

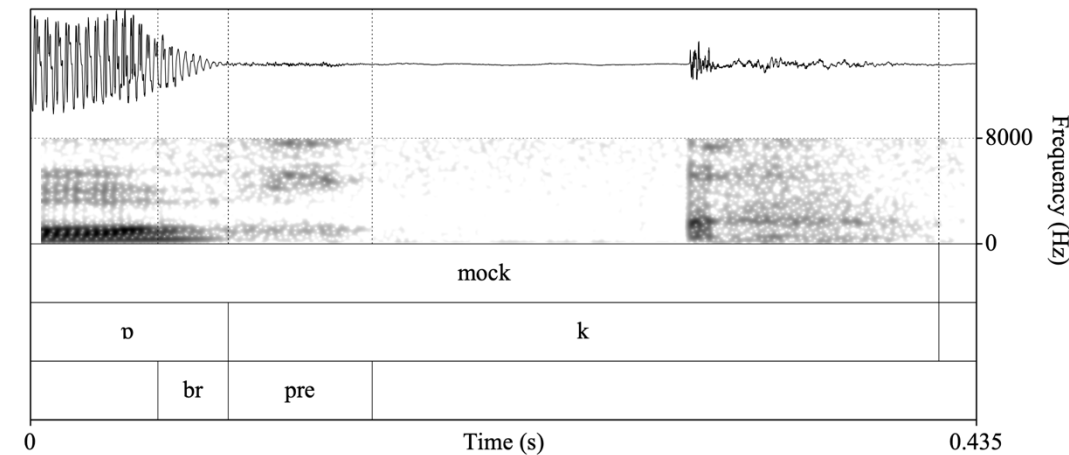
Testing indirect effects in lifespan change: A Structural Equation Modelling approach to Queen Elizabeth II's pre-aspiration

Thomas Kettig¹, Míša Hejná², Noah Henry³

¹York University, ²Aarhus Universitet, ³Universität Innsbruck

Pre-aspiration

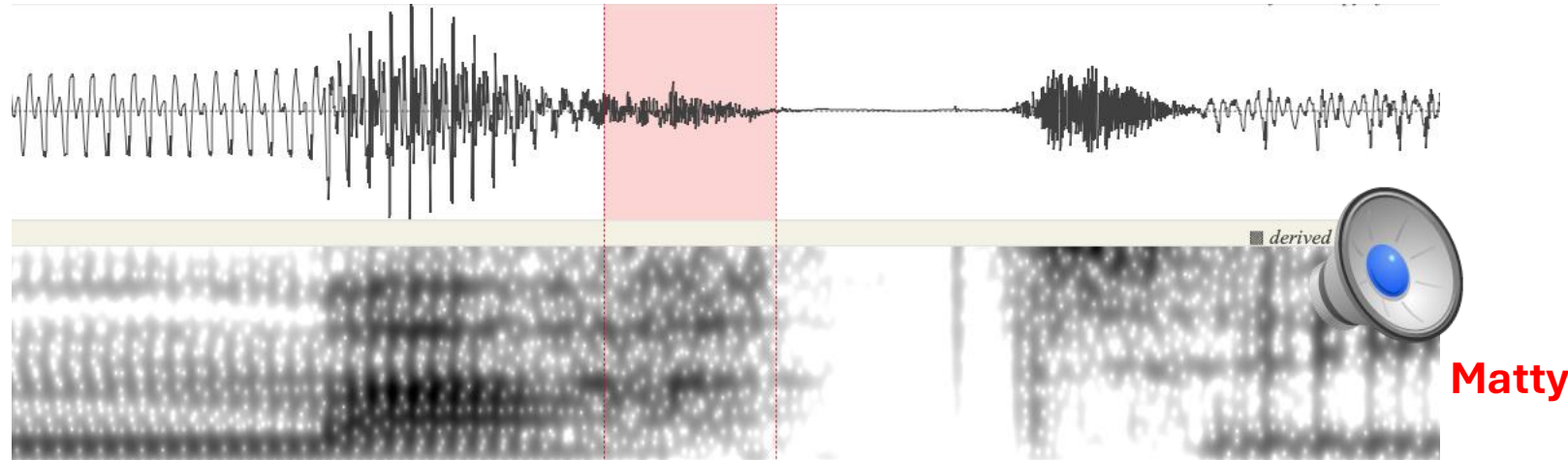
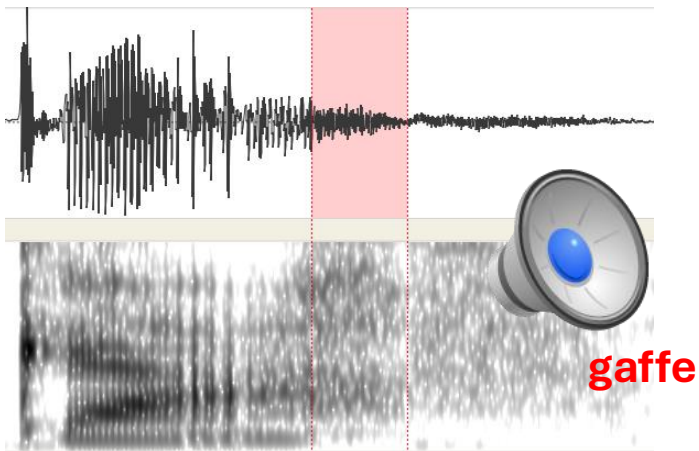
- **Glottal friction** that may occur in sequences of sonorants and phonetically voiceless obstruents
- Favoured (Hejné 2025)
 - by low vowels (vs high)
 - by phonologically short vowels (vs long)
 - by posterior places of articulation (vs anterior: /k, t, p/)
 - by prosodically prominent positions (lexical and other types of prominence)
- Noted in an **increasing number** of English accents in the UK, North America, and Aus/NZ



Welsh English 'mock'

Pre-aspiration

- Kettig (2015) found it all over in age 18–24 SSBE speakers when attempting to measure the duration of various /æ/ words



- Is it actually an innovation? Or are we just looking more closely at speech and finding it where it was rarely observed before?

Our case study: QEII

- If she pre-aspirated, then it's not innovative in SSBE
- Maybe there's age grading: are younger people more pre-aspirating?
- We have lots of data from her: Christmas speeches provide a single-style longitudinal dataset from 1952 onwards
- Can investigate both age- and phonological environment-related variation in pre-aspiration



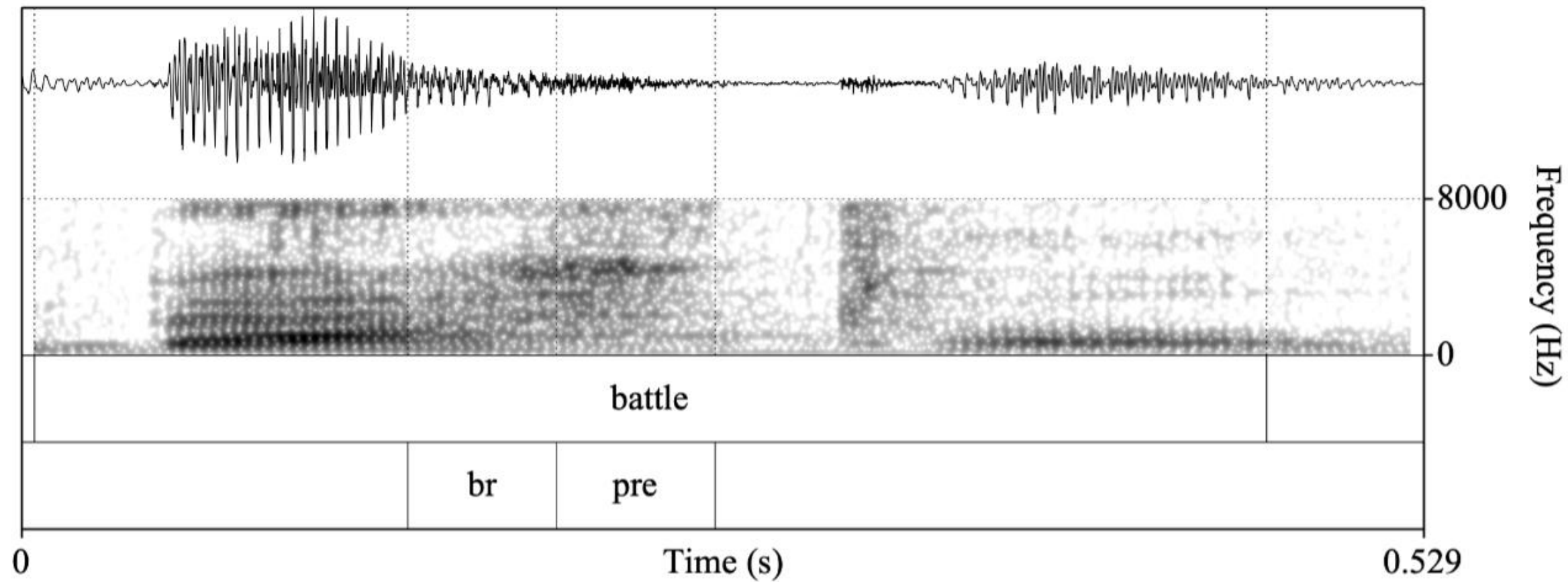
pre-aspirated “battle”

