Toward modelling indirect effects in longitudinal phonetics research: The case of Queen Elizabeth II's age, voice quality, and pre-aspiration

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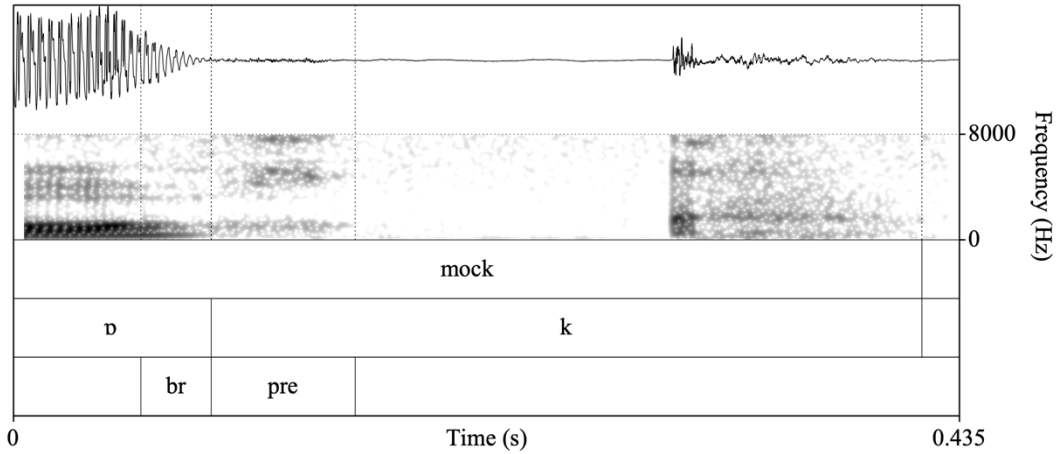
Pre-aspiration

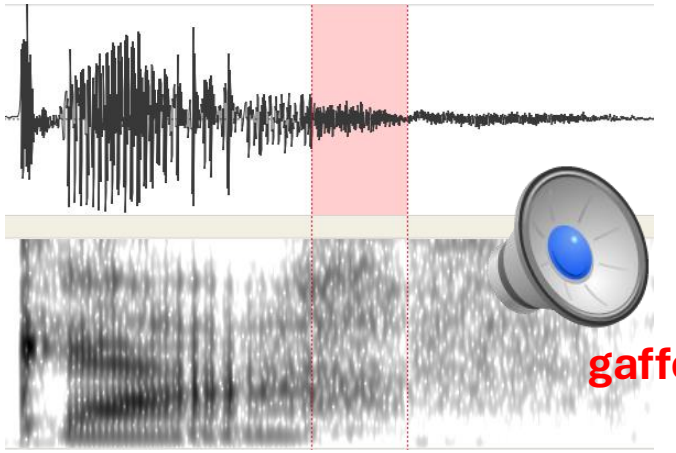
- **Glottal friction** that may occur in sequences of sonorants and phonetically voiceless obstruents
- Favoured:
  - by low vowels (vs high)
  - by phonologically short vowels (vs long)
  - by posterior places of articulation (vs anterior: /k, t, p/)
  - by prosodically prominent positions (lexical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

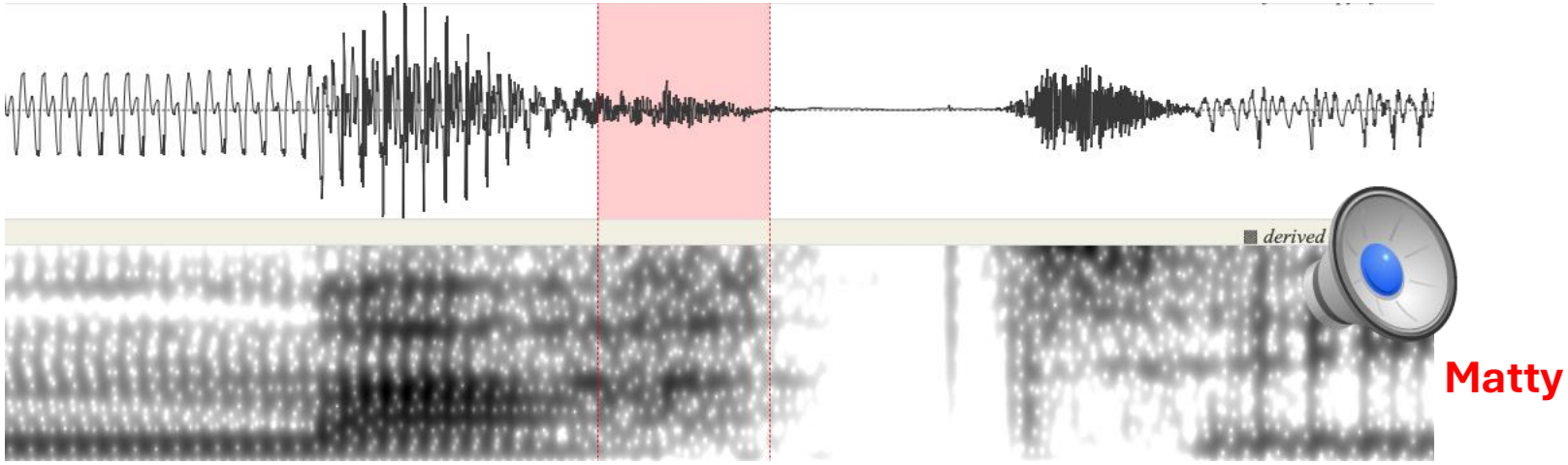


Welsh English ‘mock’

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 on the rise? 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

