    Df p.value Sig.
## 1 ct_gam_null 318.9134   5
## 2      ct_gam 315.4851  11      3.428 6.000   0.334
##
## AIC difference: 0.60, model ct_gam has lower AIC.
```

```
## Warning in compareML(ct_gam_null, ct_gam): Only small difference in ML...
```

```r
plot_smooths(ct_gam, months, facet_terms = back_o, series_length = 10, transform = exp)
```




The following models test time sample.

```
ct_gam_2 <- gam(
  count ~
    s(months, k = 3) +
    s(months, dyad, k = 2, bs = "fs", m = 1),
  data = all_tot,
  method = "ML",
  family = negbin(theta_4)
)
```

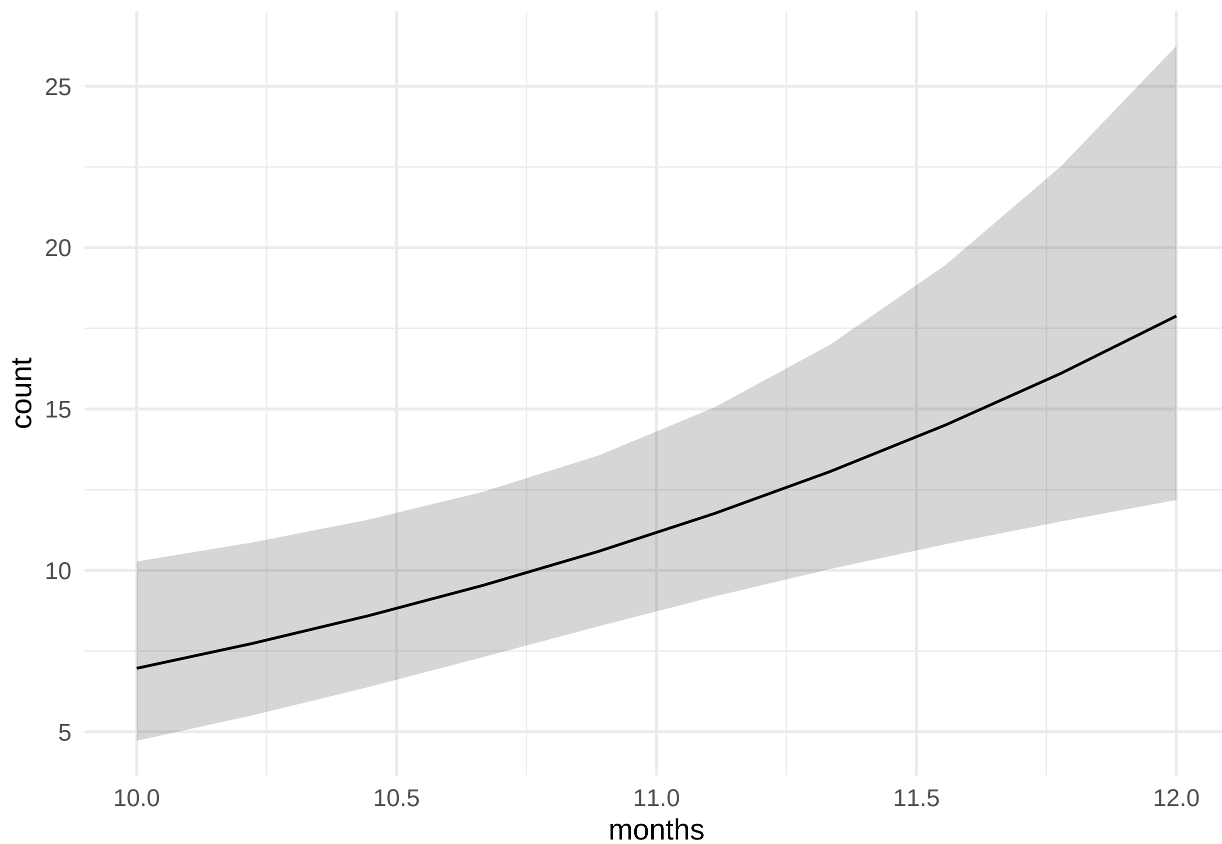
```
## Warning in gam.side(sm, X, tol = .Machine$double.eps^0.5): model has
## repeated 1-d smooths of same variable.
```

```
ct_gam_2_null <- gam(
  count ~
    # s(months, k = 3) +
    s(months, dyad, k = 2, bs = "fs", m = 1),
  data = all_tot,
  method = "ML",
  family = negbin(theta_4)
)

compareML(ct_gam_2_null, ct_gam_2)
```

```
## ct_gam_2_null: count ~ s(months, dyad, k = 2, bs = "fs", m = 1)
```

```
##
## ct_gam_2: count ~ s(months, k = 3) + s(months, dyad, k = 2, bs = "fs",
##     m = 1)
##
## Chi-square test of ML scores
## -----
##          Model    Score Edf Difference    Df p.value Sig.
## 1 ct_gam_2_null 641.7134   3
## 2      ct_gam_2 637.2323   5      4.481 2.000   0.011  *
##
## AIC difference: 6.96, model ct_gam_2 has lower AIC.

## Warning in compareML(ct_gam_2_null, ct_gam_2): Only small difference in ML...
```

```
plot_smooths(ct_gam_2, months, series_length = 10, transform = exp)
```



# 4 Analysis 1c. Predictors of pointing at 12 months

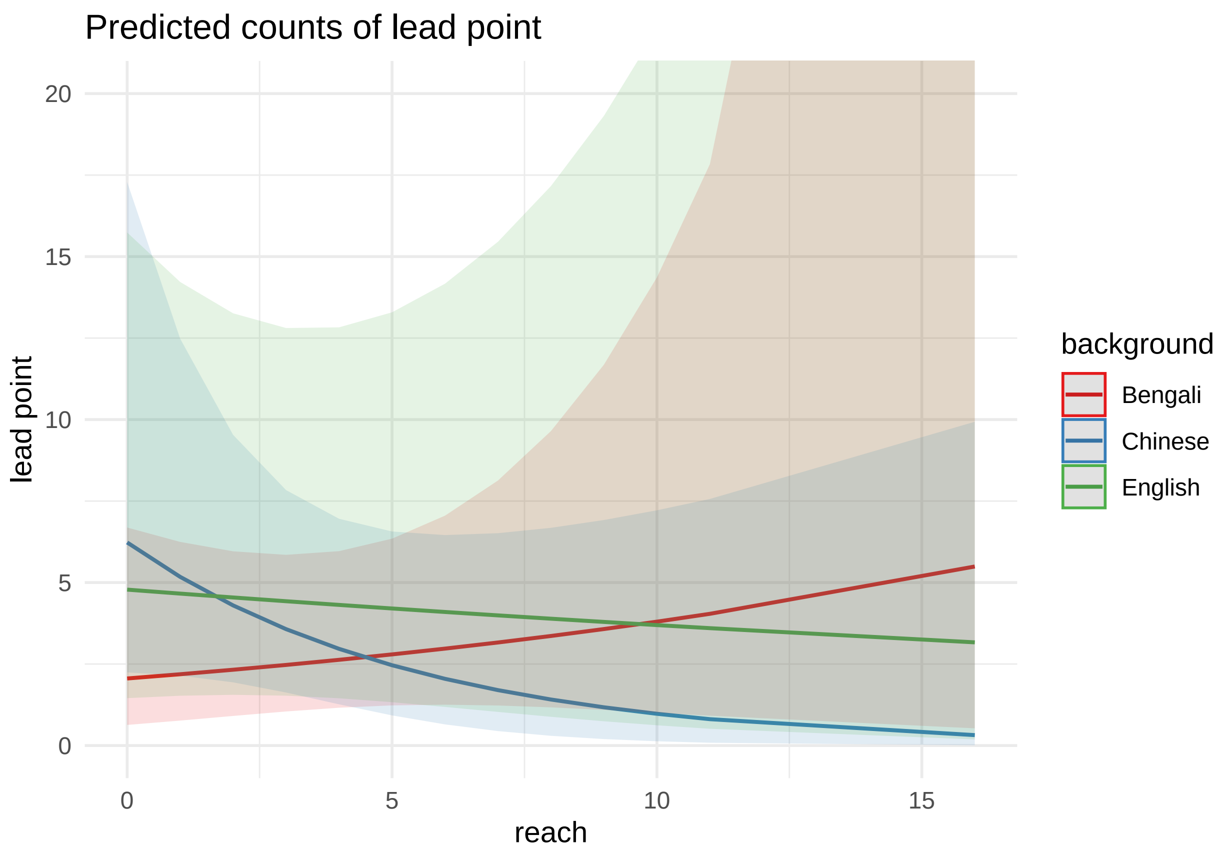
The following GLMMs test the relation between pointing as the outcome variable and reaches/HoGs.

## 4.1 Reaches

```
reach_point_lead_nb <- glm.nb(lead_point ~ reach, data = reach_point_lead)

reach_point_lm <- glmer(
  lead_point ~
    reach *
    background +
    (1|dyad),
  data = reach_point_lead,
  family = negbin(0.2681)
)
summary(reach_point_lm)
```

```
## Generalized linear mixed model fit by maximum likelihood (Laplace
##   Approximation) [glmerMod]
##  Family: Negative Binomial(0.268)  ( log )
## Formula: lead_point ~ reach * background + (1 | dyad)
##    Data: reach_point_lead
##
##      AIC      BIC   logLik deviance df.resid
##    523.3    545.1   -253.7    507.3      104
##
## Scaled residuals:
##     Min      1Q  Median      3Q     Max
## -0.5066 -0.4982 -0.3934  0.1437  3.0203
##
## Random effects:
##  Groups Name        Variance Std.Dev.
##  dyad   (Intercept) 0.1569   0.396
## Number of obs: 112, groups:  dyad, 57
##
## Fixed effects:
##                           Estimate Std. Error z value Pr(>|z|)
## (Intercept)                0.72163    0.60141   1.200    0.230
## reach                      0.06136    0.09716   0.632    0.528
## backgroundChinese          1.10777    0.72841   1.521    0.128
## backgroundEnglish          0.84357    0.68166   1.238    0.216
## reach:backgroundChinese -0.24686    0.16105  -1.533    0.125
## reach:backgroundEnglish -0.08716    0.13746  -0.634    0.526
##
## Correlation of Fixed Effects:
##             (Intr) reach  bckgrC bckgrE rch:bC
## reach       -0.724
## bckgrndChns -0.709  0.550
## bckgrndEngl -0.557  0.506  0.508
## rch:bckgrnC  0.453 -0.610 -0.710 -0.298
## rch:bckgrnE  0.449 -0.681 -0.366 -0.599  0.412
```