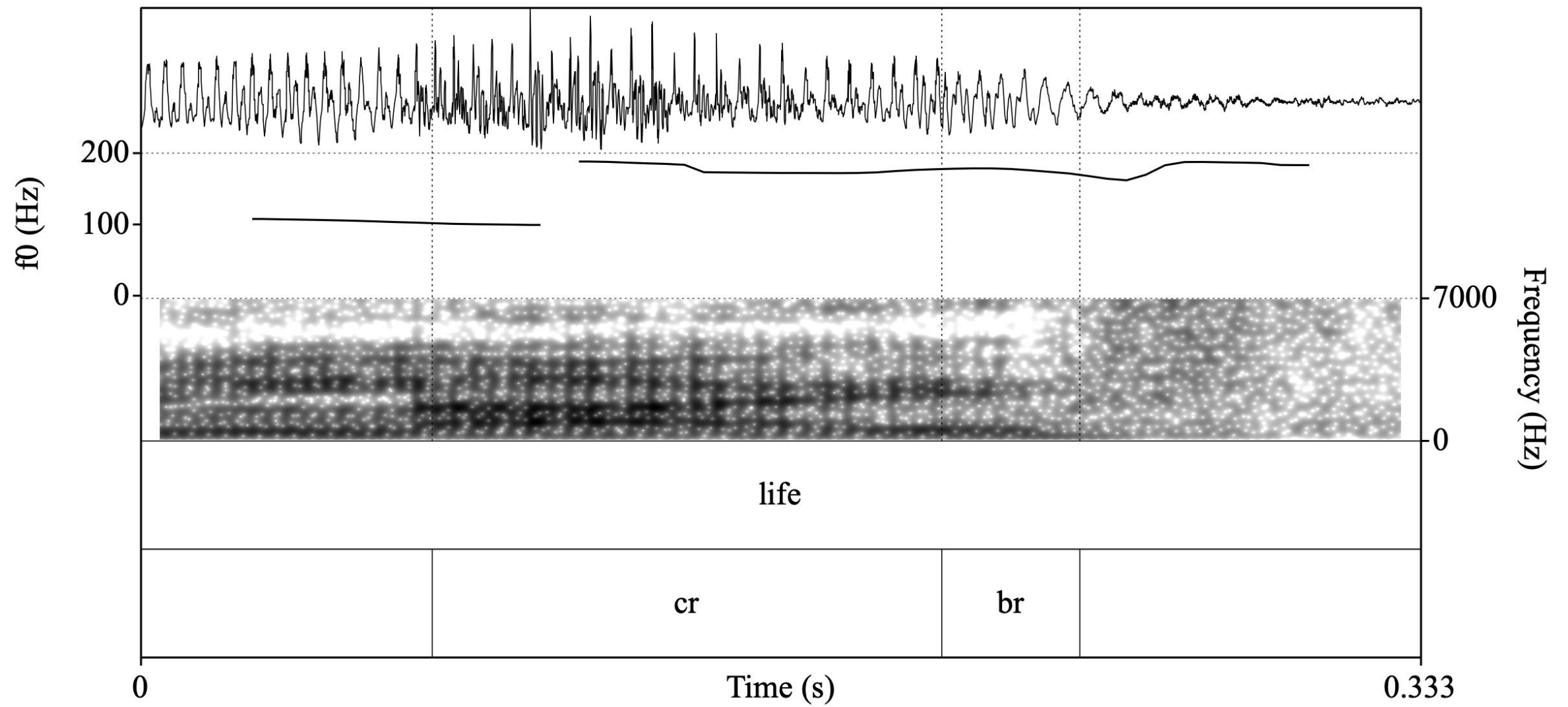
Relationship to voice quality

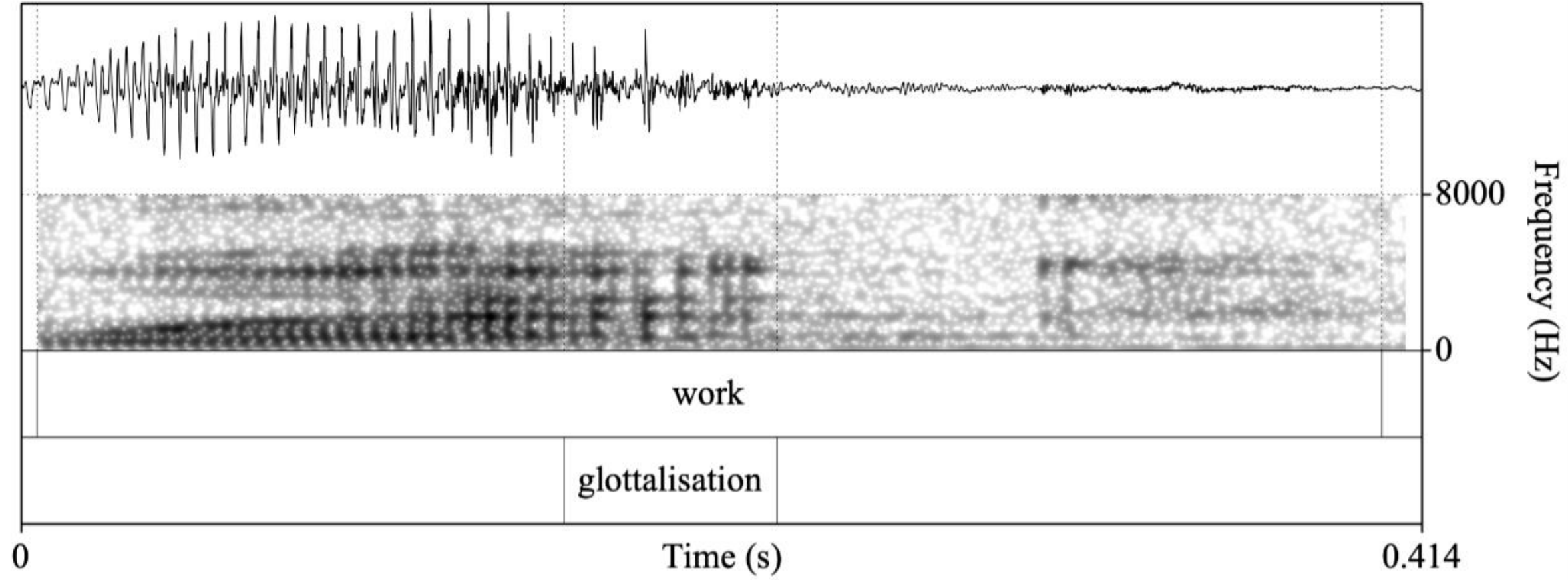
- Pre-aspiration (almost) always accompanied by local breathy voice, only rarely accompanied by glottalization (creak)
- Breathiness and glottalization can be subject to agentive/social variation, but also physiological aging processes
 - Mixed findings in the lit regarding increasing creakiness with age (e.g. Gittelsohn et al. 2021, Grama et al. 2023), not sure about breathiness (?)
 - But no (?) longitudinal studies on local phonatory variation – all research seems to be apparent-time, or longitudinal but on f0 or overall measures
- So how might breathiness and glottalization relate to pre-aspiration? Maybe age affects voice quality, which in turn feeds or bleeds pre-aspiration!