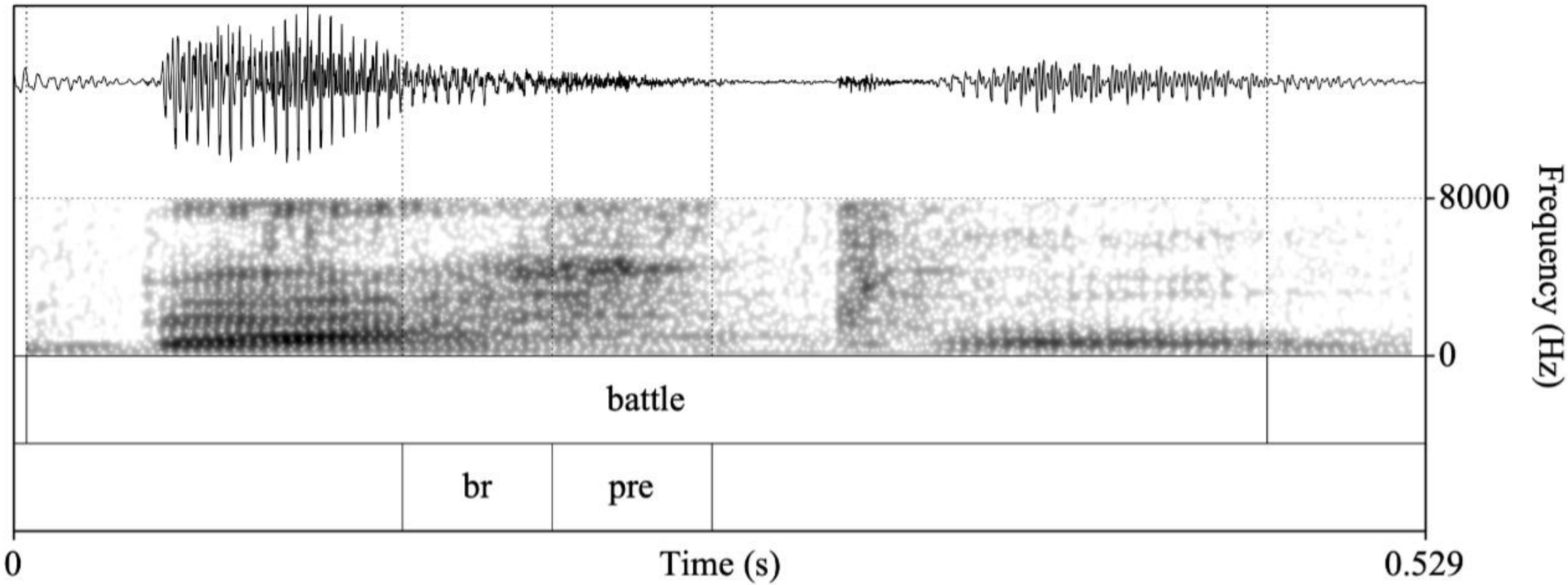
pre-aspirated "battle"