```r
plot_model(reach_point_lm, type = "pred", terms = c("reach", "background")) + coord_cartesian(ylim = c(
```




### 4.2 HoGs

```r
hg_point_lead_nb <- glm.nb(lead_point ~ ho_gv, data = filter(hg_point_lead, ho_gv < 20))

hg_point_lm <- glmer(
  lead_point ~
    ho_gv *
    background +
    (1|dyad),
  data = filter(hg_point_lead, ho_gv < 20),
  family = negbin(0.2606)
)
```

```
## boundary (singular) fit: see ?isSingular
```

```r
summary(hg_point_lm)
```

```
## Generalized linear mixed model fit by maximum likelihood (Laplace
##   Approximation) [glmerMod]
##  Family: Negative Binomial(0.261)  ( log )
```

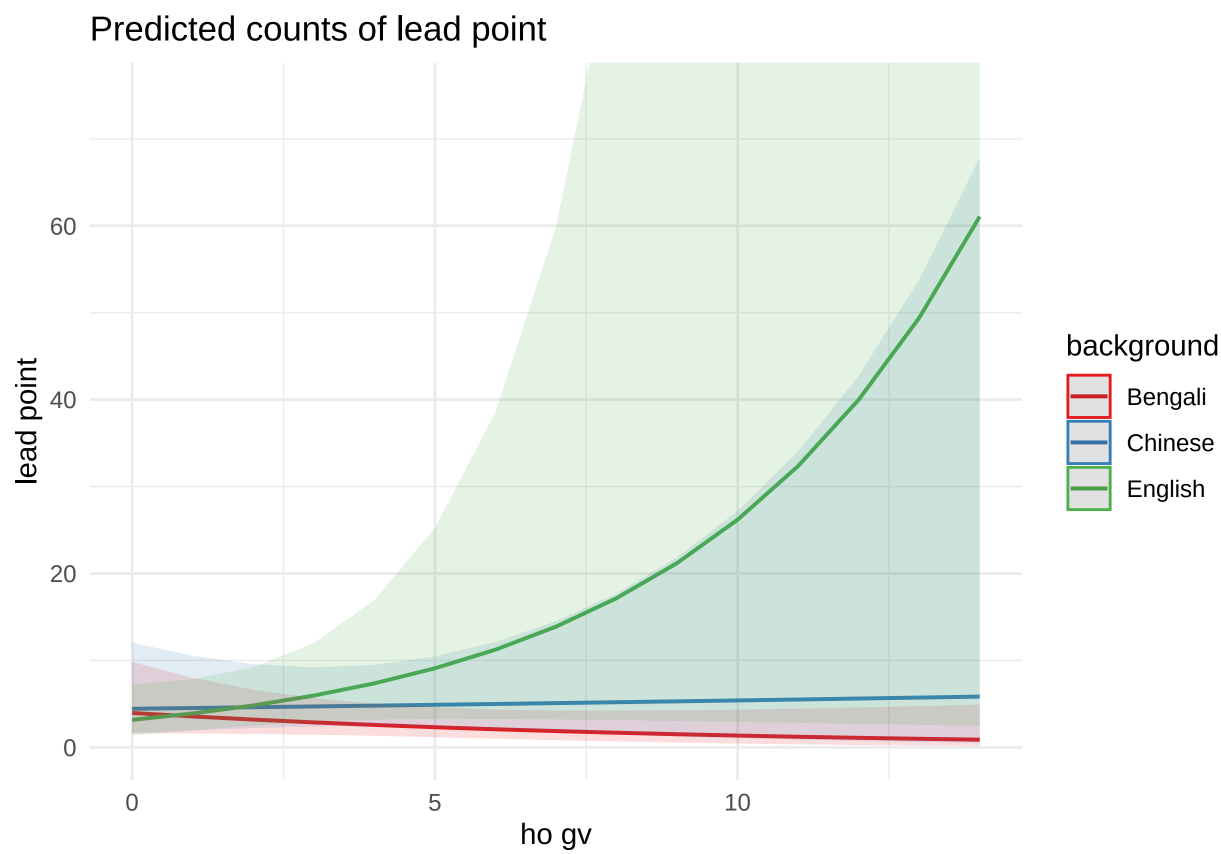
```
## Formula: lead_point ~ ho_gv * background + (1 | dyad)
##    Data: filter(hg_point_lead, ho_gv < 20)
##
##      AIC      BIC   logLik deviance df.resid
##    503.8    525.3   -243.9    487.8      101
##
## Scaled residuals:
##     Min      1Q  Median      3Q     Max
## -0.5080 -0.4942 -0.3979  0.1241  6.0969
##
## Random effects:
##  Groups Name        Variance Std.Dev.
##  dyad   (Intercept) 1.41e-10 1.187e-05
## Number of obs: 109, groups:  dyad, 57
##
## Fixed effects:
##                          Estimate Std. Error z value Pr(>|z|)
## (Intercept)               1.37529    0.46393   2.964  0.00303 **
## ho_gv                    -0.10718    0.08031  -1.335  0.18200
## backgroundChinese         0.11400    0.68904   0.165  0.86859
## backgroundEnglish        -0.22613    0.62893  -0.360  0.71919
## ho_gv:backgroundChinese   0.12680    0.13875   0.914  0.36081
## ho_gv:backgroundEnglish   0.31880    0.15566   2.048  0.04056 *
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Correlation of Fixed Effects:
##             (Intr) ho_gv  bckgrC bckgrE h_gv:C
## ho_gv       -0.681
## bckgrndChns -0.673  0.459
## bckgrndEngl -0.738  0.502  0.497
## h_gv:bckgrC  0.394 -0.579 -0.714 -0.291
## h_gv:bckgrE  0.351 -0.516 -0.237 -0.621  0.299
## convergence code: 0
## boundary (singular) fit: see ?isSingular
```

```r
hg_point_lm_null <- glmer(
  lead_point ~
    ho_gv +
    background +
    (1|dyad),
  data = filter(hg_point_lead, ho_gv < 20),
  family = negbin(0.2606)
)
anova(hg_point_lm_null, hg_point_lm)
```

```
## Data: filter(hg_point_lead, ho_gv < 20)
## Models:
## hg_point_lm_null: lead_point ~ ho_gv + background + (1 | dyad)
## hg_point_lm: lead_point ~ ho_gv * background + (1 | dyad)
##                  Df    AIC    BIC  logLik deviance  Chisq Chi Df
## hg_point_lm_null  6 504.69 520.84 -246.35   492.69
## hg_point_lm       8 503.79 525.32 -243.89   487.79 4.9055      2
##                  Pr(>Chisq)
```

```
## hg_point_lm_null
## hg_point_lm         0.08606 .
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```
plot_model(hg_point_lm, type = "pred", terms = c("ho_gv", "background")) + coord_cartesian(ylim = c(0, 
```



# 5 Analysis 2. Predictors of vocabulary scores at 12 and 18 months

## 5.1 Comprehension at 12 and 18 months

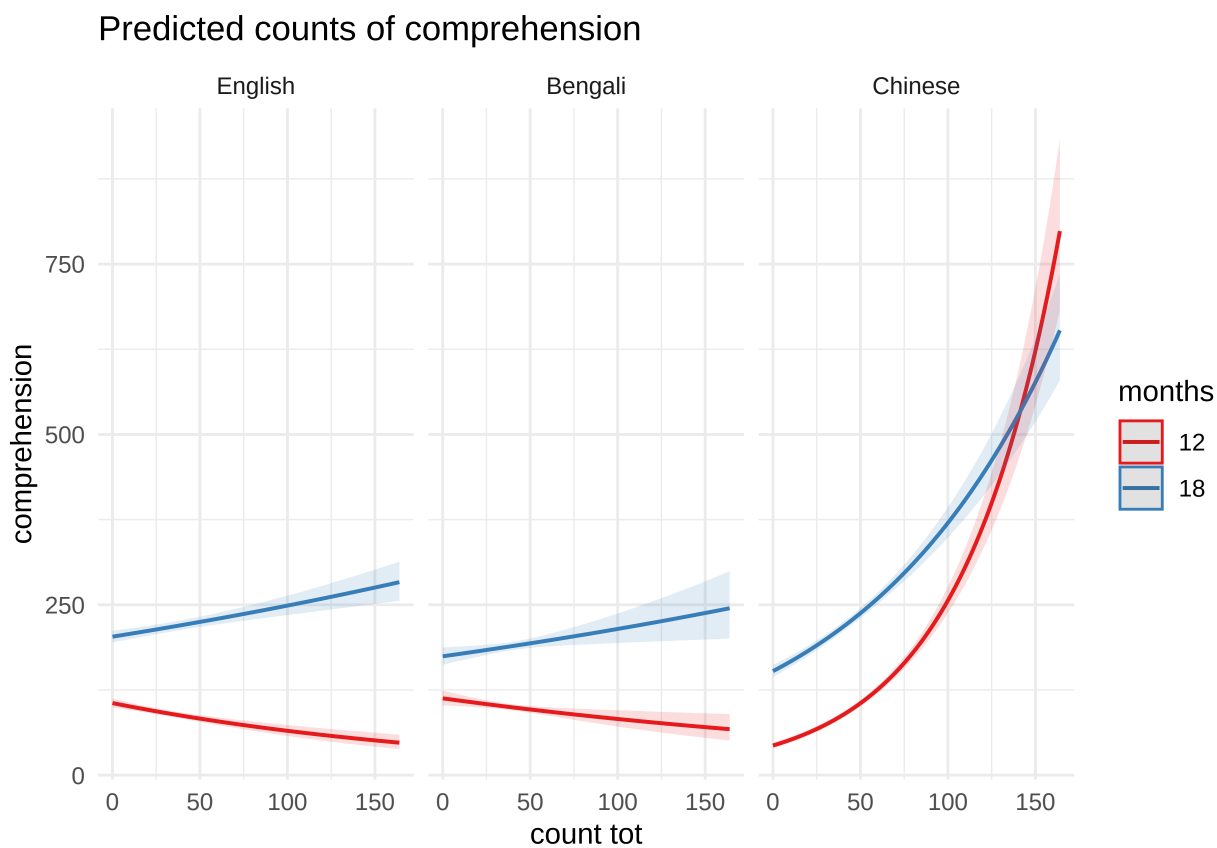
### 5.1.1 All gestures combined

