Elite Vocal Style and Mass Affective Polarization

Mathias Rask Aarhus University

Frederik Hjorth University of Copenhagen

Broader research interests

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Substantive

Conflict between notionally extreme and mainstream parties and voters

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Methodological

Using tools and data from computational social science, e.g. unstructured data, machine learning

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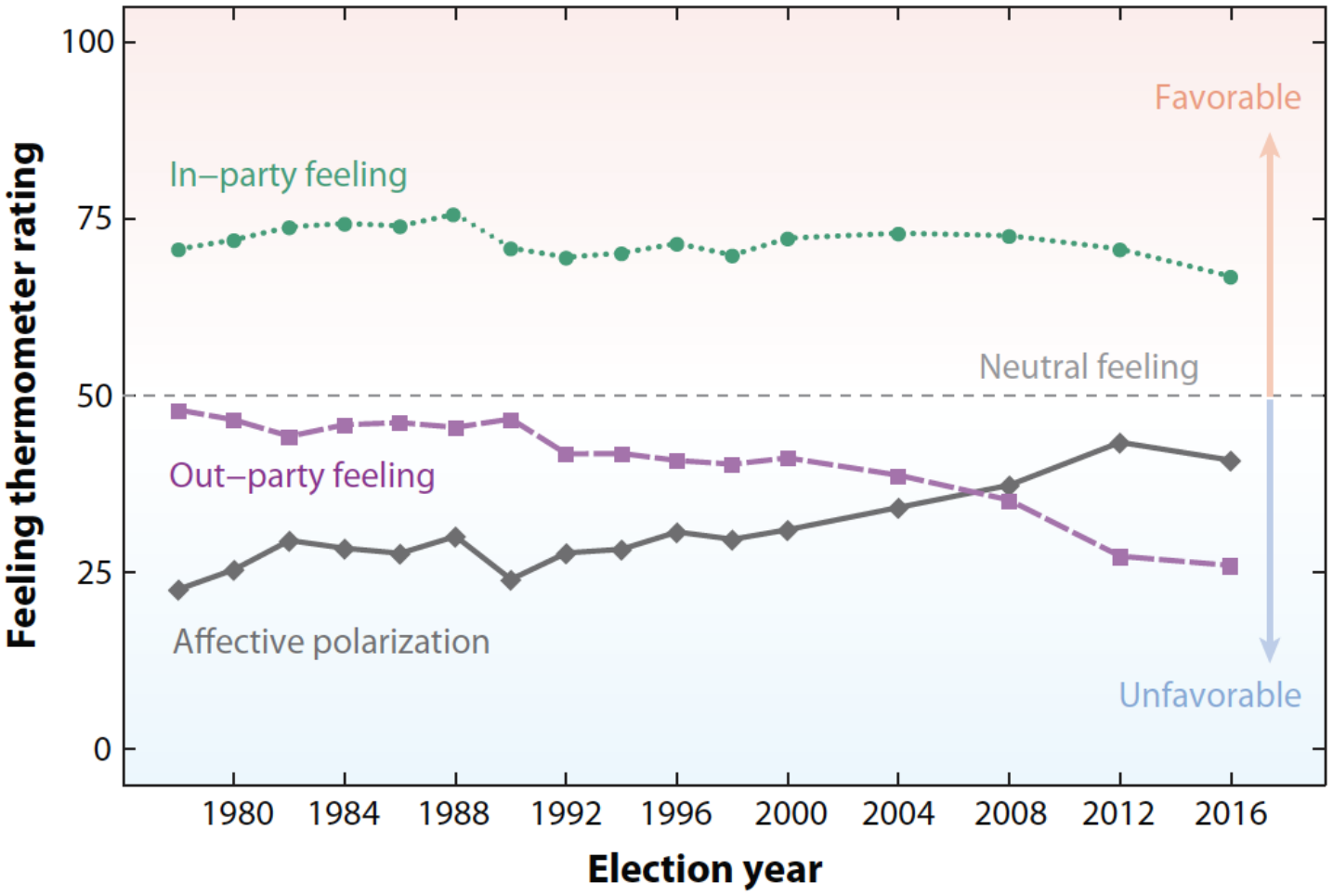
Motivation

Why are some parties disliked more than others?