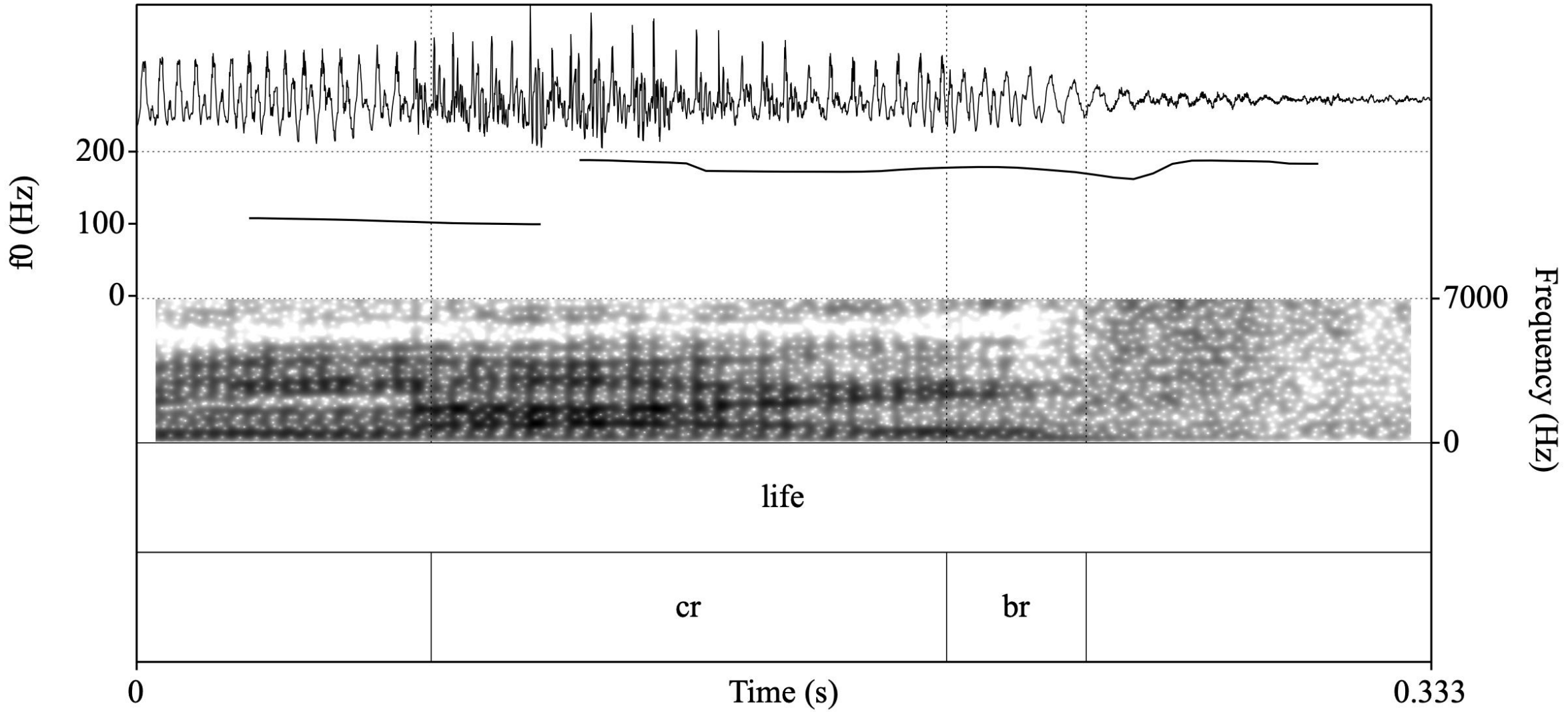
Relationship to voice quality

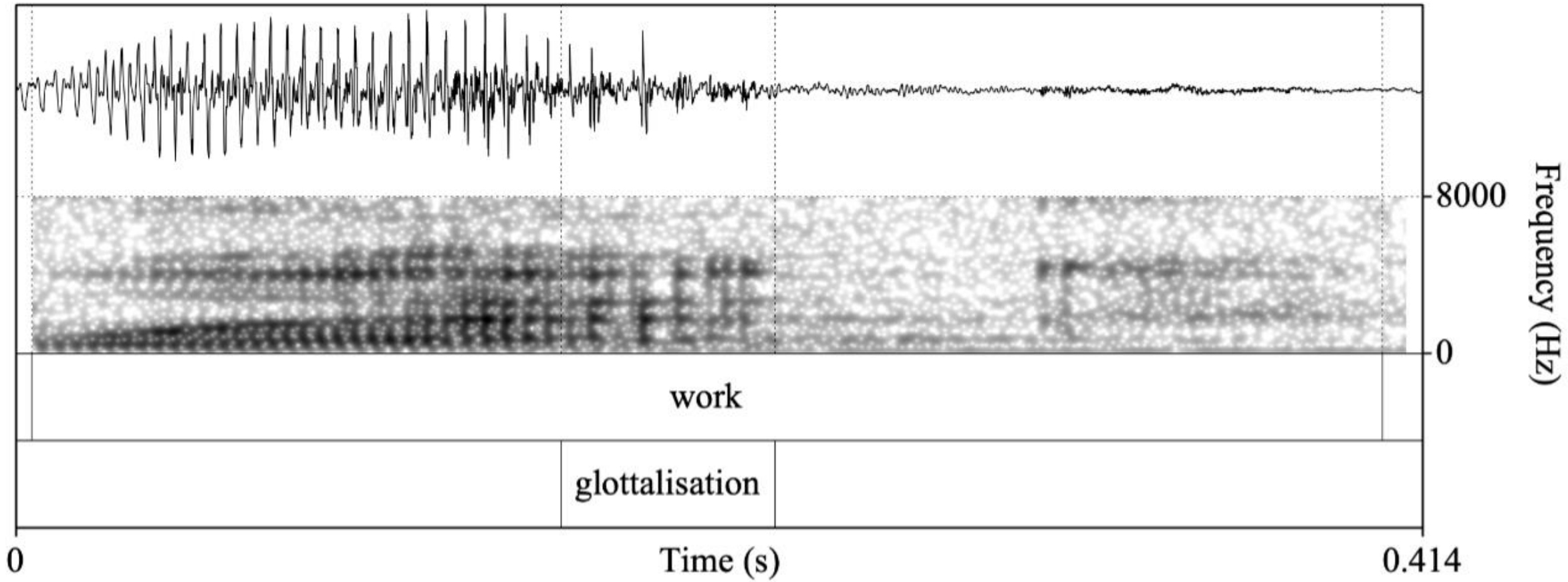
- Pre-aspiration (almost) always accompanied by local breathy voice, only rarely accompanied by glottalization (creak)
- Breathiness and glottalization can be subject to agentive/social variation, but also physiological aging processes
  - Mixed findings in the lit regarding increasing creakiness with age (e.g. Gittelson 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
- So how might breathiness and glottalization relate to pre-aspiration? Maybe age affects voice quality, which in turn feeds or bleeds pre-aspiration!