```r
all_gest_lm <- glm(
  comprehension ~
    count_tot *
    months *
    background,
  data = vocab,
  family = poisson
)
summary(all_gest_lm)
```

```
##
## Call:
## glm(formula = comprehension ~ count_tot * months * background,
##     family = poisson, data = vocab)
##
## Deviance Residuals:
##     Min       1Q   Median       3Q      Max
## -12.534   -3.589   -0.588    2.339   16.033
##
## Coefficients:
##                                       Estimate Std. Error z value
## (Intercept)                          4.6615113  0.0323369 144.155
## count_tot                           -0.0048625  0.0007949  -6.117
## months18                             0.6528243  0.0389823  16.747
## backgroundBengali                    0.0635196  0.0586909   1.082
## backgroundChinese                   -0.8899846  0.0570165 -15.609
## count_tot:months18                   0.0068861  0.0008836   7.793
## count_tot:backgroundBengali          0.0017305  0.0013854   1.249
## count_tot:backgroundChinese          0.0226132  0.0010689  21.155
## months18:backgroundBengali          -0.2163911  0.0726471  -2.979
## months18:backgroundChinese           0.6034030  0.0675504   8.933
## count_tot:months18:backgroundBengali -0.0016836  0.0016536  -1.018
## count_tot:months18:backgroundChinese -0.0157740  0.0012443 -12.677
##                                      Pr(>|z|)
## (Intercept)                           < 2e-16 ***
## count_tot                            9.53e-10 ***
## months18                              < 2e-16 ***
## backgroundBengali                      0.2791
## backgroundChinese                     < 2e-16 ***
## count_tot:months18                   6.52e-15 ***
## count_tot:backgroundBengali            0.2116
## count_tot:backgroundChinese           < 2e-16 ***
## months18:backgroundBengali             0.0029 **
## months18:backgroundChinese            < 2e-16 ***
## count_tot:months18:backgroundBengali   0.3086
## count_tot:months18:backgroundChinese  < 2e-16 ***
```

```
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## (Dispersion parameter for poisson family taken to be 1)
##
##     Null deviance: 6642.1  on 108  degrees of freedom
## Residual deviance: 3326.7  on  97  degrees of freedom
##   (11 observations deleted due to missingness)
## AIC: 4072.7
##
## Number of Fisher Scoring iterations: 5
```

```
plot_model(all_gest_lm, type = "pred", terms = c("count_tot", "months", "background"))
```



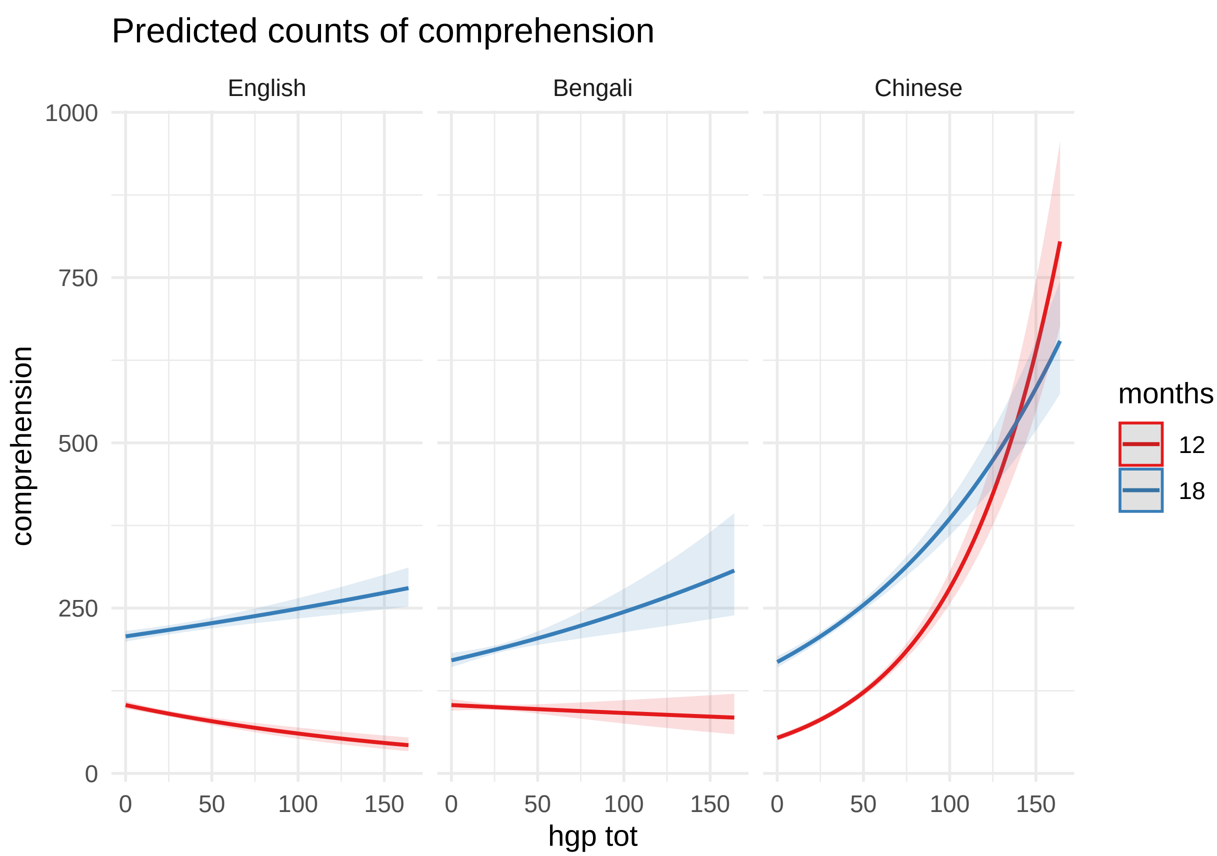

#### 5.1.2 HoGs + points

```
hgp_lm <- glm(
  comprehension ~
    hgp_tot *
    months *
    background,
  data = vocab,
  family = poisson()
```

```r
)
summary(hgp_lm)
```

```
##
## Call:
## glm(formula = comprehension ~ hgp_tot * months * background,
##     family = poisson(), data = vocab)
##
## Deviance Residuals:
##      Min        1Q    Median        3Q       Max
## -12.0912   -4.0304   -0.3296    2.6629   17.5976
##
## Coefficients:
##                                      Estimate Std. Error z value Pr(>|z|)
## (Intercept)                         4.6377993  0.0292714 158.441  < 2e-16
## hgp_tot                            -0.0053955  0.0008347  -6.464 1.02e-10
## months18                            0.6962163  0.0354287  19.651  < 2e-16
## backgroundBengali                   0.0003589  0.0522614   0.007  0.99452
## backgroundChinese                  -0.6535607  0.0506378 -12.907  < 2e-16
## hgp_tot:months18                    0.0072361  0.0009178   7.885 3.16e-15
## hgp_tot:backgroundBengali           0.0041596  0.0015628   2.662  0.00778
## hgp_tot:backgroundChinese           0.0218970  0.0011069  19.782  < 2e-16
## months18:backgroundBengali         -0.1927418  0.0644893  -2.989  0.00280
## months18:backgroundChinese          0.4461919  0.0600587   7.429 1.09e-13
## hgp_tot:months18:backgroundBengali -0.0024355  0.0018614  -1.308  0.19074
## hgp_tot:months18:backgroundChinese -0.0154648  0.0012786 -12.095  < 2e-16
##
## (Intercept)                        ***
## hgp_tot                            ***
## months18                           ***
## backgroundBengali
## backgroundChinese                  ***
## hgp_tot:months18                   ***
## hgp_tot:backgroundBengali          **
## hgp_tot:backgroundChinese          ***
## months18:backgroundBengali         **
## months18:backgroundChinese         ***
## hgp_tot:months18:backgroundBengali
## hgp_tot:months18:backgroundChinese ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## (Dispersion parameter for poisson family taken to be 1)
##
##     Null deviance: 6642.1  on 108  degrees of freedom
## Residual deviance: 3459.2  on  97  degrees of freedom
##   (11 observations deleted due to missingness)
## AIC: 4205.2
##
## Number of Fisher Scoring iterations: 5
```