Source: https://www.theguardian.com/politics/2014/may/20/ukip-manifesto-europe-immigration

Central to current concerns about affective polarization



Source: Iyengar, S., Lelkes, Y., Levendusky, M., Malhotra, N., & Westwood, S. J. (2019). The origins and consequences of affective polarization in the United States. *Annual review of political science*, 22, 129-146.

What drives affective polarization?

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- social sorting [9]

Source: https://www.scientificamerican.com/article/why-hatred-and-othering-of-political-foes-has-spiked-to-extreme-levels/

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- our focus here: **elite social interaction**

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- social sorting [9]
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- rising salience of 'second-dimension' issues [5]
- our focus here: **elite social interaction**
- argument: elite social interaction conveys outparty dislike

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Nonverbal aspects of elite interaction I

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- we focus on **nonverbal interaction**

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Nonverbal aspects of elite interaction I

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- we focus on **nonverbal interaction**
- essential part of interpersonal communication
- challenge existing literature's focus on verbal content
- $\rightsquigarrow$ existing evidence underestimates extent of elite partisan hostility

Nonverbal aspects of elite interaction II

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- focus here: vocal style

Nonverbal aspects of elite interaction II

- focus here: vocal style
- legislators use vocal style to express indignation at other parties, signaling target party extremity

Source: https://www.dr.dk/ligetil/se-statsministerens-aabningstale-i-folketinget-paa-100-sekunder & https://www.tv2ostjylland.dk/oestjylland/folketingets-aabning-statsministeren-vil-lave-store-aendringer

Nonverbal aspects of elite interaction II

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- we are agnostic wrt. intentionality

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Hypothesis 3

Between-party indignation is positively associated with between-party affective polarization among voters.

Data and Methods

Data Collection: Audio recordings

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- extract audio channel from video using `ffmpeg`

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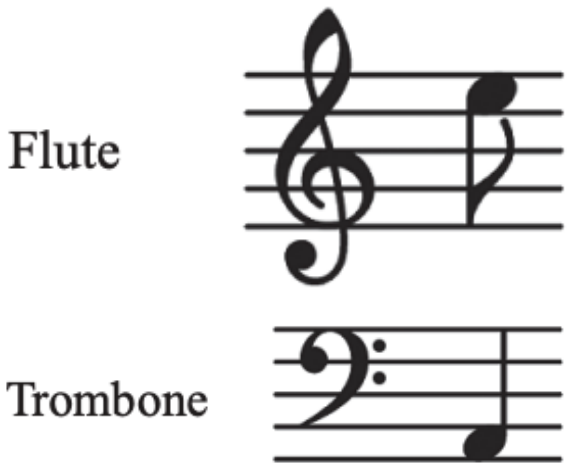

High vs. low pitch illustration from Knox & Lucas [6]

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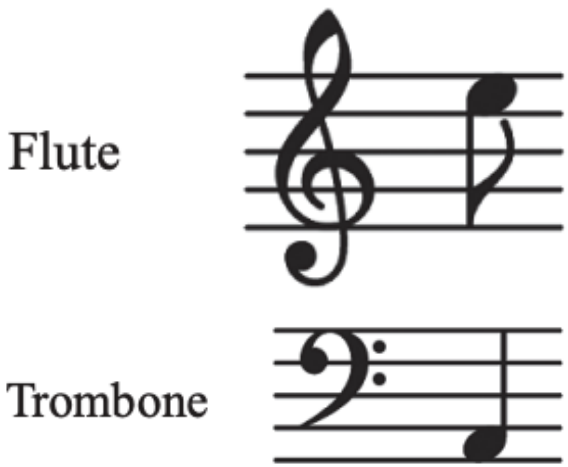