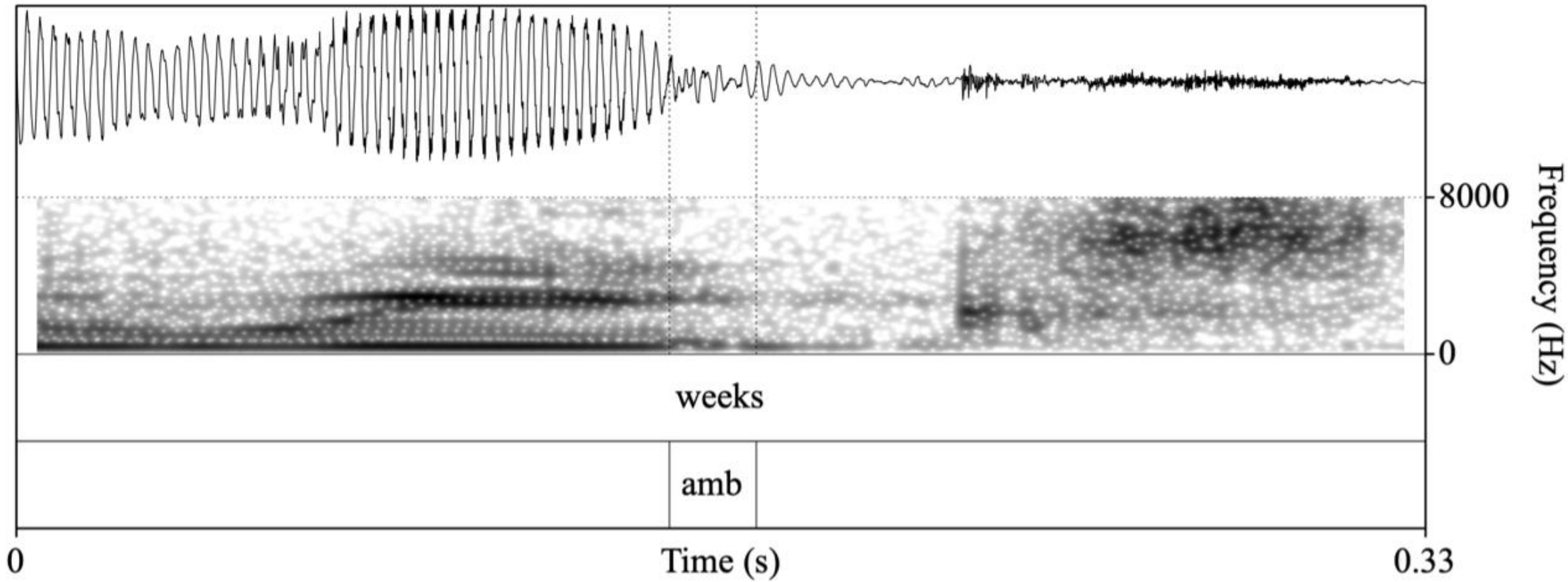
Coding acoustic data

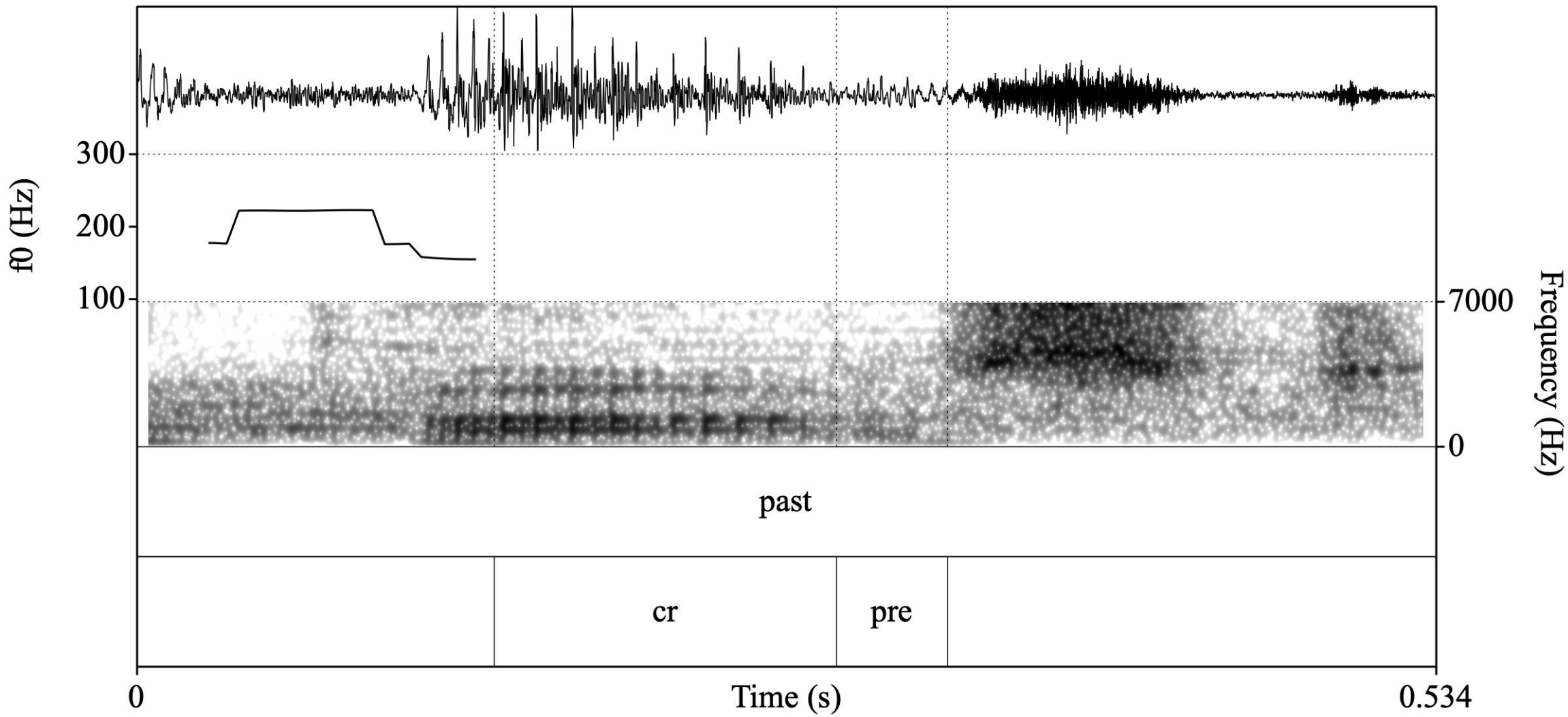
- Identified all possible pre-aspiration environments through 18 speeches from 1952 (age 26) to 2018 (age 92)
  - Stressed vowel + voiceless obstruent sequences: 2,061 tokens
- Voiceless **pre-aspiration** identified by presence of voiceless friction dispersed across different frequencies
- Local **breathiness** 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