```r
plot_model(hgp_lm, type = "pred", terms = c("hgp_tot", "months", "background"))
```



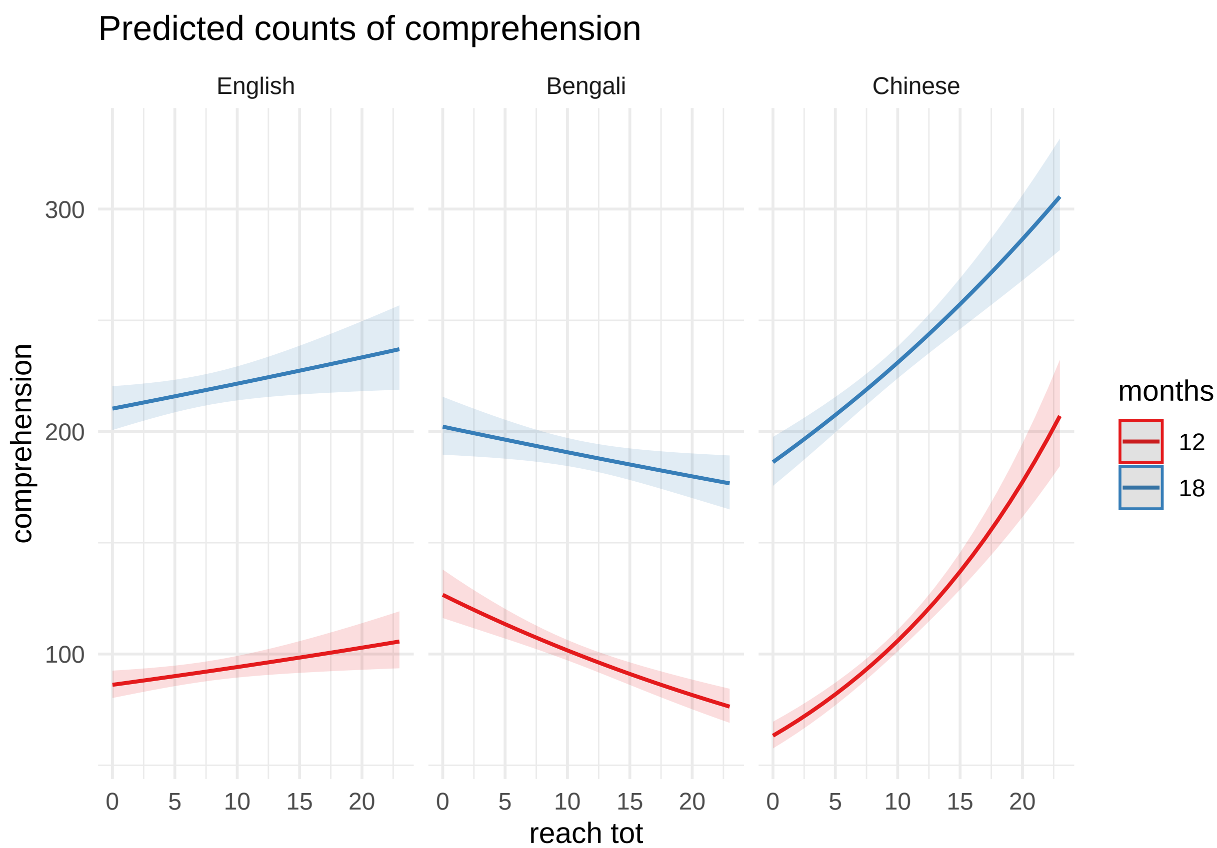

#### 5.1.3 Reaches

```r
reach_lm <- glm(
  comprehension ~
    reach_tot *
    months *
    background,
  data = vocab,
  family = poisson()
)
summary(reach_lm)
```

```
##
## Call:
## glm(formula = comprehension ~ reach_tot * months * background,
##     family = poisson(), data = vocab)
##
## Deviance Residuals:
##      Min        1Q    Median        3Q       Max
## -15.0397   -4.2179   -0.4216    3.4316   17.2738
##
```

```
## Coefficients:
##                                      Estimate Std. Error z value Pr(>|z|)
## (Intercept)                          4.456258   0.036398 122.433  < 2e-16
## reach_tot                            0.008853   0.003627   2.441  0.01465
## months18                             0.892274   0.043543  20.492  < 2e-16
## backgroundBengali                    0.384841   0.057007   6.751 1.47e-11
## backgroundChinese                   -0.308676   0.060521  -5.100 3.39e-07
## reach_tot:months18                  -0.003657   0.004337  -0.843  0.39916
## reach_tot:backgroundBengali         -0.030842   0.005119  -6.024 1.70e-09
## reach_tot:backgroundChinese          0.042672   0.005541   7.701 1.35e-14
## months18:backgroundBengali          -0.424152   0.069985  -6.061 1.36e-09
## months18:backgroundChinese           0.187235   0.071705   2.611  0.00902
## reach_tot:months18:backgroundBengali  0.019788   0.006201   3.191  0.00142
## reach_tot:months18:backgroundChinese -0.026341   0.006649  -3.961 7.45e-05
##
## (Intercept)                         ***
## reach_tot                           *
## months18                            ***
## backgroundBengali                   ***
## backgroundChinese                   ***
## reach_tot:months18
## reach_tot:backgroundBengali         ***
## reach_tot:backgroundChinese         ***
## months18:backgroundBengali          ***
## months18:backgroundChinese          **
## reach_tot:months18:backgroundBengali **
## reach_tot:months18:backgroundChinese ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## (Dispersion parameter for poisson family taken to be 1)
##
##     Null deviance: 6642.1  on 108  degrees of freedom
## Residual deviance: 4011.7  on  97  degrees of freedom
##   (11 observations deleted due to missingness)
## AIC: 4757.8
##
## Number of Fisher Scoring iterations: 5
```

```r
plot_model(reach_lm, type = "pred", terms = c("reach_tot", "months", "background"))
```



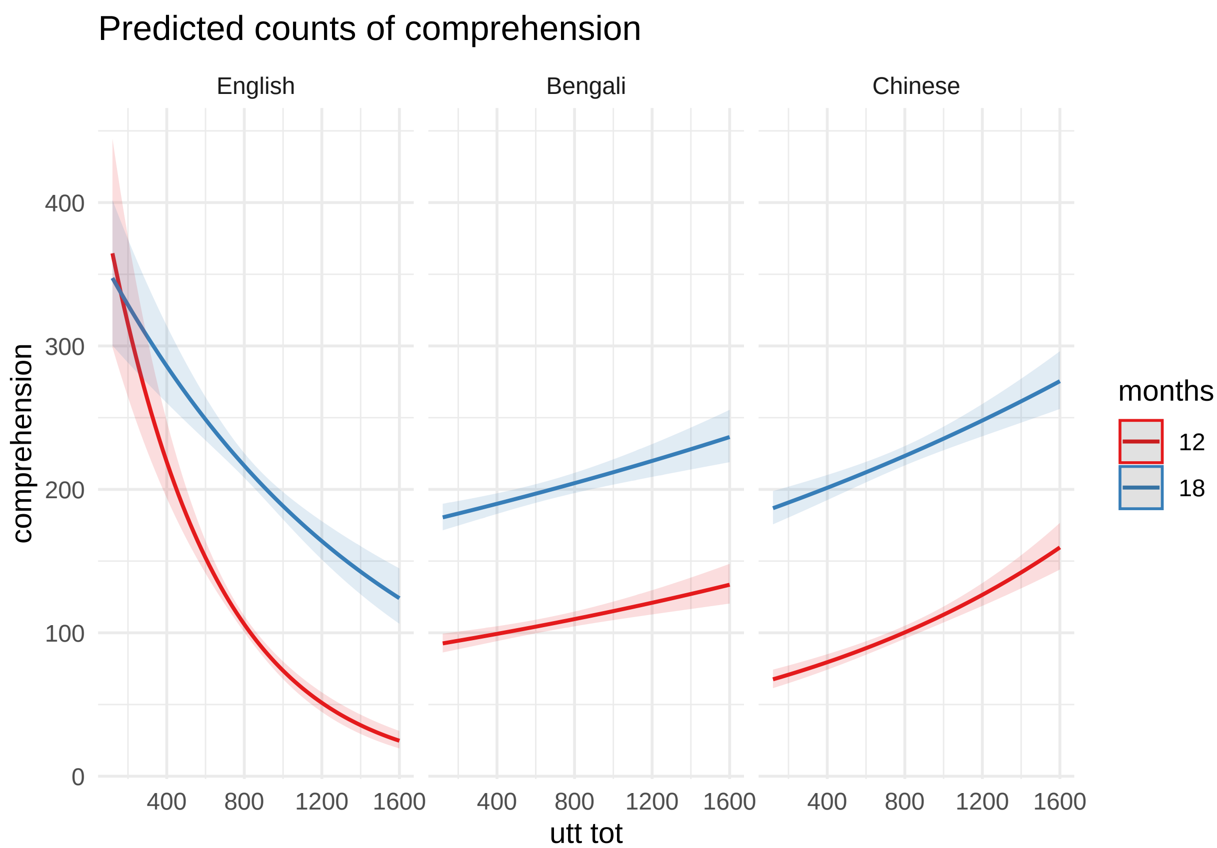

#### 5.1.4 Maternal utterances

```
utt_lm <- glm(
  comprehension ~
    utt_tot *
    months *
    background,
  data = vocab,
  family = poisson()
)
summary(utt_lm)
```

```
##
## Call:
## glm(formula = comprehension ~ utt_tot * months * background,
##     family = poisson(), data = vocab)
##
## Deviance Residuals:
##     Min       1Q   Median       3Q      Max
## -14.146   -4.714   -1.202    3.528   16.309
##
## Coefficients:
##                                       Estimate Std. Error z value Pr(>|z|)
## (Intercept)                          6.1169916  0.1184273  51.652  < 2e-16
```