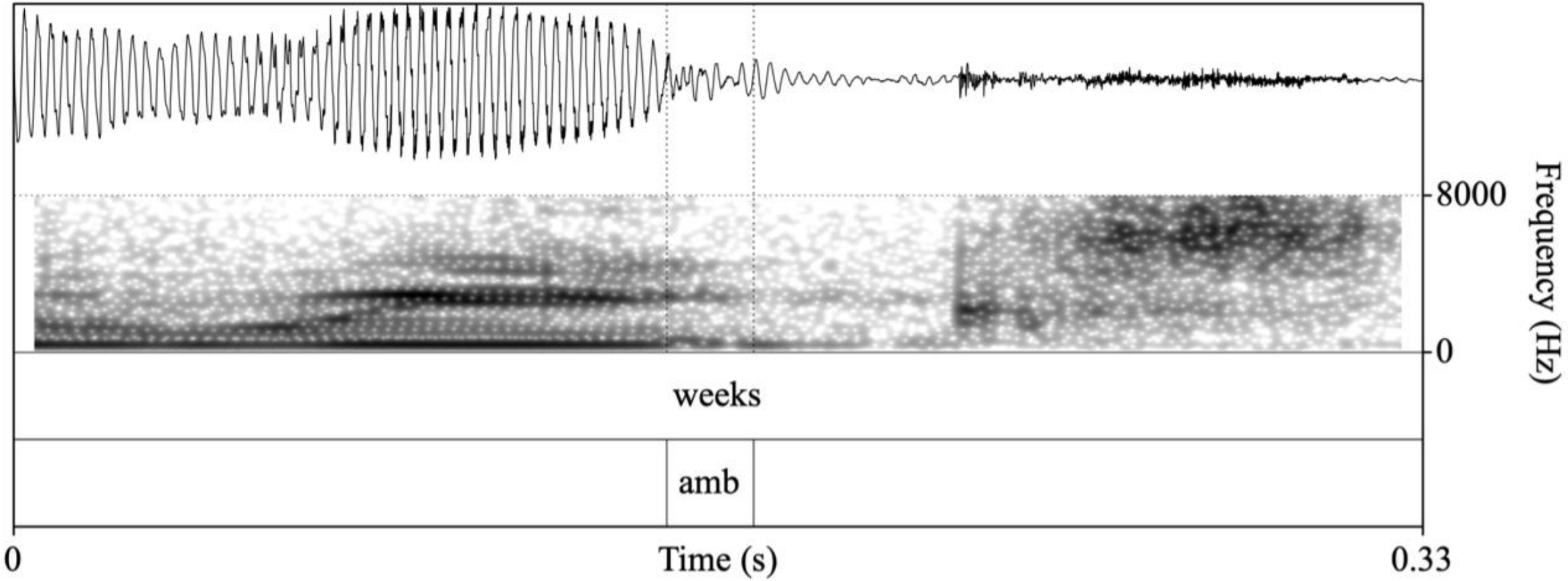
Coding acoustic data

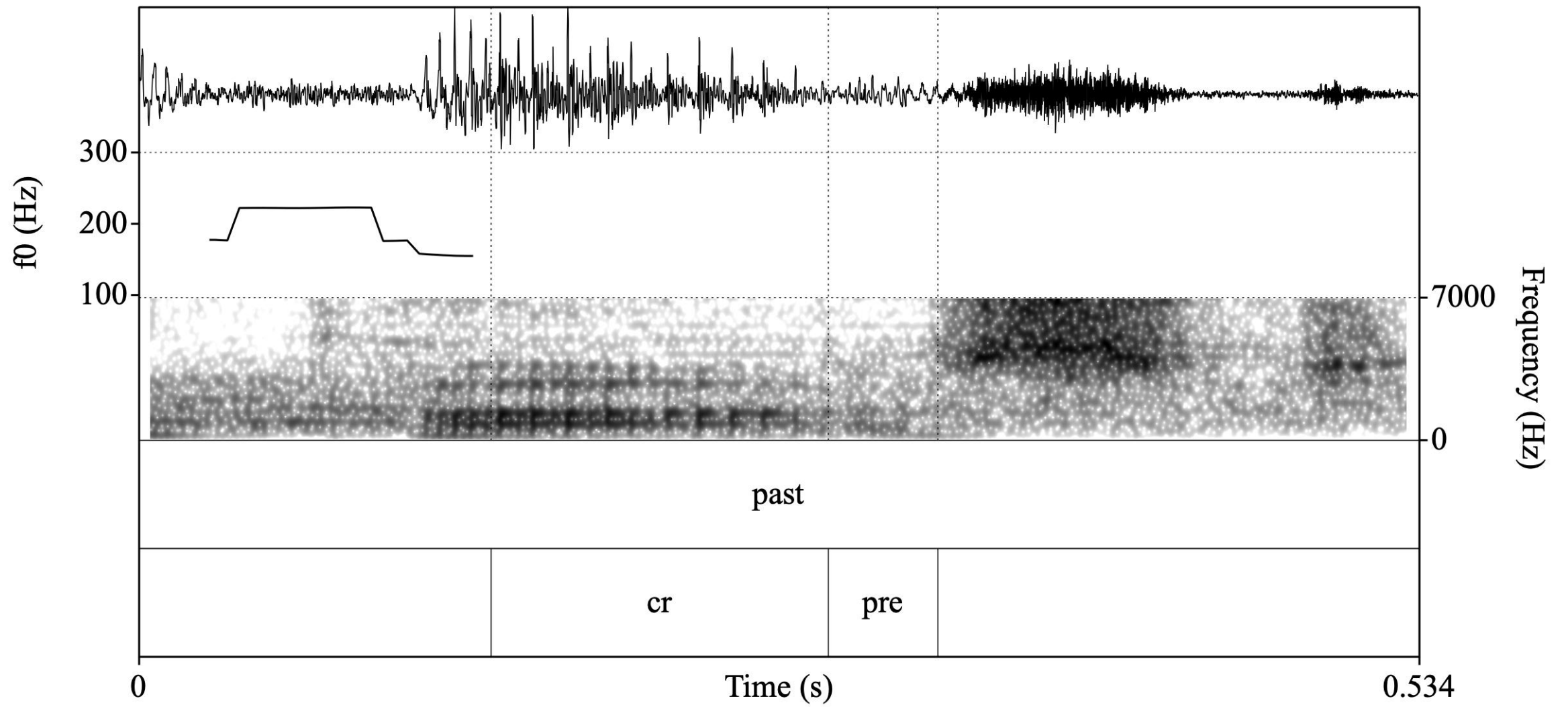
- Identified all possible pre-aspiration environments through 18 speeches from 1952 (age 26) to 2018 (age 92)
 - Stressed vowel + voiceless obstruent sequences: 2,061 tokens
- Voiceless **pre-aspiration** identified by presence of voiceless friction dispersed across different frequencies
- Local **breathiness** identified by an increase in glottal friction following the modal part of the vowel
- **Glottalization** identified as a period of irregular phonation or a sudden drop in f0
- Each phenomenon coded for binary presence/absence, since archival quality of data not high enough for exact durations