8000
Frequency (Hz)
0
battle
br
pre
0
Time (s)
0.529

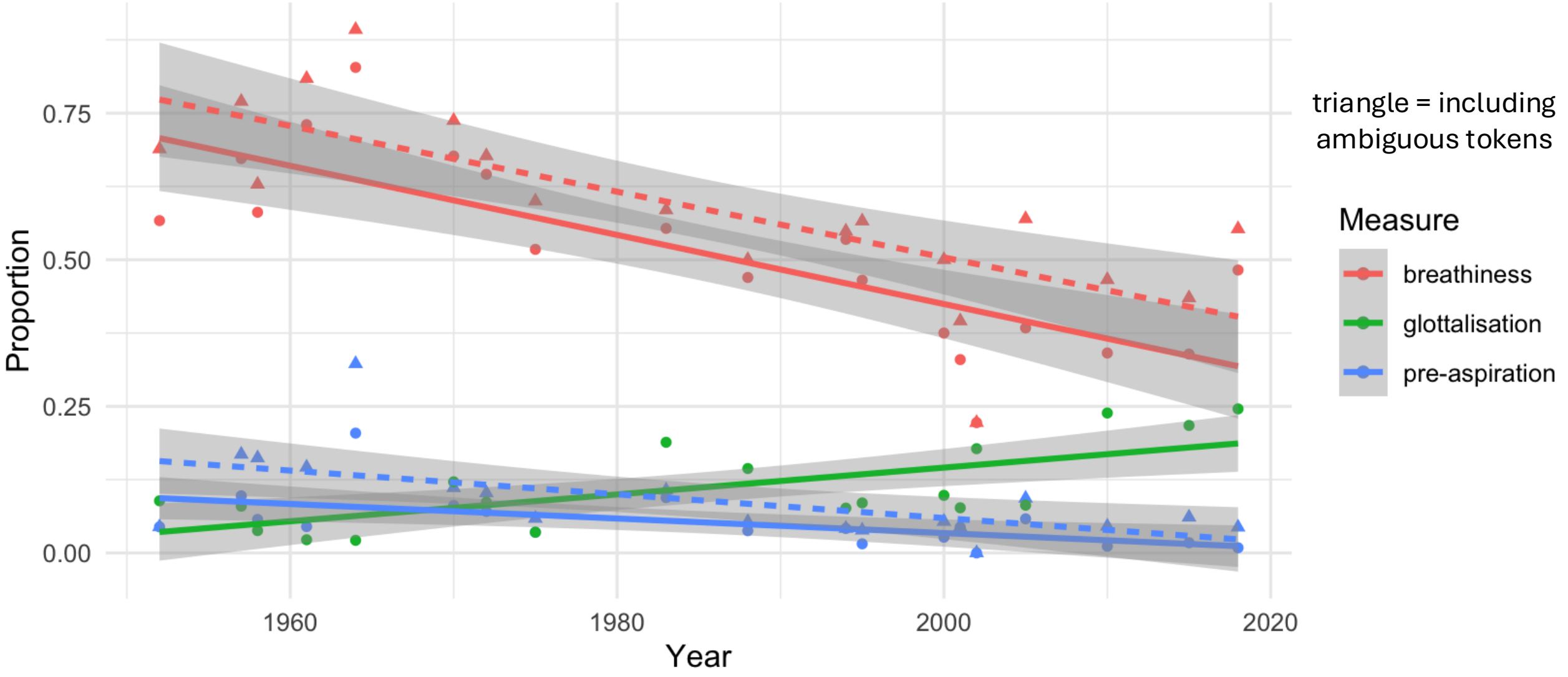

f0 (Hz)
200
100
0
7000
0
Frequency (Hz)
life
cr
br
0
Time (s)
0.333

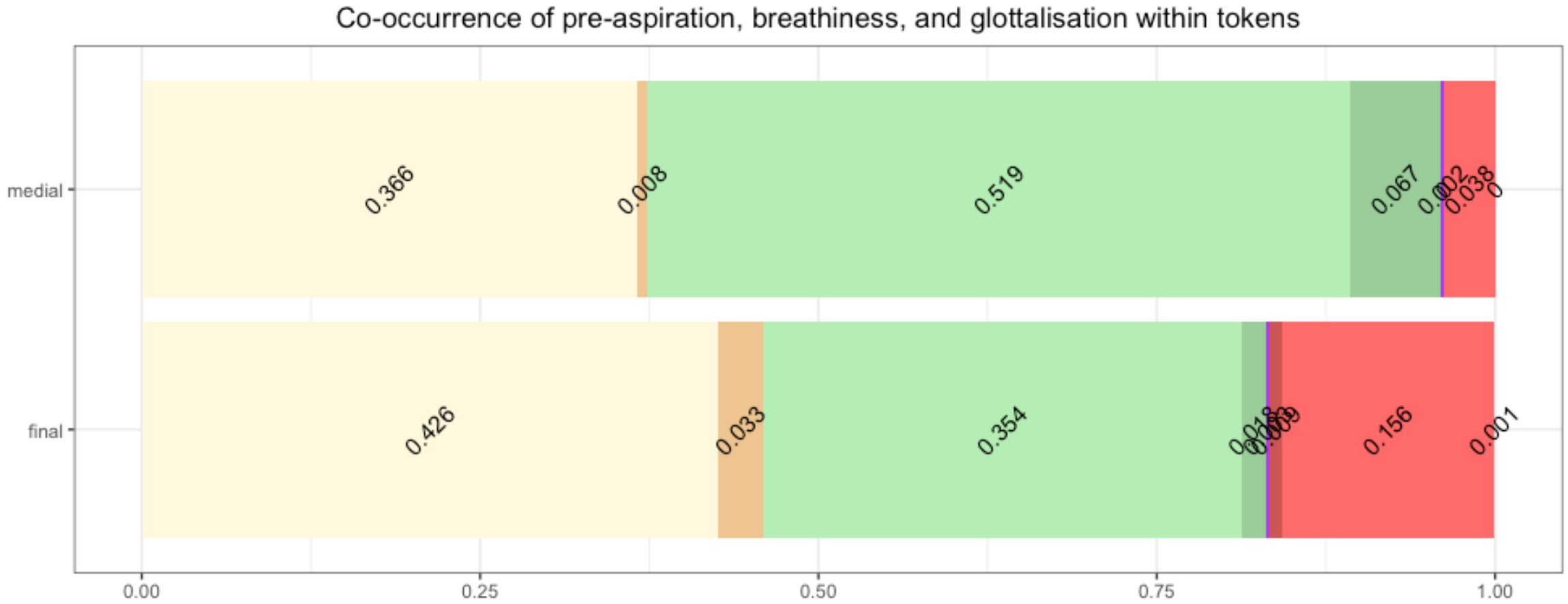

8000
0
Frequency (Hz)
work
glottalisation
0
Time (s)
0.414


8000
Frequency (Hz)
0
weeks
amb
0
Time (s)
0.33


f0 (Hz)
300
200
100
7000
0
Frequency (Hz)
past
cr
pre
0
Time (s)
0.534

What the longitudinal data look like:





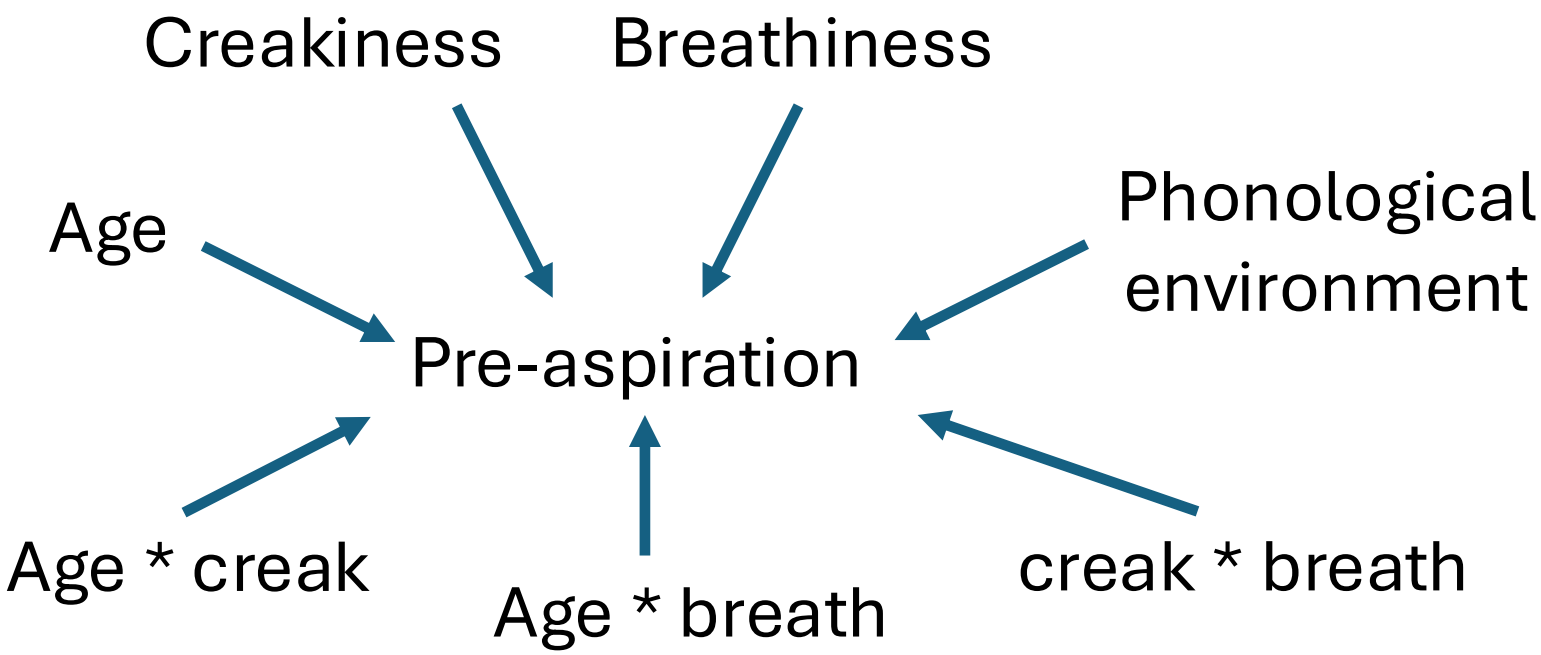
Foot-medial vs. foot-final makes a difference