```
## utt_tot                          -0.0018179  0.0001481 -12.277  < 2e-16
## months18                         -0.1830862  0.1463324  -1.251    0.211
## backgroundBengali                -1.6180843  0.1253368 -12.910  < 2e-16
## backgroundChinese                -1.9734461  0.1306492 -15.105  < 2e-16
## utt_tot:months18                  0.0011224  0.0001787   6.281 3.37e-10
## utt_tot:backgroundBengali         0.0020650  0.0001566  13.186  < 2e-16
## utt_tot:backgroundChinese         0.0023984  0.0001599  14.996  < 2e-16
## months18:backgroundBengali        0.8579418  0.1548619   5.540 3.02e-08
## months18:backgroundChinese        1.2385528  0.1605040   7.717 1.19e-14
## utt_tot:months18:backgroundBengali -0.0011869  0.0001896  -6.259 3.87e-10
## utt_tot:months18:backgroundChinese -0.0014408  0.0001932  -7.457 8.82e-14
##
## (Intercept)                      ***
## utt_tot                          ***
## months18
## backgroundBengali                ***
## backgroundChinese                ***
## utt_tot:months18                 ***
## utt_tot:backgroundBengali        ***
## utt_tot:backgroundChinese        ***
## months18:backgroundBengali       ***
## months18:backgroundChinese       ***
## utt_tot:months18:backgroundBengali ***
## utt_tot:months18:backgroundChinese ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## (Dispersion parameter for poisson family taken to be 1)
##
##     Null deviance: 5914.0  on 98  degrees of freedom
## Residual deviance: 3642.8  on 87  degrees of freedom
##   (21 observations deleted due to missingness)
## AIC: 4324.5
##
## Number of Fisher Scoring iterations: 5
```

```r
plot_model(utt_lm, type = "pred", terms = c("utt_tot", "months", "background"))
```



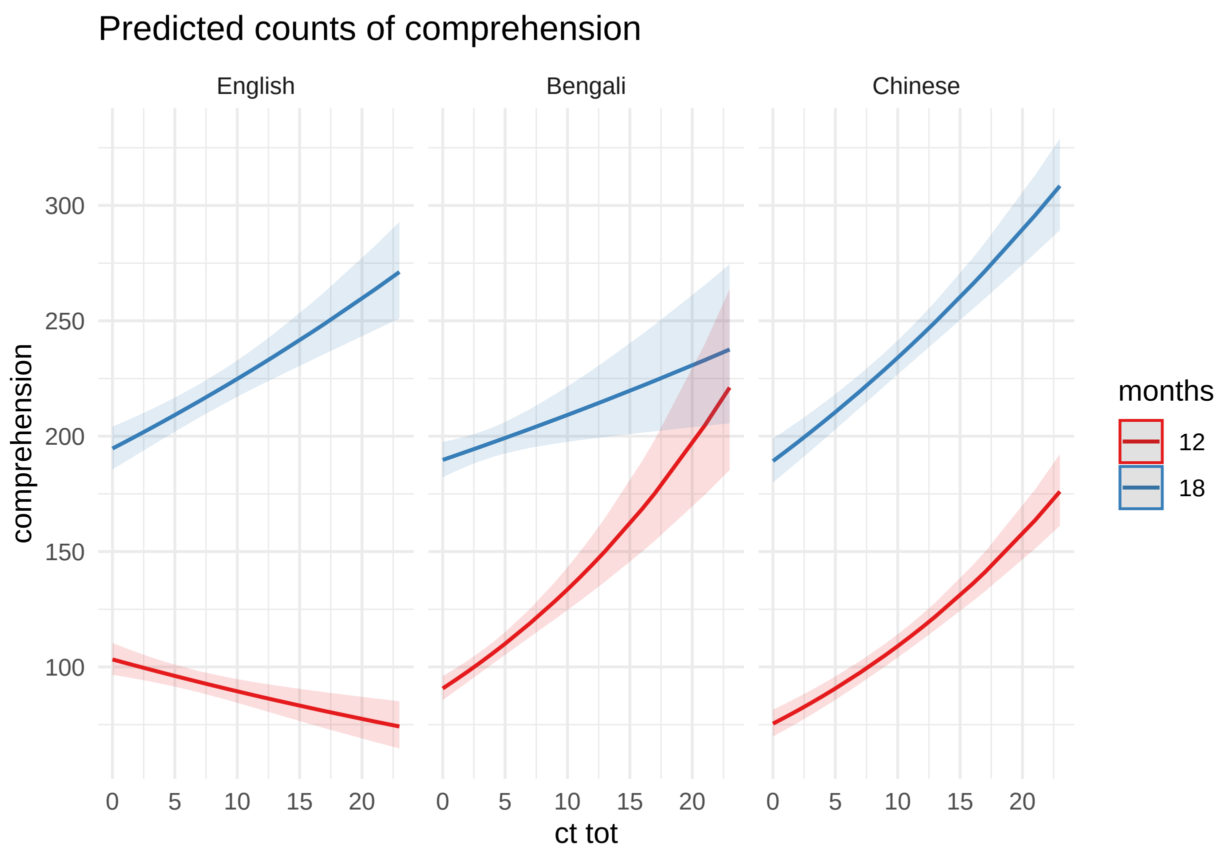

#### 5.1.5 Contingent talks

```r
ct_lm <- glm(
  comprehension ~
    ct_tot *
    months *
    background,
  data = filter(vocab, ct_tot < 30),
  family = poisson()
)
summary(ct_lm)
```

```
##
## Call:
## glm(formula = comprehension ~ ct_tot * months * background, family = poisson(),
##     data = filter(vocab, ct_tot < 30))
##
## Deviance Residuals:
##      Min        1Q    Median        3Q       Max
## -13.4501   -4.6077   -0.2327    3.4079   19.6808
##
## Coefficients:
##                                     Estimate Std. Error z value Pr(>|z|)
## (Intercept)                         4.637232   0.034058 136.157  < 2e-16
```

```
## ct_tot                             -0.014368   0.003855  -3.727 0.000194
## months18                            0.633921   0.041849  15.148  < 2e-16
## backgroundBengali                  -0.130032   0.044814  -2.902 0.003713
## backgroundChinese                  -0.314289   0.051969  -6.048 1.47e-09
## ct_tot:months18                     0.028783   0.004487   6.415 1.41e-10
## ct_tot:backgroundBengali            0.053121   0.005997   8.857  < 2e-16
## ct_tot:backgroundChinese            0.051221   0.004907  10.439  < 2e-16
## months18:backgroundBengali          0.104409   0.054990   1.899 0.057603
## months18:backgroundChinese          0.286084   0.062807   4.555 5.24e-06
## ct_tot:months18:backgroundBengali -0.057756   0.007397  -7.808 5.80e-15
## ct_tot:months18:backgroundChinese -0.044388   0.005814  -7.635 2.26e-14
##
## (Intercept)                       ***
## ct_tot                            ***
## months18                          ***
## backgroundBengali                 **
## backgroundChinese                 ***
## ct_tot:months18                   ***
## ct_tot:backgroundBengali          ***
## ct_tot:backgroundChinese          ***
## months18:backgroundBengali        .
## months18:backgroundChinese        ***
## ct_tot:months18:backgroundBengali ***
## ct_tot:months18:backgroundChinese ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## (Dispersion parameter for poisson family taken to be 1)
##
##     Null deviance: 6335.5  on 104  degrees of freedom
## Residual deviance: 3804.5  on  93  degrees of freedom
##   (1 observation deleted due to missingness)
## AIC: 4526.8
##
## Number of Fisher Scoring iterations: 5
```

```
plot_model(ct_lm, type = "pred", terms = c("ct_tot", "months", "background"))
```




### 5.2 Production at 12 and 18 months

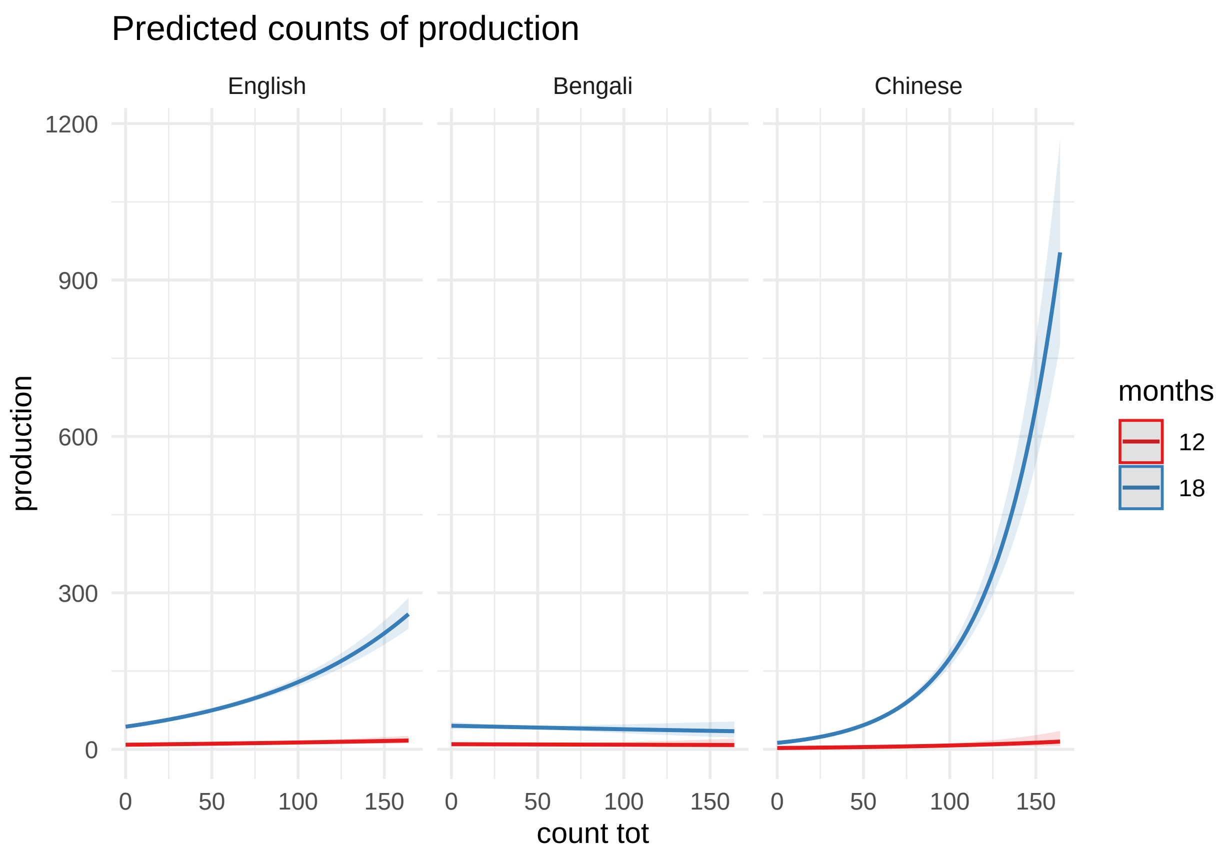
#### 5.2.1 All gestures combined