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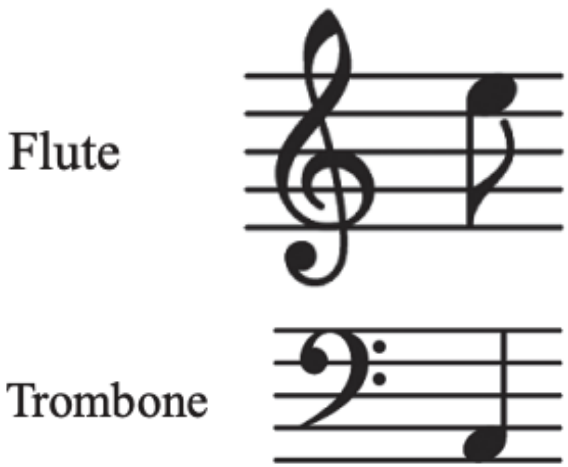

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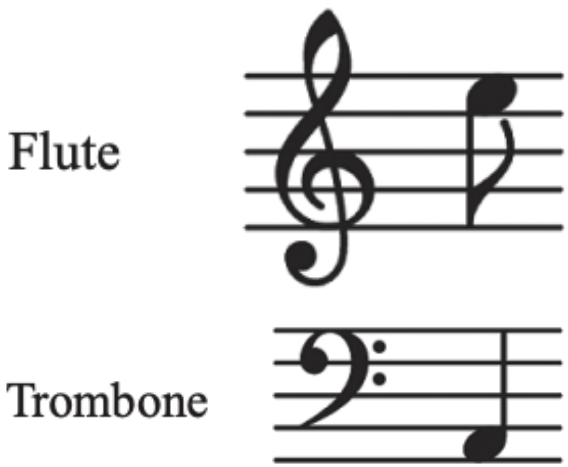

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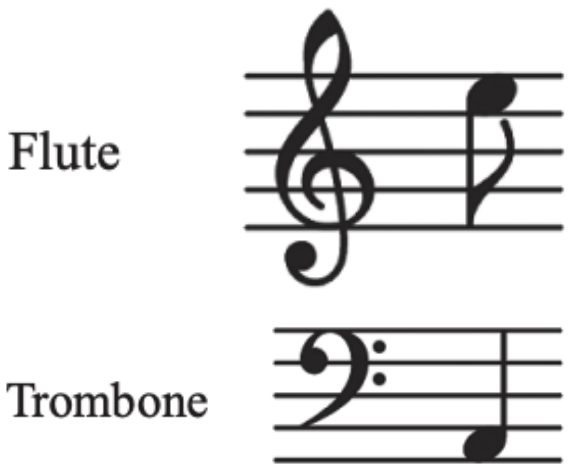

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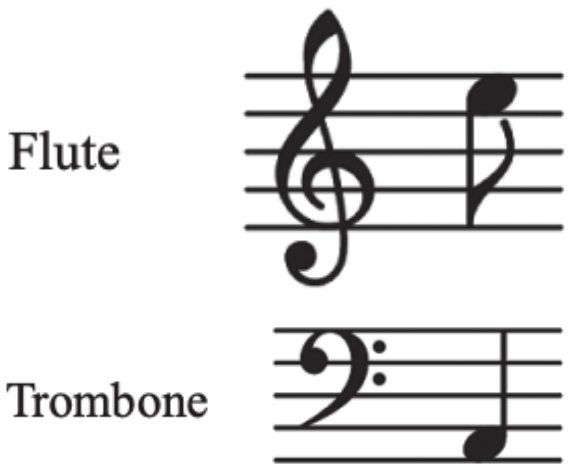