***Mat**ty* ***Mat**t*

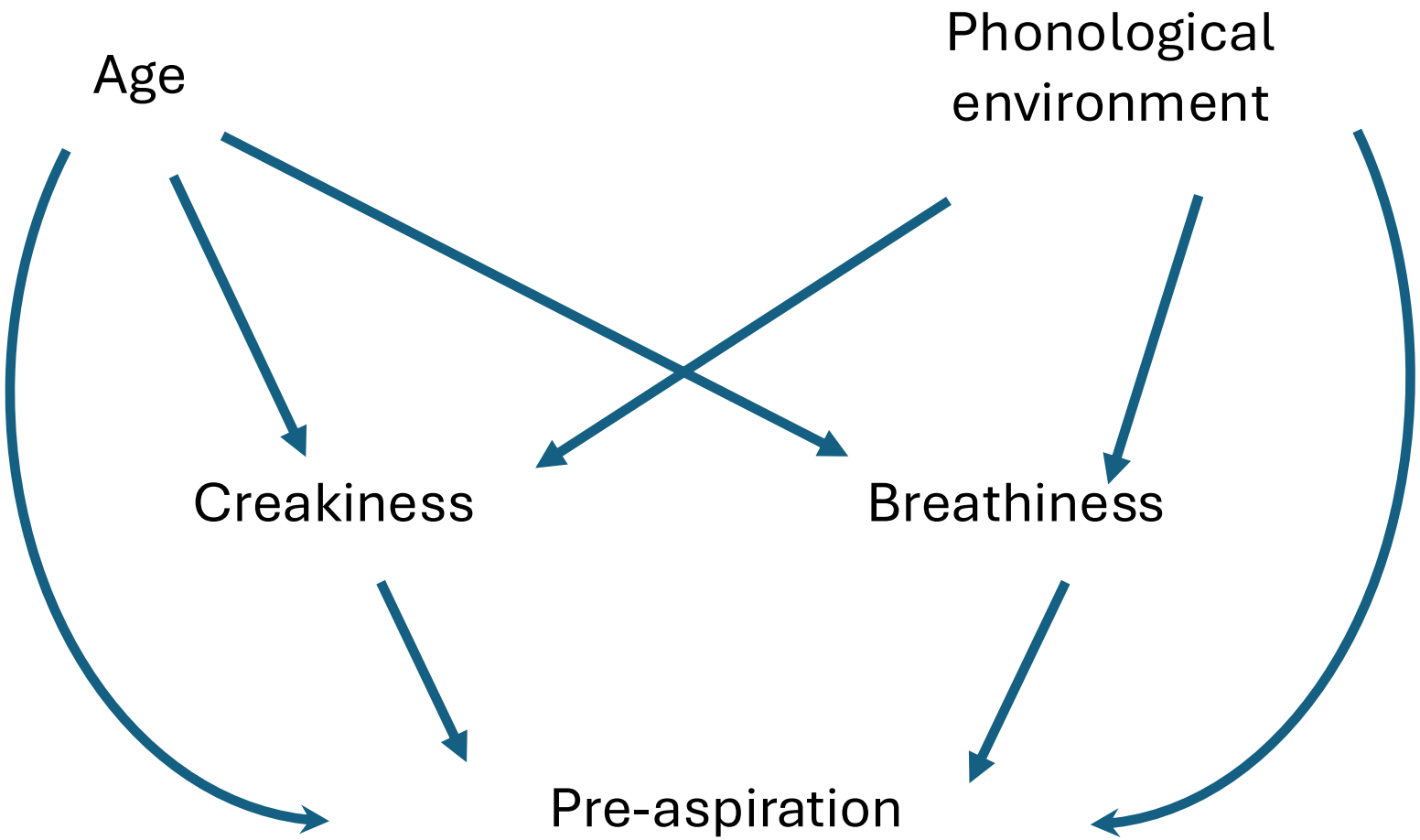
(Kettig & Hejná 2026)

How we might be tempted to model it with glmer

pre ~ age + creakiness + breathiness + environment + (1|word)