```
all_gest_prod <- glm(
  production ~
    count_tot *
    months *
    background,
  data = vocab,
  family = poisson()
)
summary(all_gest_prod)
```

```
##
## Call:
## glm(formula = production ~ count_tot * months * background, family = poisson(),
##     data = vocab)
##
## Deviance Residuals:
##     Min       1Q   Median       3Q      Max
## -9.4957  -4.2027  -1.2293   0.9099  28.3218
##
```

```
## Coefficients:
##                                       Estimate Std. Error z value Pr(>|z|)
## (Intercept)                           2.166316   0.098032  22.098  < 2e-16
## count_tot                             0.003990   0.001628   2.451   0.0142
## months18                              1.601423   0.106336  15.060  < 2e-16
## backgroundBengali                     0.106356   0.189875   0.560   0.5754
## backgroundChinese                    -1.270756   0.241938  -5.252 1.50e-07
## count_tot:months18                    0.006925   0.001700   4.074 4.62e-05
## count_tot:backgroundBengali          -0.005035   0.004041  -1.246   0.2127
## count_tot:backgroundChinese           0.006937   0.004082   1.699   0.0892
## months18:backgroundBengali           -0.064505   0.208611  -0.309   0.7572
## months18:backgroundChinese            0.011565   0.256854   0.045   0.9641
## count_tot:months18:backgroundBengali -0.007497   0.004425  -1.694   0.0902
## count_tot:months18:backgroundChinese  0.008679   0.004237   2.048   0.0405
##
## (Intercept)                          ***
## count_tot                            *
## months18                             ***
## backgroundBengali
## backgroundChinese                    ***
## count_tot:months18                   ***
## count_tot:backgroundBengali
## count_tot:backgroundChinese          .
## months18:backgroundBengali
## months18:backgroundChinese
## count_tot:months18:backgroundBengali .
## count_tot:months18:backgroundChinese *
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## (Dispersion parameter for poisson family taken to be 1)
##
##     Null deviance: 6616.0  on 108  degrees of freedom
## Residual deviance: 3247.6  on  97  degrees of freedom
##   (11 observations deleted due to missingness)
## AIC: 3711.3
##
## Number of Fisher Scoring iterations: 6
```

```r
plot_model(all_gest_prod, type = "pred", terms = c("count_tot", "months", "background"))
```



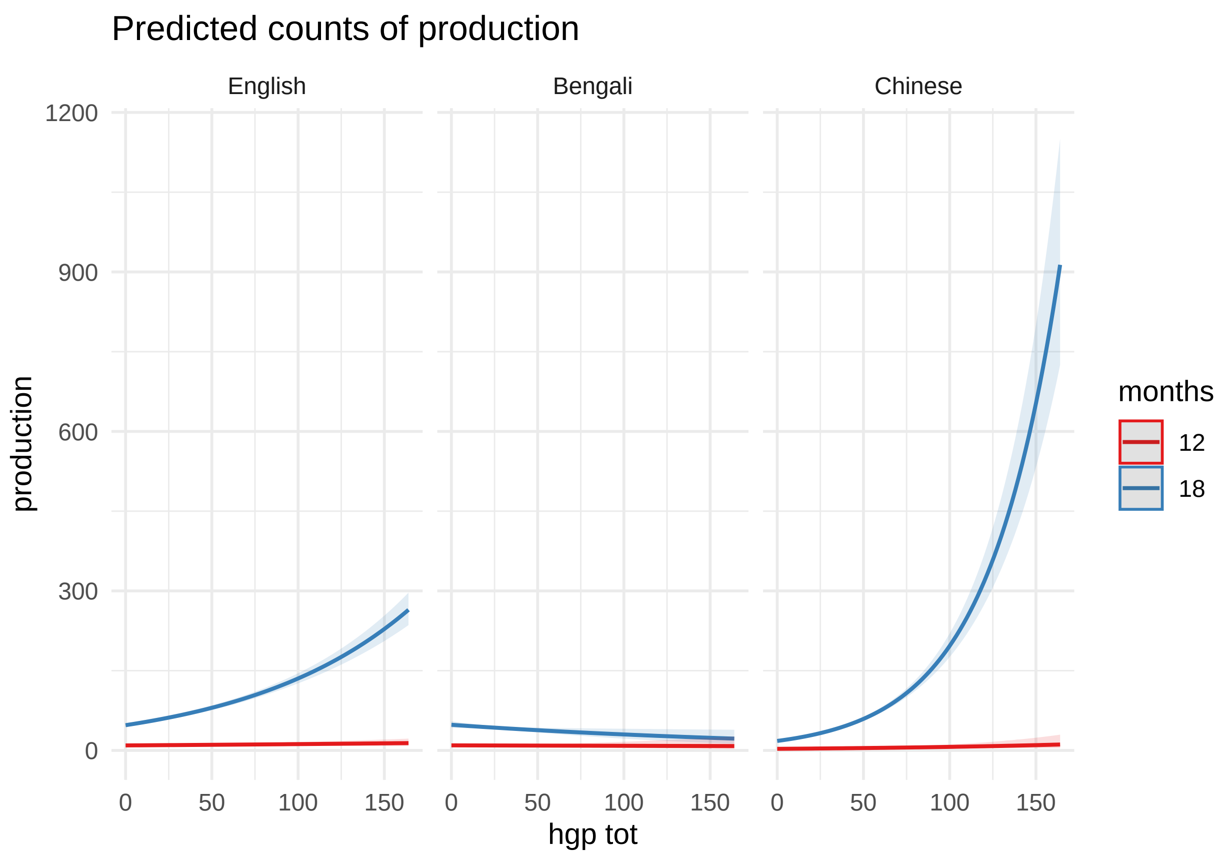

#### 5.2.2 HoGs + point

```
hgp_prod <- glm(
  production ~
    hgp_tot *
    months *
    background,
  data = vocab,
  poisson()
)
summary(hgp_prod)
```

```
##
## Call:
## glm(formula = production ~ hgp_tot * months * background, family = poisson(),
##     data = vocab)
##
## Deviance Residuals:
##      Min        1Q    Median        3Q       Max
## -10.1715   -4.3463   -1.2156    0.8963   28.5549
##
## Coefficients:
##                                       Estimate Std. Error z value Pr(>|z|)
## (Intercept)                           2.245524   0.089517  25.085  < 2e-16
```

```
## hgp_tot                              0.002311   0.001714   1.348   0.1776
## months18                             1.615544   0.097321  16.600  < 2e-16
## backgroundBengali                    0.011640   0.167801   0.069   0.9447
## backgroundChinese                   -1.137042   0.209942  -5.416 6.09e-08
## hgp_tot:months18                     0.008156   0.001776   4.592 4.38e-06
## hgp_tot:backgroundBengali           -0.003219   0.004646  -0.693   0.4883
## hgp_tot:backgroundChinese            0.005629   0.004230   1.331   0.1833
## months18:backgroundBengali           0.003230   0.184145   0.018   0.9860
## months18:backgroundChinese           0.158991   0.223274   0.712   0.4764
## hgp_tot:months18:backgroundBengali -0.011967   0.005105  -2.344   0.0191
## hgp_tot:months18:backgroundChinese  0.007893   0.004380   1.802   0.0715
##
## (Intercept)                        ***
## hgp_tot
## months18                           ***
## backgroundBengali
## backgroundChinese                  ***
## hgp_tot:months18                   ***
## hgp_tot:backgroundBengali
## hgp_tot:backgroundChinese
## months18:backgroundBengali
## months18:backgroundChinese
## hgp_tot:months18:backgroundBengali *
## hgp_tot:months18:backgroundChinese .
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## (Dispersion parameter for poisson family taken to be 1)
##
##     Null deviance: 6616.0  on 108  degrees of freedom
## Residual deviance: 3391.2  on  97  degrees of freedom
##   (11 observations deleted due to missingness)
## AIC: 3854.9
##
## Number of Fisher Scoring iterations: 6
```