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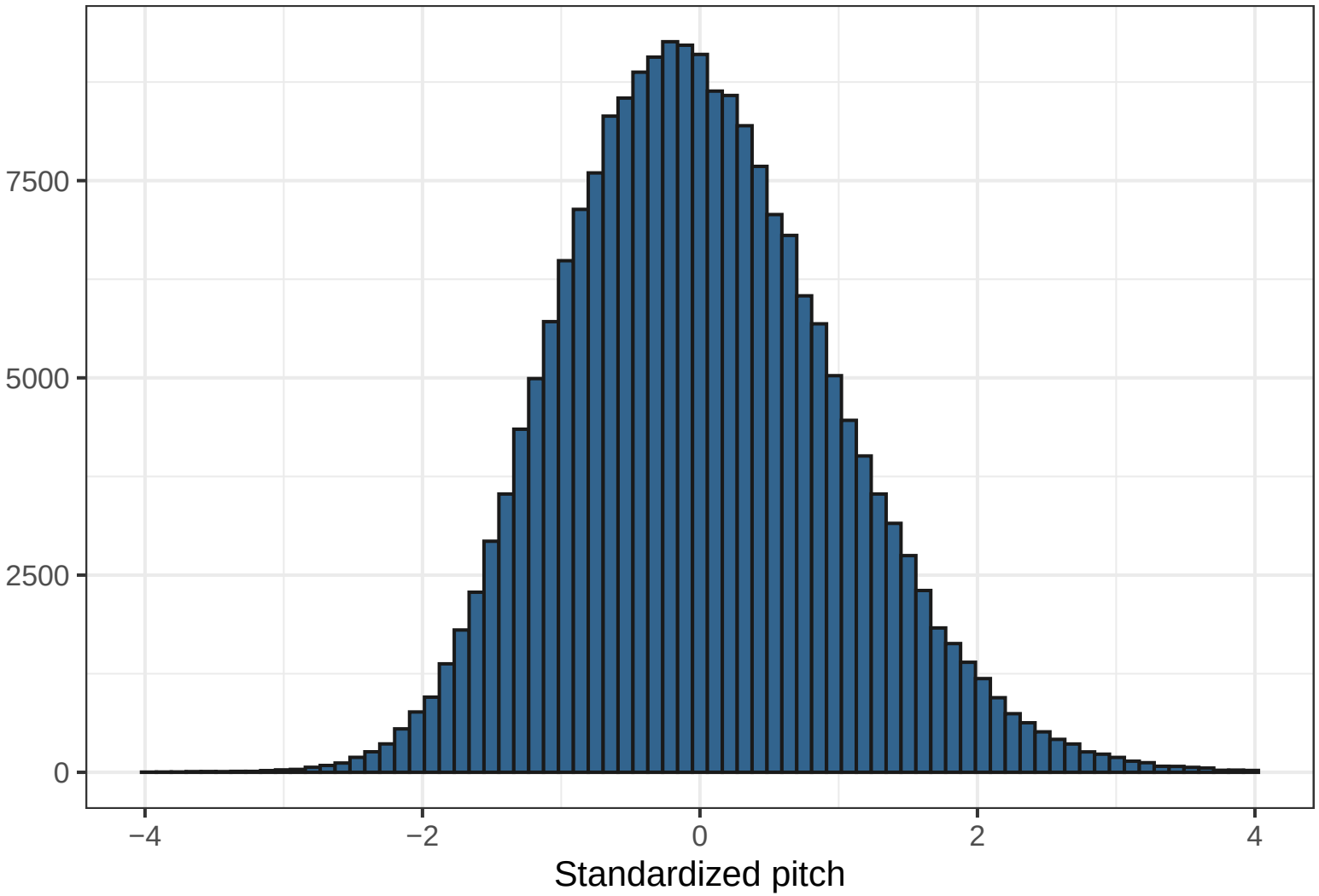
▸ Additional detail