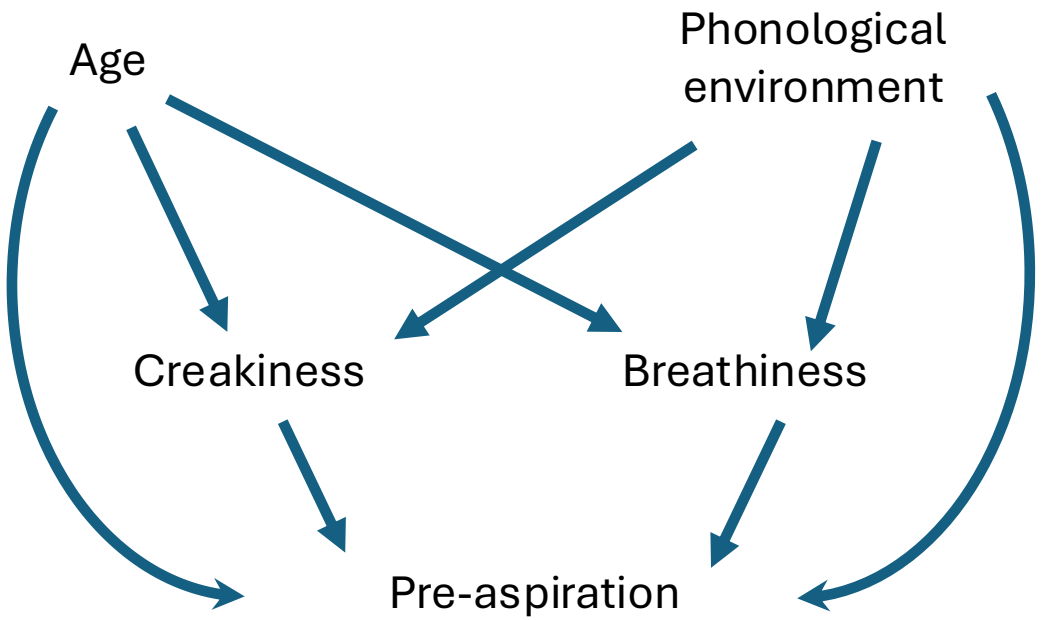


But what if we think there might be indirect effects?



But what if we think there might be indirect effects?

- 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 -> M = path *a*
  - M -> 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 SEM results for this datasest

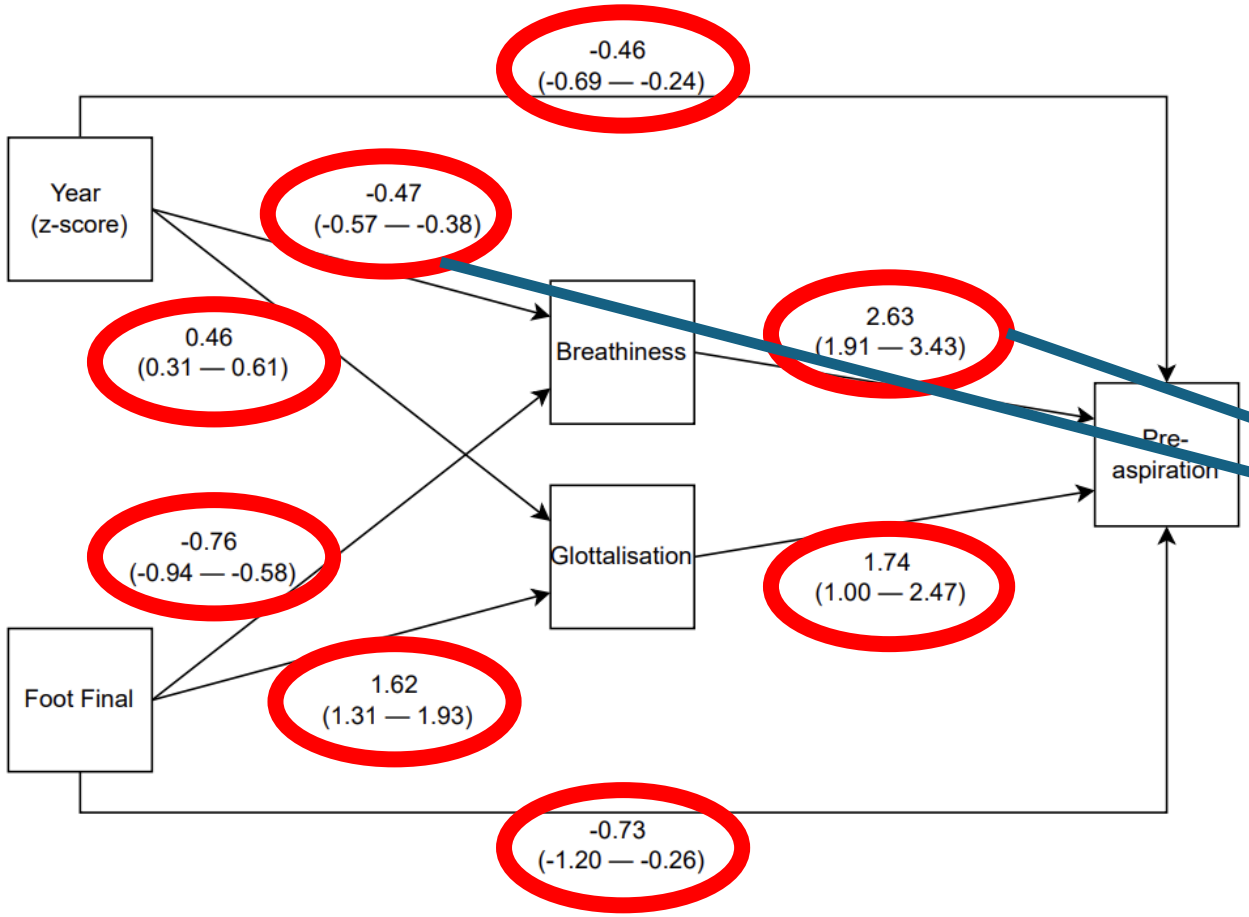


Fig. 1. Summary of direct effects within the model. Estimates represent log-odds with 95% credible intervals.