```
plot_model(hgp_prod, type = "pred", terms = c("hgp_tot", "months", "background"))
```



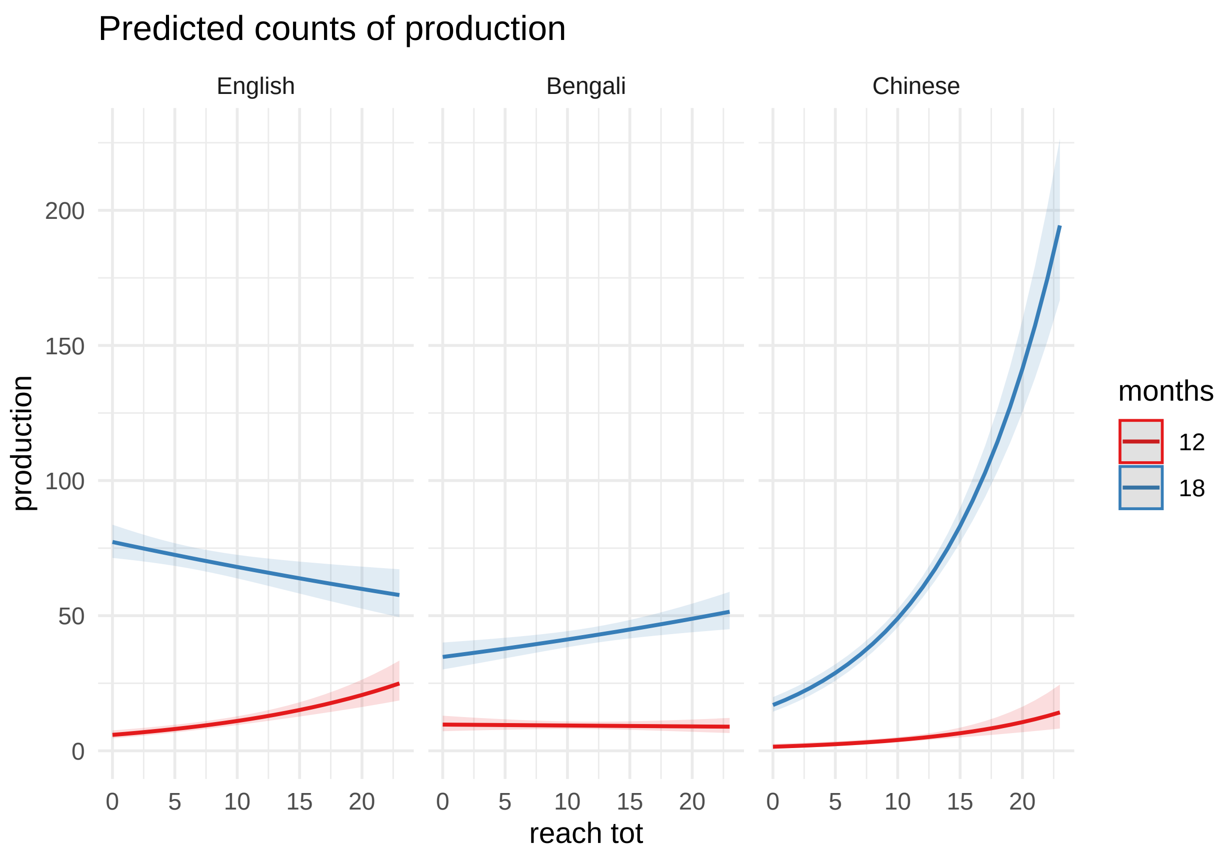

#### 5.2.3 Reaches

```
reach_prod <- glm(
  production ~
    reach_tot *
    months *
    background,
  data = vocab,
  family = poisson()
)
summary(reach_prod)
```

```
##
## Call:
## glm(formula = production ~ reach_tot * months * background, family = poisson(),
##     data = vocab)
##
## Deviance Residuals:
##     Min       1Q   Median       3Q      Max
## -11.152   -4.326   -1.274    1.089   27.720
##
## Coefficients:
##                                        Estimate Std. Error z value Pr(>|z|)
## (Intercept)                             1.77394    0.12626  14.050  < 2e-16
```

```
## reach_tot                              0.06271    0.01005   6.239 4.40e-10
## months18                               2.57343    0.13262  19.405  < 2e-16
## backgroundBengali                      0.49872    0.19502   2.557 0.010549
## backgroundChinese                     -1.36596    0.30542  -4.472 7.73e-06
## reach_tot:months18                    -0.07546    0.01097  -6.877 6.11e-12
## reach_tot:backgroundBengali           -0.06637    0.01531  -4.336 1.45e-05
## reach_tot:backgroundChinese            0.03494    0.02410   1.450 0.147099
## months18:backgroundBengali            -1.29841    0.21214  -6.121 9.32e-10
## months18:backgroundChinese            -0.15125    0.31853  -0.475 0.634915
## reach_tot:months18:backgroundBengali   0.09620    0.01679   5.729 1.01e-08
## reach_tot:months18:backgroundChinese   0.08389    0.02529   3.317 0.000909
##
## (Intercept)                          ***
## reach_tot                            ***
## months18                             ***
## backgroundBengali                    *
## backgroundChinese                    ***
## reach_tot:months18                   ***
## reach_tot:backgroundBengali          ***
## reach_tot:backgroundChinese
## months18:backgroundBengali           ***
## months18:backgroundChinese
## reach_tot:months18:backgroundBengali ***
## reach_tot:months18:backgroundChinese ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## (Dispersion parameter for poisson family taken to be 1)
##
##     Null deviance: 6616.0  on 108  degrees of freedom
## Residual deviance: 3934.9  on  97  degrees of freedom
##   (11 observations deleted due to missingness)
## AIC: 4398.6
##
## Number of Fisher Scoring iterations: 6
```

```
plot_model(reach_prod, type = "pred", terms = c("reach_tot", "months", "background"))
```



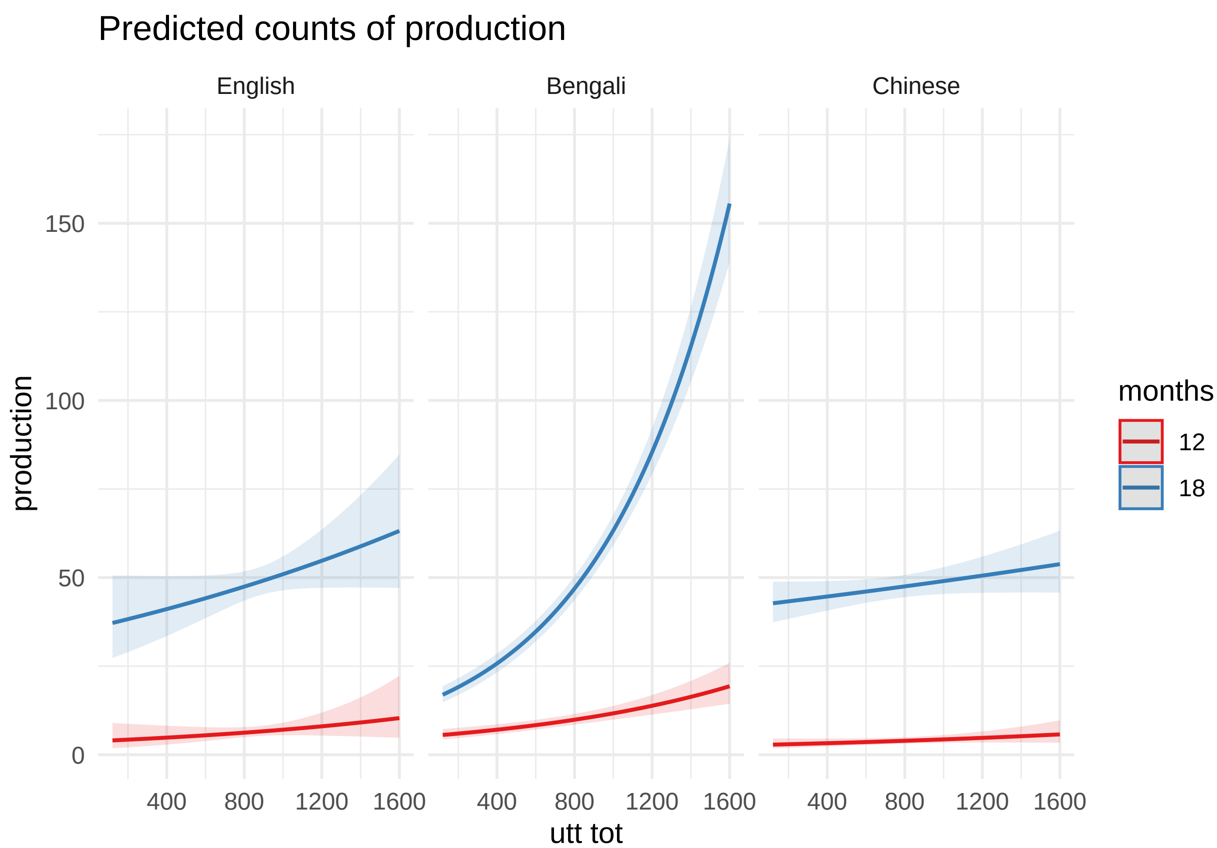

### 5.2.4 Maternal utterances

```
utt_prod <- glm(
  production ~
    utt_tot *
    months *
    background,
  data = vocab,
  family = poisson()
)
summary(utt_prod)
```

```
##
## Call:
## glm(formula = production ~ utt_tot * months * background, family = poisson(),
##     data = vocab)
##
## Deviance Residuals:
##     Min       1Q   Median       3Q      Max
## -15.241   -3.563   -1.206    1.294   21.551
##
## Coefficients:
##                                       Estimate Std. Error z value Pr(>|z|)
## (Intercept)                          1.3192300  0.4676905   2.821  0.00479
```

```
## utt_tot                              0.0006349  0.0005199   1.221  0.22202
## months18                             2.2536527  0.5013805   4.495 6.96e-06
## backgroundBengali                    0.2990578  0.4911280   0.609  0.54258
## backgroundChinese                   -0.3297520  0.5434137  -0.607  0.54397
## utt_tot:months18                    -0.0002767  0.0005571  -0.497  0.61938
## utt_tot:backgroundBengali            0.0002044  0.0005441   0.376  0.70713
## utt_tot:backgroundChinese           -0.0001612  0.0006045  -0.267  0.78978
## months18:backgroundBengali          -1.2230964  0.5287705  -2.313  0.02072
## months18:backgroundChinese           0.4936444  0.5778999   0.854  0.39299
## utt_tot:months18:backgroundBengali   0.0009362  0.0005839   1.603  0.10887
## utt_tot:months18:backgroundChinese -0.0000419  0.0006432  -0.065  0.94806
##
## (Intercept)                        **
## utt_tot
## months18                           ***
## backgroundBengali
## backgroundChinese
## utt_tot:months18
## utt_tot:backgroundBengali
## utt_tot:backgroundChinese
## months18:backgroundBengali         *
## months18:backgroundChinese
## utt_tot:months18:backgroundBengali
## utt_tot:months18:backgroundChinese
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## (Dispersion parameter for poisson family taken to be 1)
##
##     Null deviance: 5308.0  on 98  degrees of freedom
## Residual deviance: 3069.1  on 87  degrees of freedom
##   (21 observations deleted due to missingness)
## AIC: 3480.5
##
## Number of Fisher Scoring iterations: 6
```