▸ Low pitch example

▸ High pitch example

Distribution of standardized pitch



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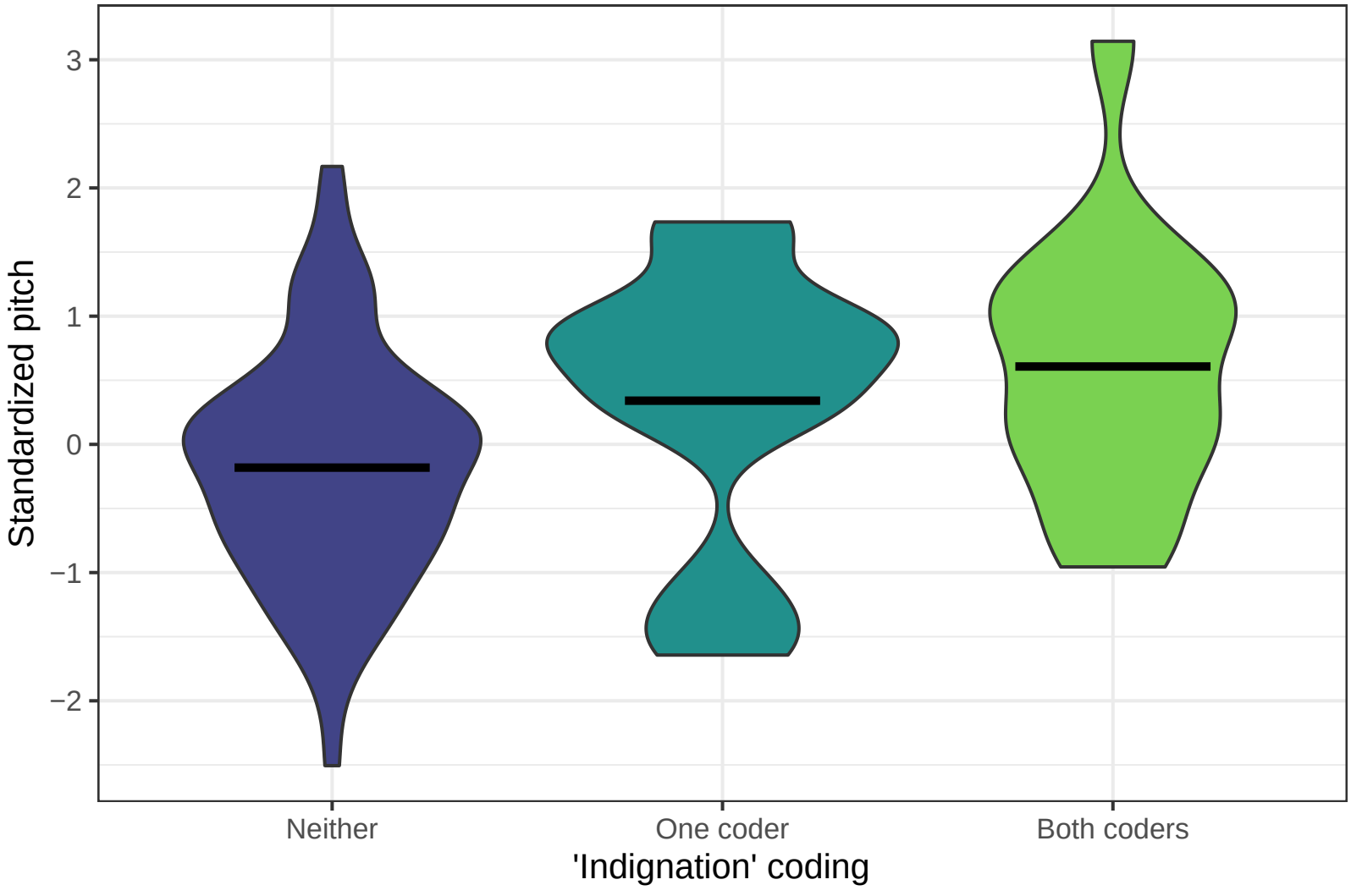