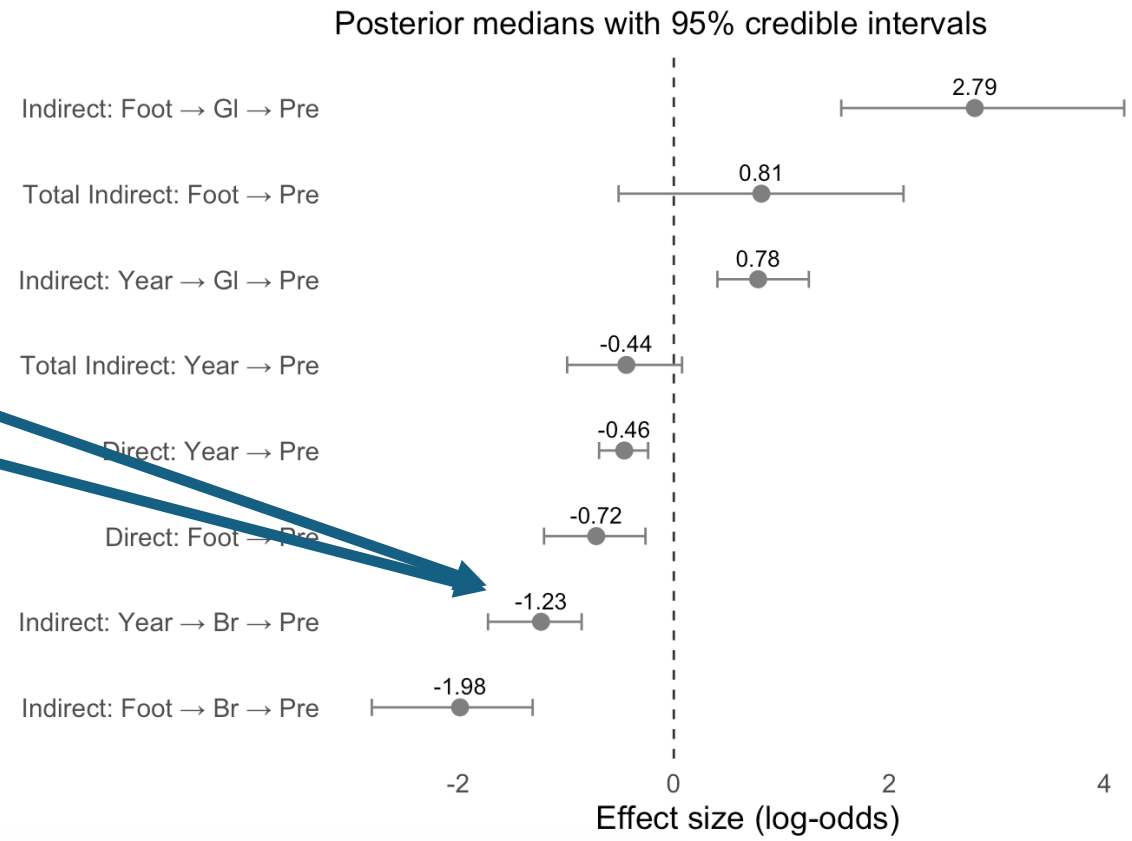
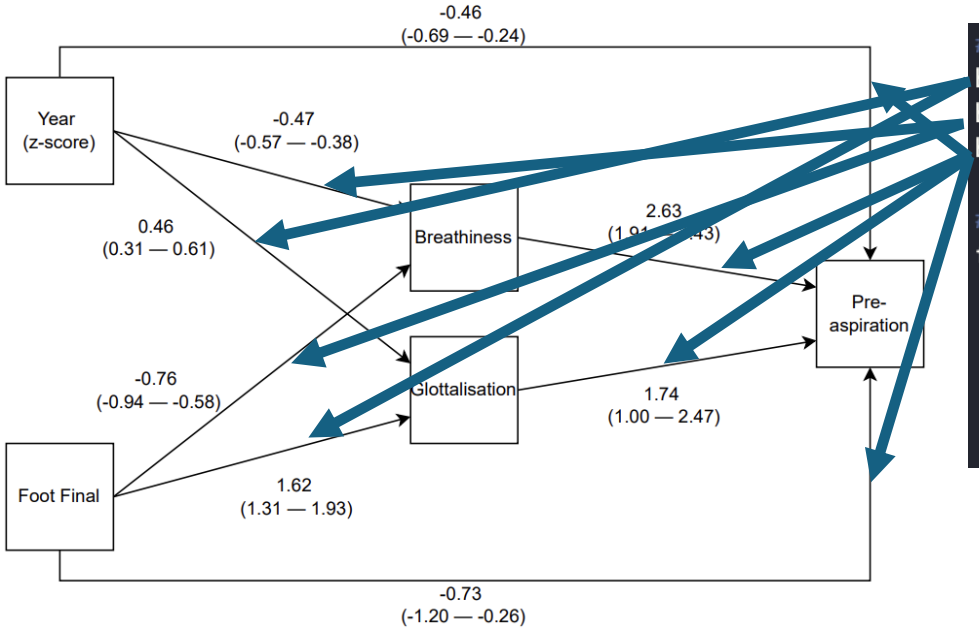
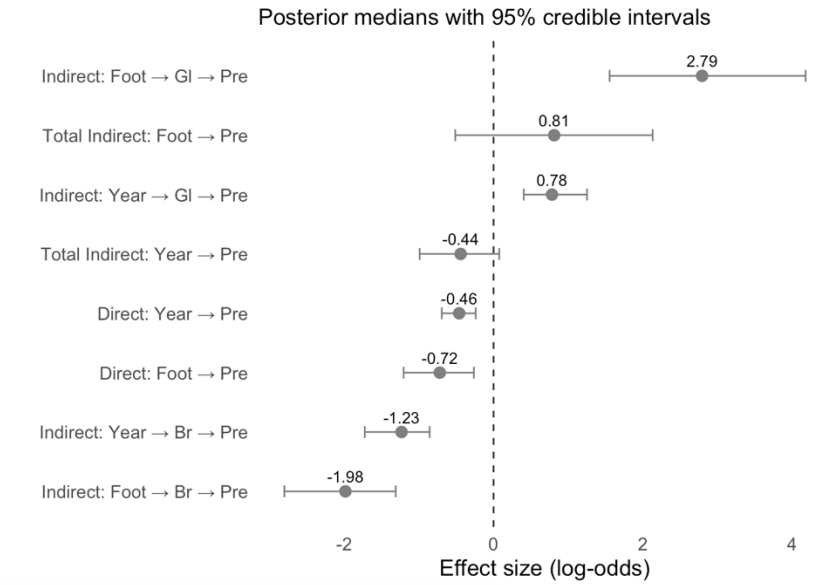


Fig. 2. Summary of indirect effects within model. Estimates represent log-odds with 95% credible intervals.




```r
# 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))
```




```r
#### 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)
```

Summary

- SEM and other mediated modelling approaches could help us better approach situations where we suspect indirect effects
  - Could especially be the case for lifespan changes, where aging might be more directly affecting one or more variables which in turn feed or bleed other phenomena
- Not many other people in phonetics doing this, but some have been using it, particularly for exploratory analyses
  - See work by Amanda Doucette, Jeanne Brown (McGill)
  - Let us know if you're aware of others doing mediated modeling!
- 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

References

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