```r
plot_model(utt_prod, type = "pred", terms = c("utt_tot", "months", "background"))
```



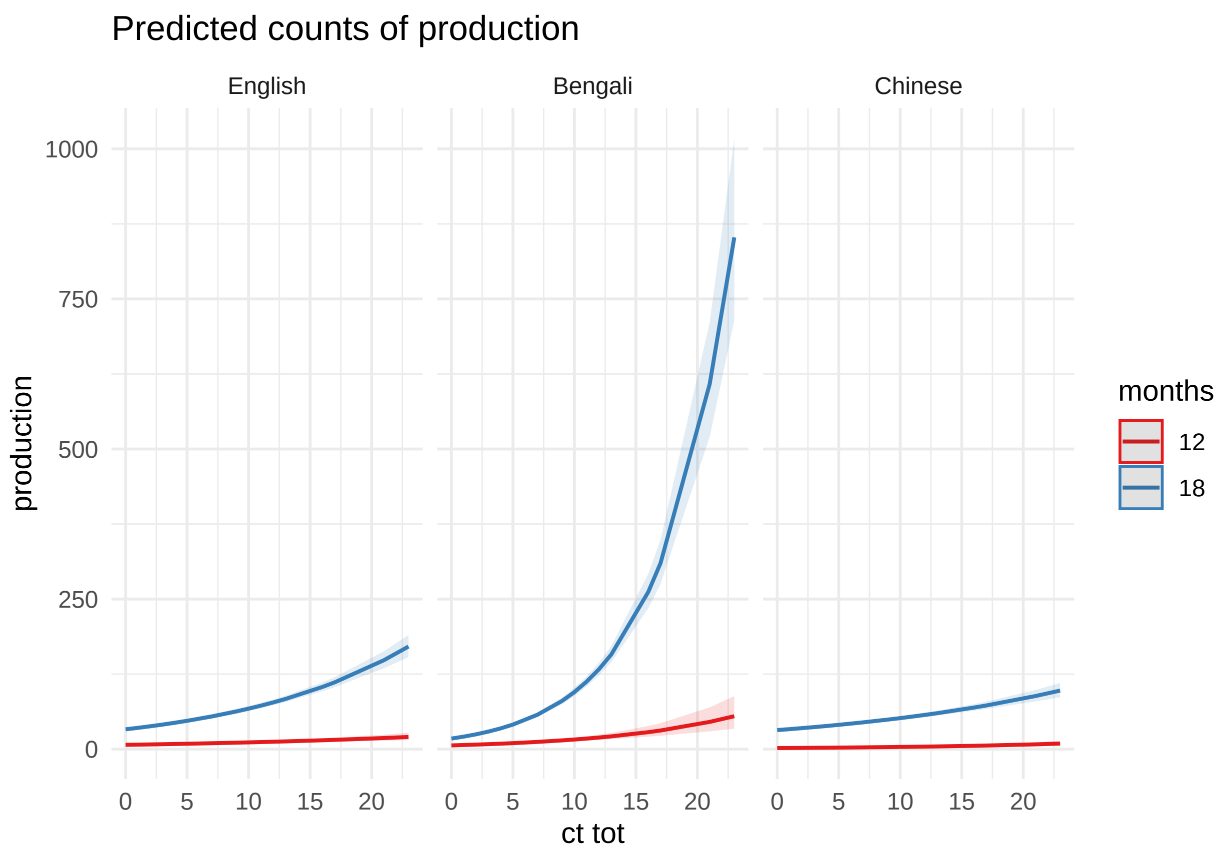

### 5.2.5 Contingent talks

```
ct_prod <- glm(
  production ~
    ct_tot *
    months *
    background,
  data = filter(vocab, ct_tot < 30),
  family = poisson()
)
summary(ct_prod)
```

```
##
## Call:
## glm(formula = production ~ ct_tot * months * background, family = poisson(),
##     data = filter(vocab, ct_tot < 30))
##
## Deviance Residuals:
##     Min       1Q   Median       3Q      Max
## -10.399   -3.871   -1.082    1.232   19.069
##
## Coefficients:
##                                      Estimate Std. Error z value Pr(>|z|)
## (Intercept)                          1.964853   0.116021  16.935  < 2e-16
```

```
## ct_tot                              0.045305   0.009572   4.733 2.21e-06
## months18                            1.530771   0.127526  12.004  < 2e-16
## backgroundBengali                  -0.140679   0.157079  -0.896  0.37047
## backgroundChinese                  -1.389104   0.264167  -5.258 1.45e-07
## ct_tot:months18                     0.026242   0.010293   2.550  0.01078
## ct_tot:backgroundBengali            0.049489   0.016404   3.017  0.00255
## ct_tot:backgroundChinese            0.026008   0.018783   1.385  0.16617
## months18:backgroundBengali         -0.487944   0.175556  -2.779  0.00545
## months18:backgroundChinese          1.348792   0.275822   4.890 1.01e-06
## ct_tot:months18:backgroundBengali   0.047711   0.017752   2.688  0.00719
## ct_tot:months18:backgroundChinese -0.048643   0.019651  -2.475  0.01331
##
## (Intercept)                       ***
## ct_tot                            ***
## months18                          ***
## backgroundBengali
## backgroundChinese                 ***
## ct_tot:months18                   *
## ct_tot:backgroundBengali          **
## ct_tot:backgroundChinese
## months18:backgroundBengali        **
## months18:backgroundChinese        ***
## ct_tot:months18:backgroundBengali **
## ct_tot:months18:backgroundChinese *
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## (Dispersion parameter for poisson family taken to be 1)
##
##     Null deviance: 6123.3  on 104  degrees of freedom
## Residual deviance: 2765.6  on  93  degrees of freedom
##   (1 observation deleted due to missingness)
## AIC: 3209.7
##
## Number of Fisher Scoring iterations: 6
```

```r
plot_model(ct_prod, type = "pred", terms = c("ct_tot", "months", "background"))
```


Predicted counts of production
English
Bengali
Chinese
1000
750
500
250
0
production
0
5
10
15
20
ct tot
months
12
18

# 6 R session

```r
sessionInfo()
```

```
## R version 3.5.3 (2019-03-11)
## Platform: x86_64-apple-darwin15.6.0 (64-bit)
## Running under: macOS Mojave 10.14.5
##
## Matrix products: default
## BLAS: /Library/Frameworks/R.framework/Versions/3.5/Resources/lib/libRblas.0.dylib
## LAPACK: /Library/Frameworks/R.framework/Versions/3.5/Resources/lib/libRlapack.dylib
##
## locale:
## [1] en_GB.UTF-8/en_GB.UTF-8/en_GB.UTF-8/C/en_GB.UTF-8/en_GB.UTF-8
##
## attached base packages:
## [1] stats     graphics  grDevices utils     datasets  methods   base
##
## other attached packages:
##  [1] sjPlot_2.6.3      simr_1.0.5        effects_4.1-1
##  [4] carData_3.0-2     lmerTest_3.1-0    lme4_1.1-21
##  [7] Matrix_1.2-17     tidymv_2.2.0      itsadug_2.3
## [10] plotfunctions_1.3 mgcv_1.8-28       nlme_3.1-140
## [13] forcats_0.4.0     stringr_1.4.0     dplyr_0.8.2
## [16] purrr_0.3.2       readr_1.3.1       tidyr_0.8.3
## [19] tibble_2.1.3      ggplot2_3.2.0     tidyverse_1.2.1
## [22] MASS_7.3-51.4
##
## loaded via a namespace (and not attached):
##  [1] TH.data_1.0-10      minqa_1.2.4         colorspace_1.4-1
##  [4] rio_0.5.16          sjlabelled_1.1.0    snakecase_0.11.0
##  [7] estimability_1.3    rstudioapi_0.10     glmmTMB_0.2.3
## [10] mvtnorm_1.0-11      lubridate_1.7.4     xml2_1.2.0
## [13] codetools_0.2-16    splines_3.5.3       mnormt_1.5-5
## [16] knitr_1.23          sjmisc_2.8.1        jsonlite_1.6
## [19] nloptr_1.2.1        ggeffects_0.11.0    pbkrtest_0.4-7
## [22] broom_0.5.2         binom_1.1-1         compiler_3.5.3
## [25] httr_1.4.0          sjstats_0.17.5      emmeans_1.3.5.1
## [28] backports_1.1.4     assertthat_0.2.1    lazyeval_0.2.2
## [31] survey_3.36         cli_1.1.0           htmltools_0.3.6
## [34] tools_3.5.3         coda_0.19-2         gtable_0.3.0
## [37] glue_1.3.1          Rcpp_1.0.1          cellranger_1.1.0
## [40] iterators_1.0.10    psych_1.8.12        insight_0.4.0
## [43] xfun_0.8            openxlsx_4.1.0.1    rvest_0.3.4
## [46] zoo_1.8-6           scales_1.0.0        hms_0.4.2
## [49] parallel_3.5.3      sandwich_2.5-1      RColorBrewer_1.1-2
## [52] TMB_1.7.15          yaml_2.2.0          curl_3.3
## [55] stringi_1.4.3       bayestestR_0.2.2    plotrix_3.7-6
## [58] boot_1.3-22         zip_2.0.3           rlang_0.4.0
## [61] pkgconfig_2.0.2     evaluate_0.14       lattice_0.20-38
## [64] labeling_0.3        tidyselect_0.2.5    plyr_1.8.4
## [67] magrittr_1.5        R6_2.4.0            generics_0.0.2
```

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## [70] multcomp_1.4-10     RLRsim_3.1-3        DBI_1.0.0
## [73] pillar_1.4.2        haven_2.1.0         foreign_0.8-71
## [76] withr_2.1.2         survival_2.44-1.1   abind_1.4-5
## [79] nnet_7.3-12         performance_0.2.0   modelr_0.1.4
## [82] crayon_1.3.4        car_3.0-3           rmarkdown_1.13
## [85] grid_3.5.3          readxl_1.3.1        data.table_1.12.2
## [88] digest_0.6.19       xtable_1.8-4        numDeriv_2016.8-1.1
## [91] munsell_0.5.0       mitools_2.4
```