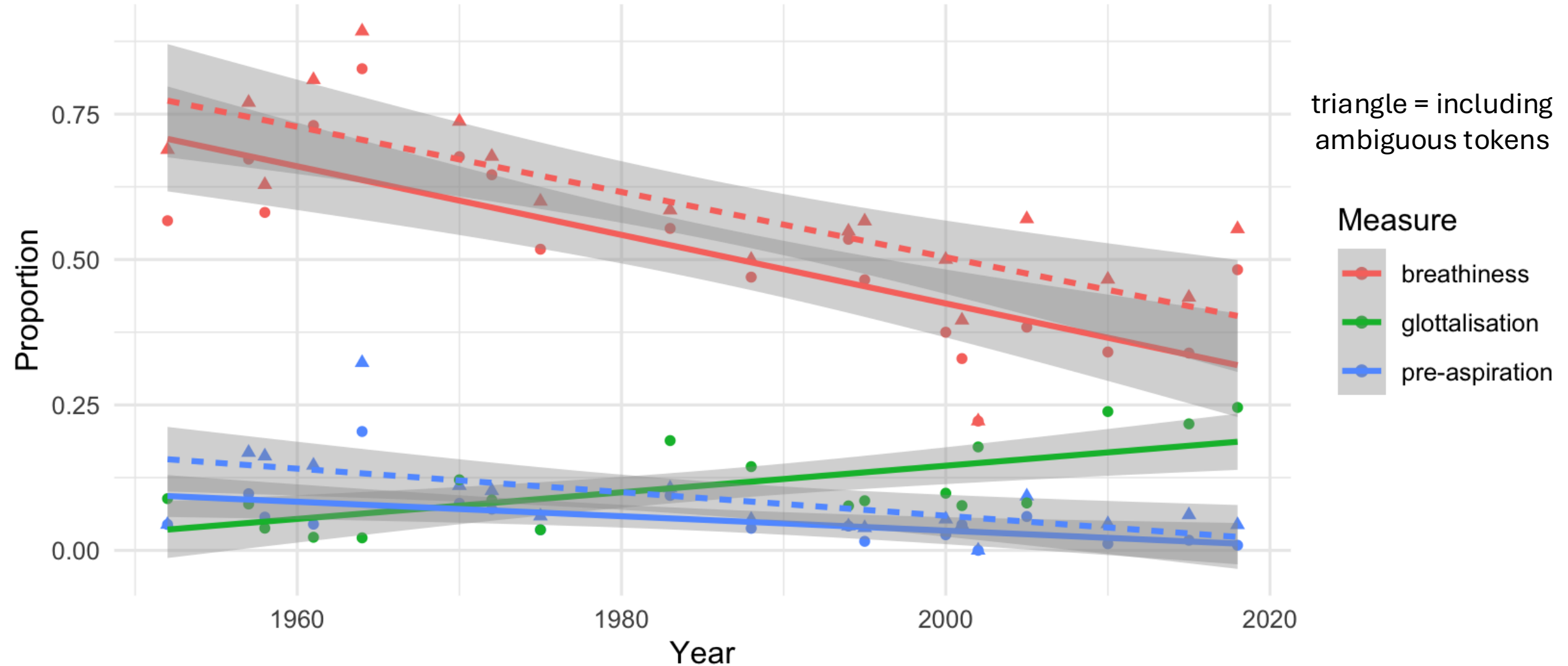




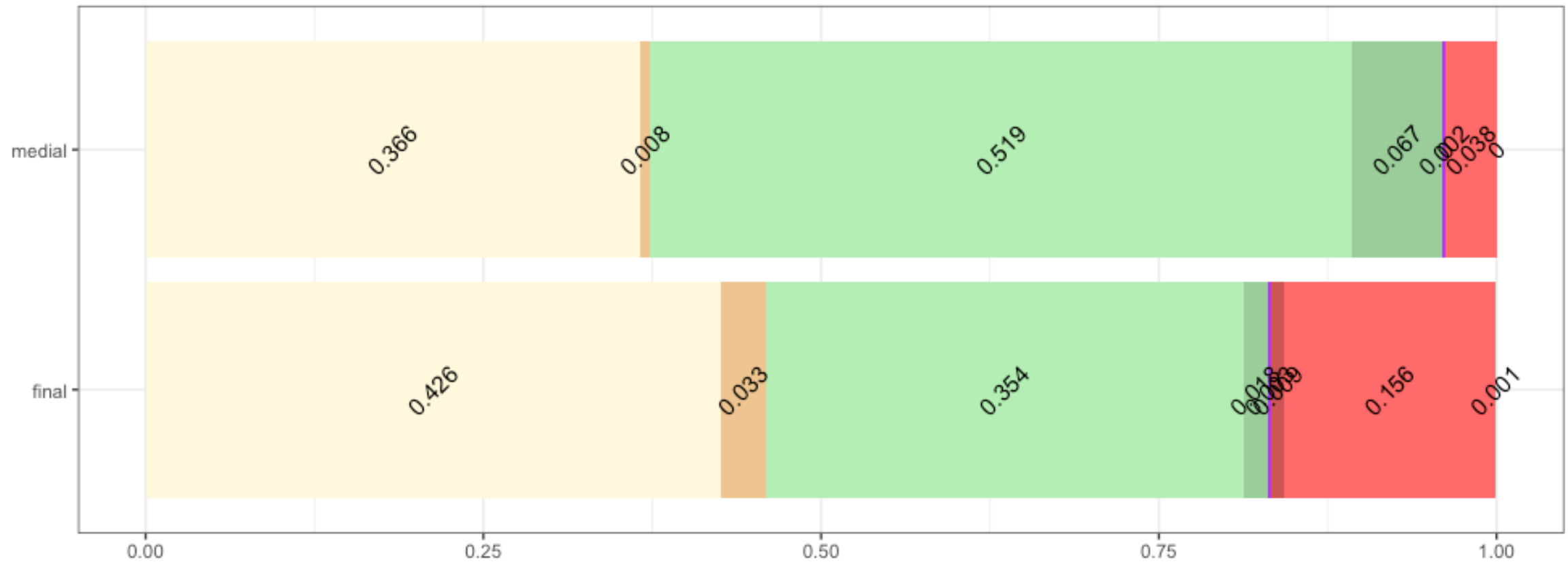




What the longitudinal data look like:



Co-occurrence of pre-aspiration, breathiness, and glottalisation within tokens

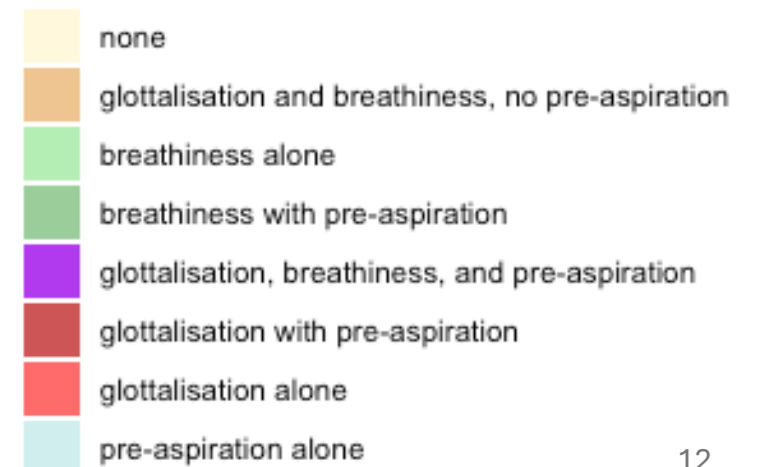


Foot-medial vs. foot-final makes a difference

Matty

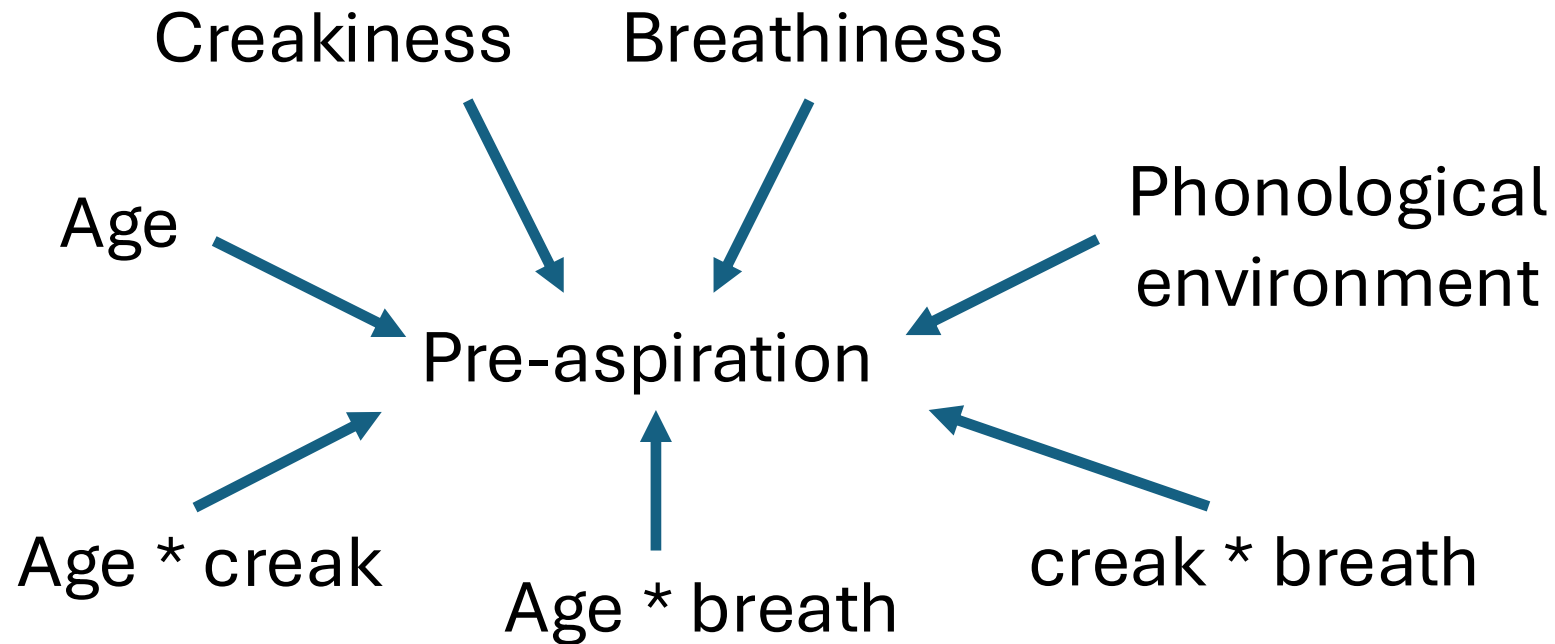
Matt

(Kettig & Hejná 2026)

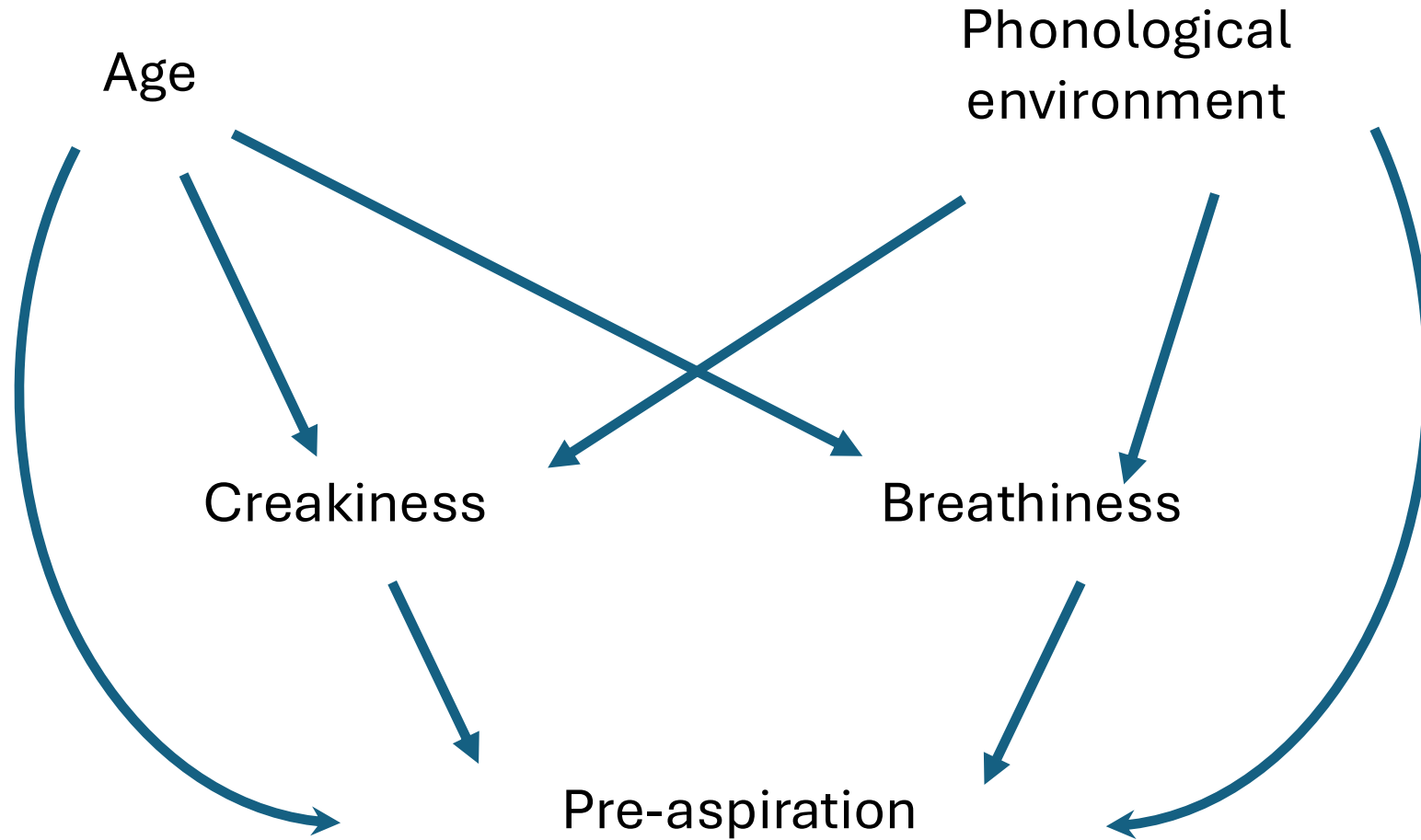


How we might be tempted to model it with glmer

$\text{pre} \sim \text{age} + \text{creakiness} + \text{breathiness} + \text{environment} + (1|\text{word})$

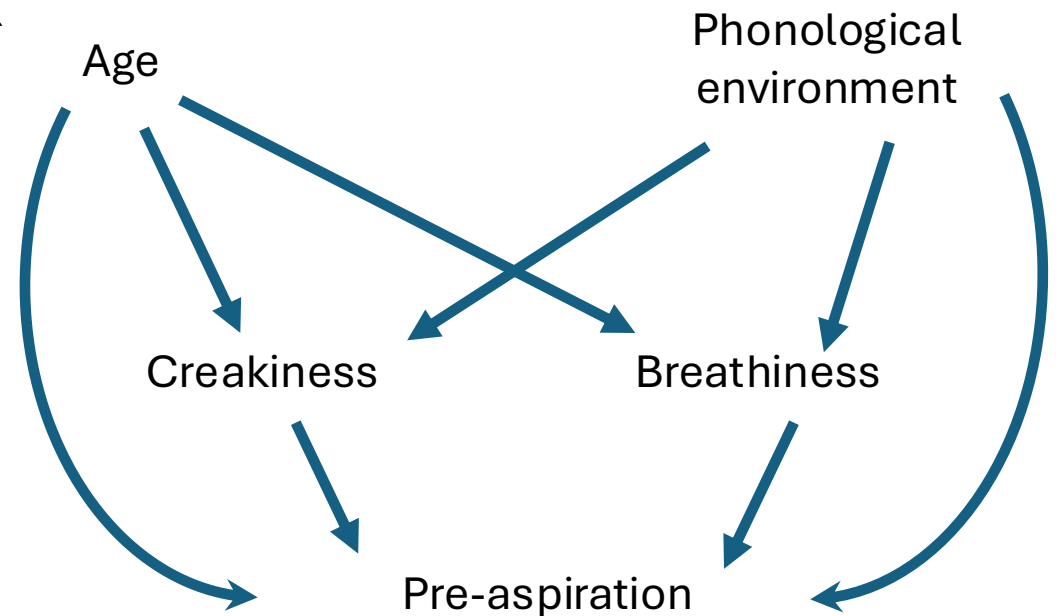


But what if we think there might be indirect effects?