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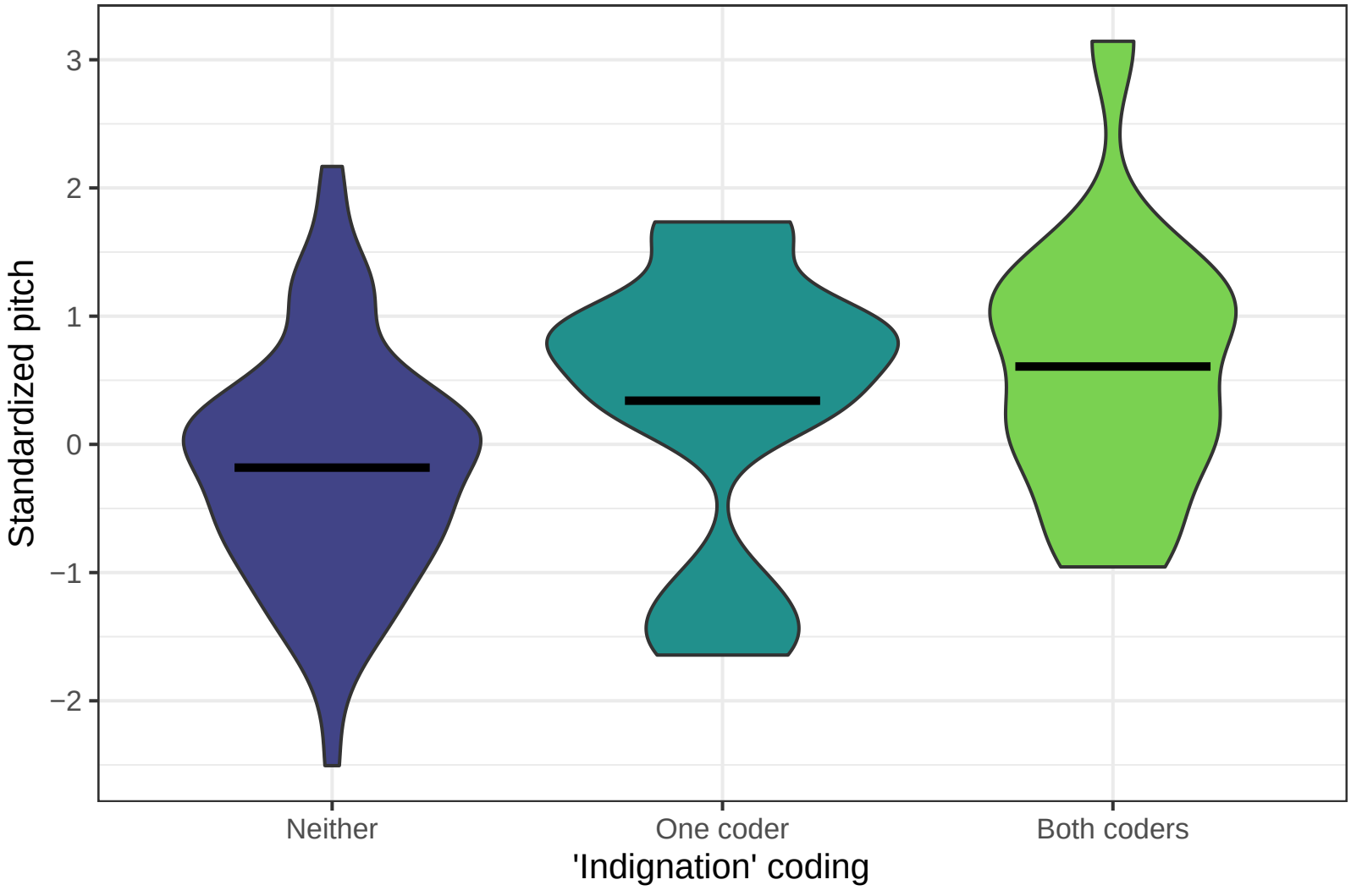