Mediation analysis

- Indirect effect: the portion of a predictor's (X) influence on an outcome (Y) that is explained by X influencing a mediator (M) which in turn influences Y (Agler & De Boeck 2017)
 - $X \rightarrow M$ = path a
 - $M \rightarrow Y$ = path b
 - Indirect effects are estimated as the product of coefficients of these paths (i.e., $a \times b$)
- Bayesian mediation (Yuan & McKinnon 2009) using brms package in R (Bürkner 2017)
- First estimate all direct effects in the model, then take posterior draws of those parameters to compute indirect effects and their credible intervals
- We use logit link function since all endogenous variables are binary here



Our mediation analysis for this dataset

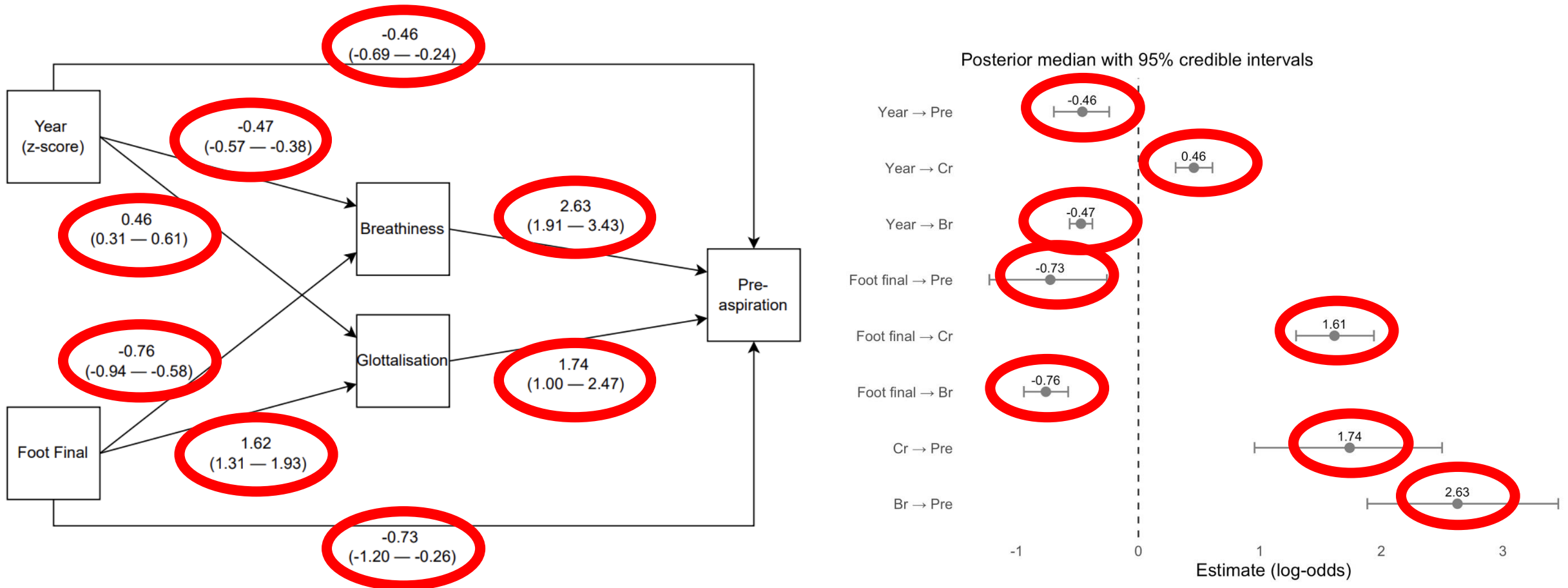
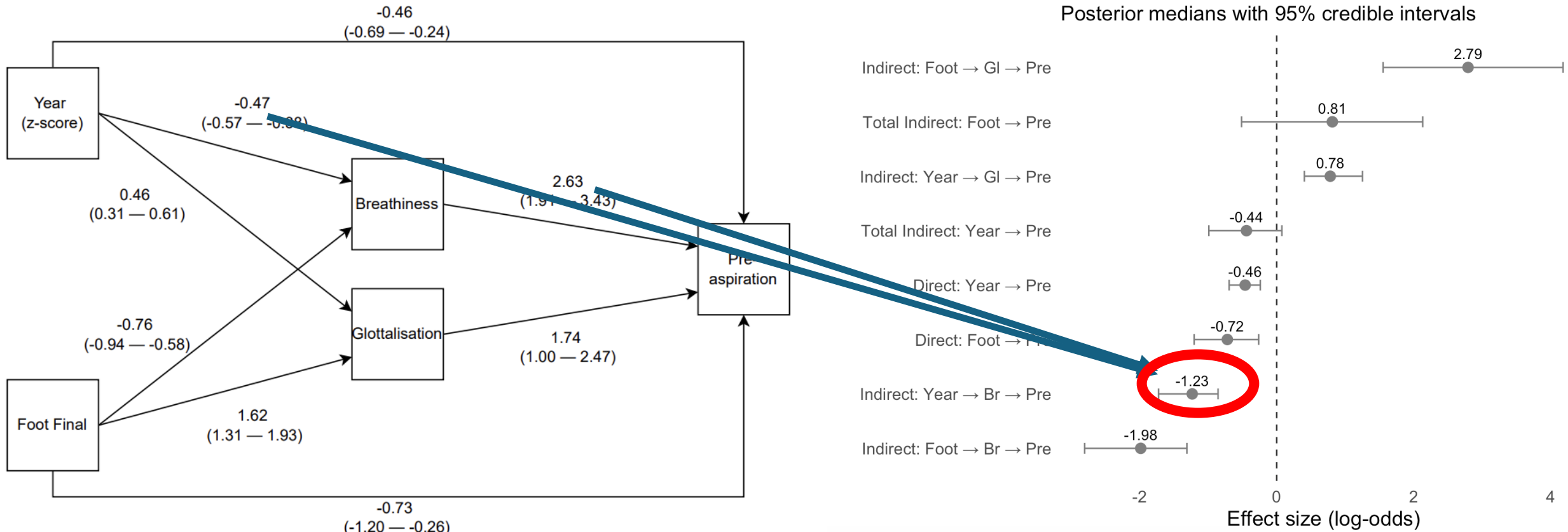


Fig. 1. Summary of direct effects within the model. Estimates represent log-odds with 95% credible intervals.

Our mediation analysis for this dataset



Our mediation analysis for this dataset

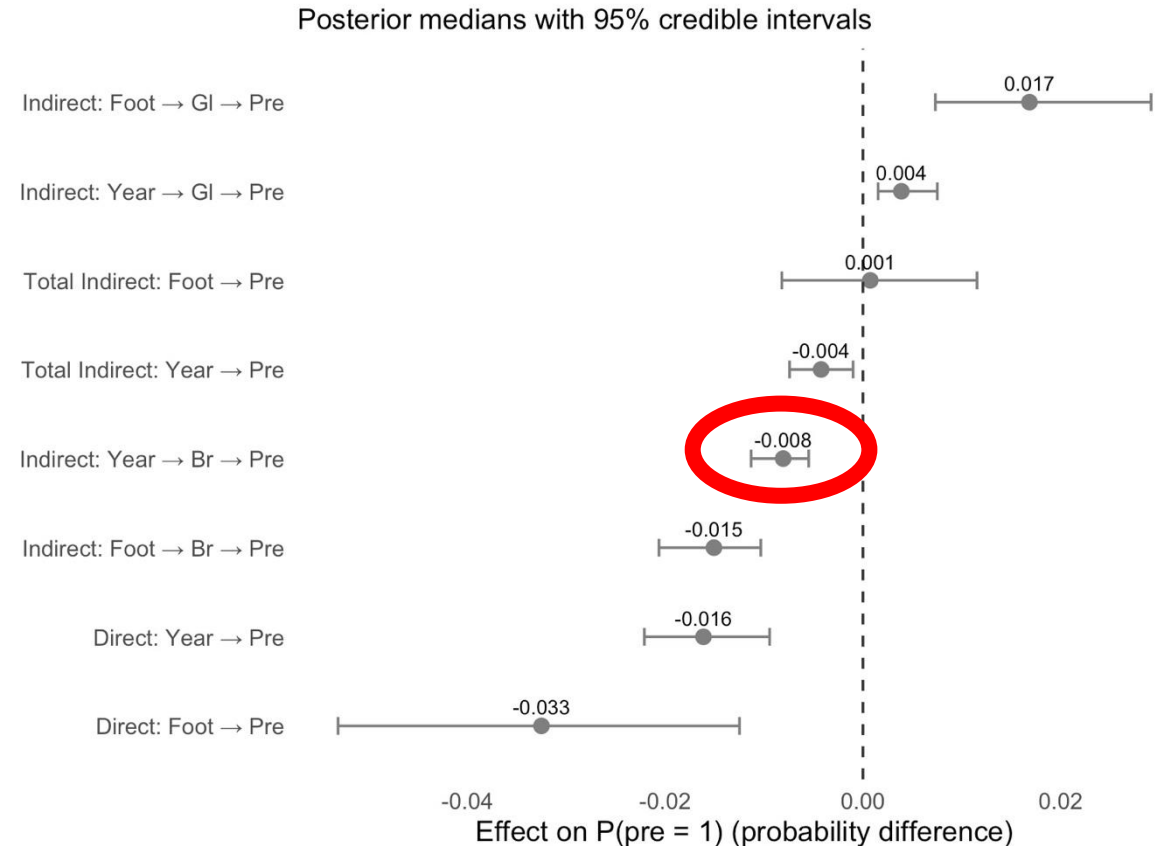
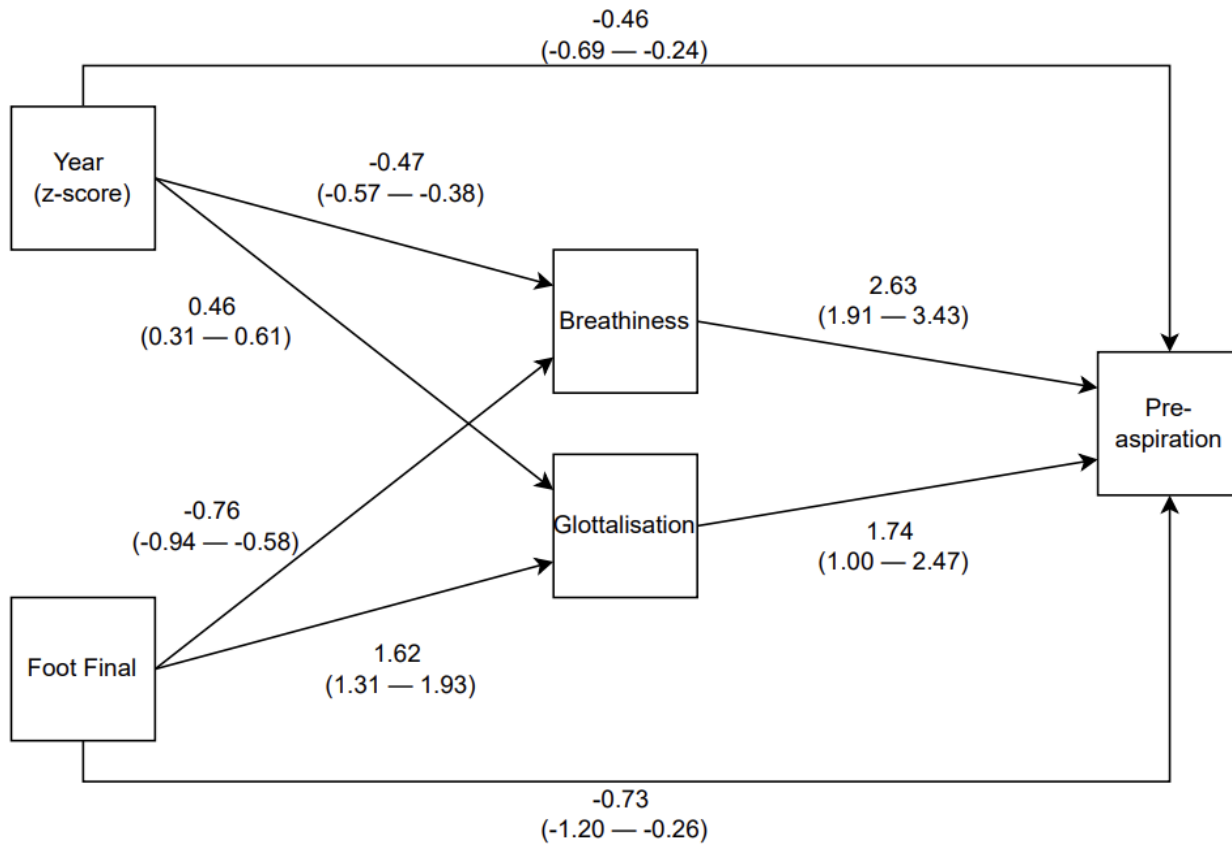
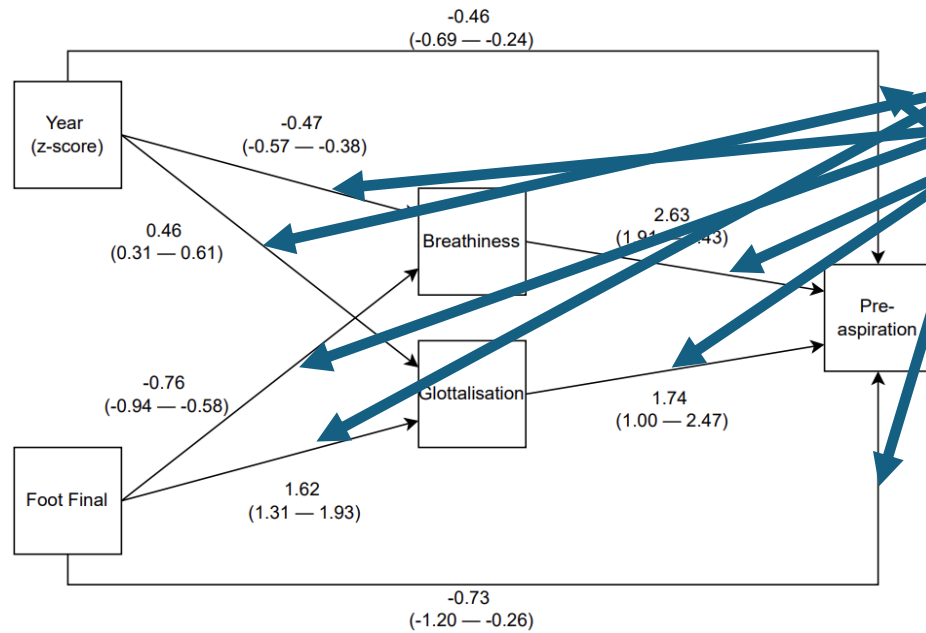


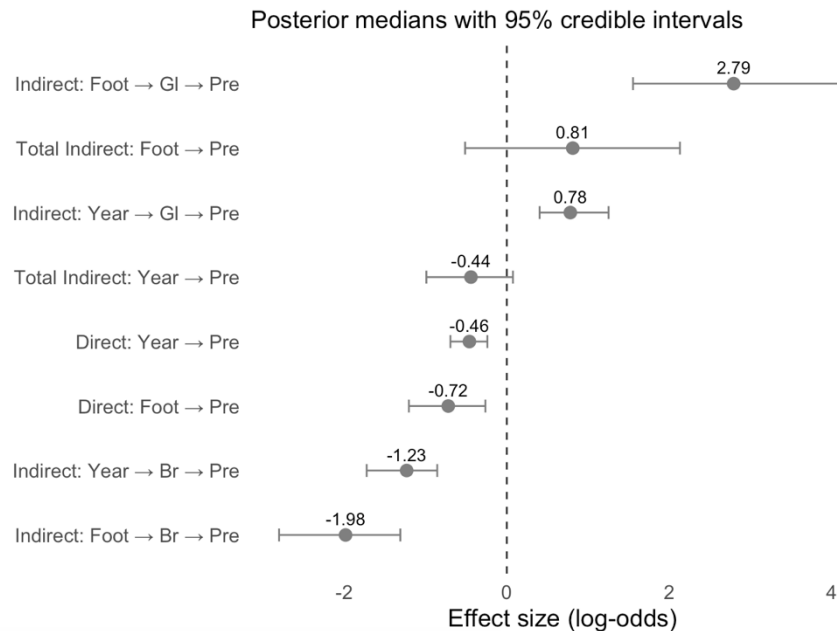
Fig. 1. Summary of direct effects within the model. Estimates represent log-odds with 95% credible intervals. **Fig. 2.** Summary of indirect effects within model. Estimates represent log-odds with 95% credible intervals.