$\rightsquigarrow$ coder agreement = 87 pct., Krippendorff's $\alpha = .62$

Validation II: Correlation w. text sentiment

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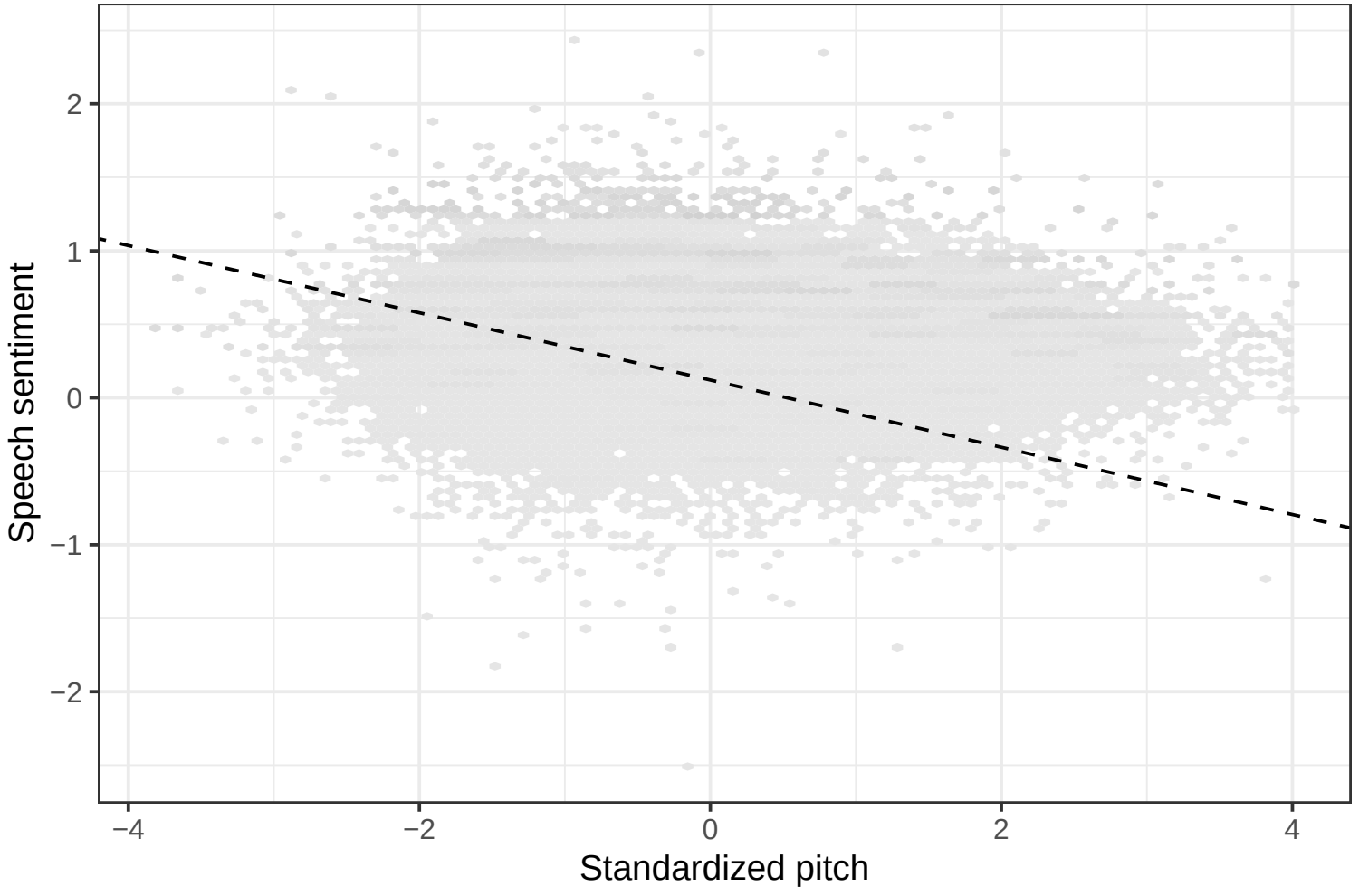