(after Imai et al. 2010 algorithm run to account for these being logistic regressions rather than linear – thanks Morgan Sonderegger for pointing this out, and Josh Lee for implementation method!)



```
# specific effects
bf_cr <- bf(cr ~ Year_scaled + foot_final, family = bernoulli(link = "logit"))
bf_br <- bf(br ~ Year_scaled + foot_final, family = bernoulli(link = "logit"))
bf_pre <- bf(pre ~ Year_scaled + foot_final + cr + br, family = bernoulli(link = "logit"))

# fit model
fit_brms_med_o <- brm(bf_cr + bf_br + bf_pre + set_rescor(FALSE),
  data = aggregated_data_NoInitial,
  chains = 4,
  cores = 4,
  iter = 4000,
  control = list(adapt_delta = 0.95))
```

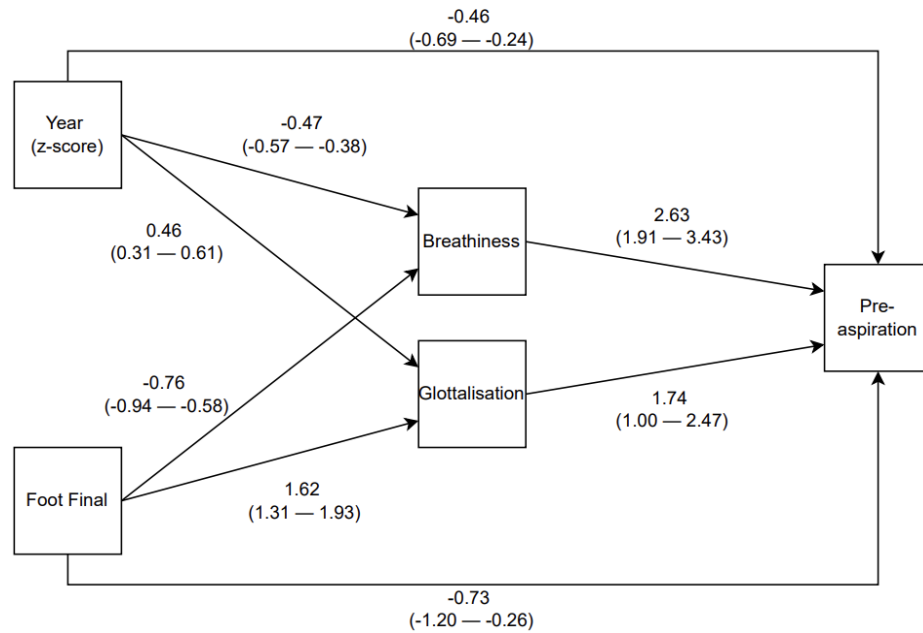


```
#### posterior indirect effects (08/01/2026) ####

# extract posterior draws
posterior <- posterior_samples(fit_brms_med_o)

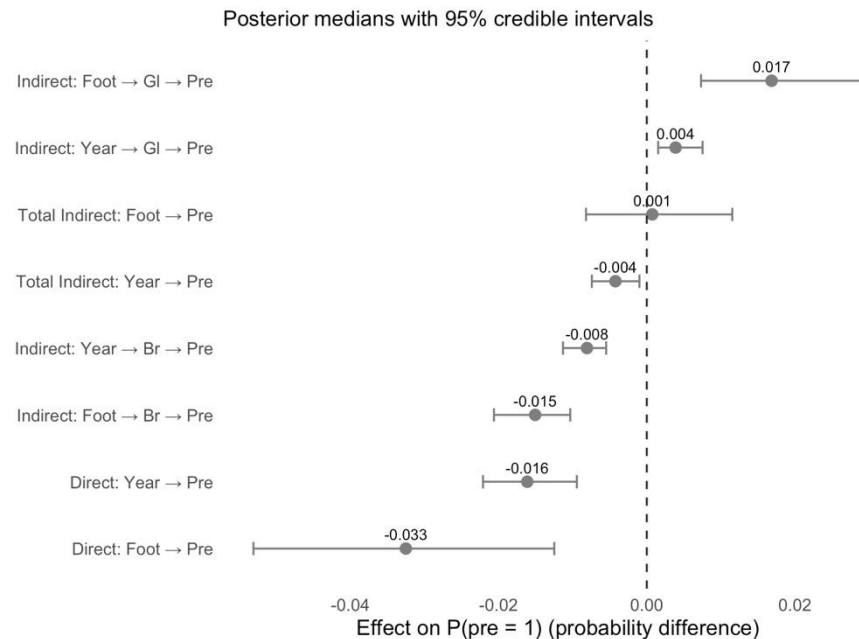
# compute indirect effects for each posterior draw
posterior <- posterior |>
  mutate(
    # indirect effects for Year
    indirect_cr_Year = b_pre_cr * b_cr_Year_scaled,
    indirect_br_Year = b_pre_br * b_br_Year_scaled,
    total_indirect_Year = indirect_cr_Year + indirect_br_Year,
    direct_Year = b_pre_Year_scaled,

    # indirect effects for foot_final
    indirect_cr_FF = b_pre_cr * b_cr_foot_final,
    indirect_br_FF = b_pre_br * b_br_foot_final,
    total_indirect_FF = indirect_cr_FF + indirect_br_FF,
    direct_FF = b_pre_foot_final)
```



```
# specific effects
bf_cr <- bf(cr ~ Year_scaled + foot_final, family = bernoulli(link = "logit"))
bf_br <- bf(br ~ Year_scaled + foot_final, family = bernoulli(link = "logit"))
bf_pre <- bf(pre ~ Year_scaled + foot_final + cr + br, family = bernoulli(link = "logit"))

# fit model
fit_brms_med_o <- brm(bf_cr + bf_br + bf_pre + set_rescor(FALSE),
  data = aggregated_data_NoInitial,
  chains = 4,
  cores = 4,
  iter = 4000,
  control = list(adapt_delta = 0.95))
```



```
#### posterior indirect effects (08/01/2026) ####

# extract posterior draws
posterior <- posterior_samples(fit_brms_med_o)

# compute indirect effects for each posterior draw
posterior <- posterior |>
  mutate(
    # indirect effects for Year
    indirect_cr_Year = b_pre_cr * b_cr_Year_scaled,
    indirect_br_Year = b_pre_br * b_br_Year_scaled,
    total_indirect_Year = indirect_cr_Year + indirect_br_Year,
    direct_Year = b_pre_Year_scaled,

    # indirect effects for foot_final
    indirect_cr_FF = b_pre_cr * b_cr_foot_final,
    indirect_br_FF = b_pre_br * b_br_foot_final,
    total_indirect_FF = indirect_cr_FF + indirect_br_FF,
    direct_FF = b_pre_foot_final)
```

(after Imai et al. 2010 algorithm applied)

Summary

- Mediated modelling approaches could help us better approach situations where we suspect indirect effects
- Our case study here has various limitations (binary coding, relatively small data, single speaker) but this approach should be able to handle lots of data structures and hypotheses
- Not many people in socio/phonetics doing this, but on the rise!
 - Cohen-Priva & Gleason (2020) on lenition
 - Coretta (2026) on intrinsic vowel duration
 - Lipari et al. (2026) on social vs. physiological variation in /s/
 - Brown & Sonderegger (2026) on social vs. physiological variation in F0
 - Byun & Lee (2026) on vowel devoicing and duration
- Would be very useful to add to our toolkit as sociolinguists!