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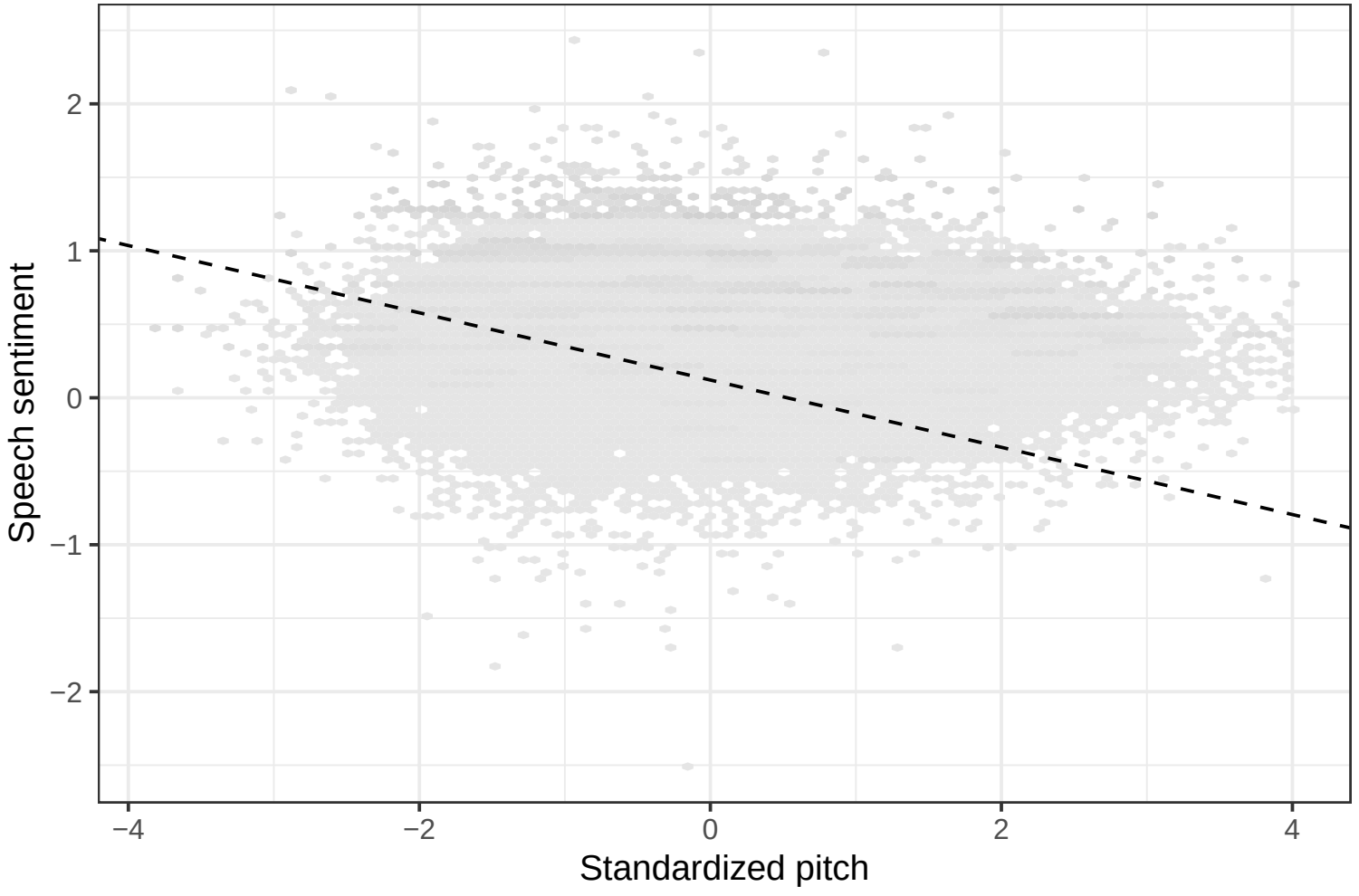

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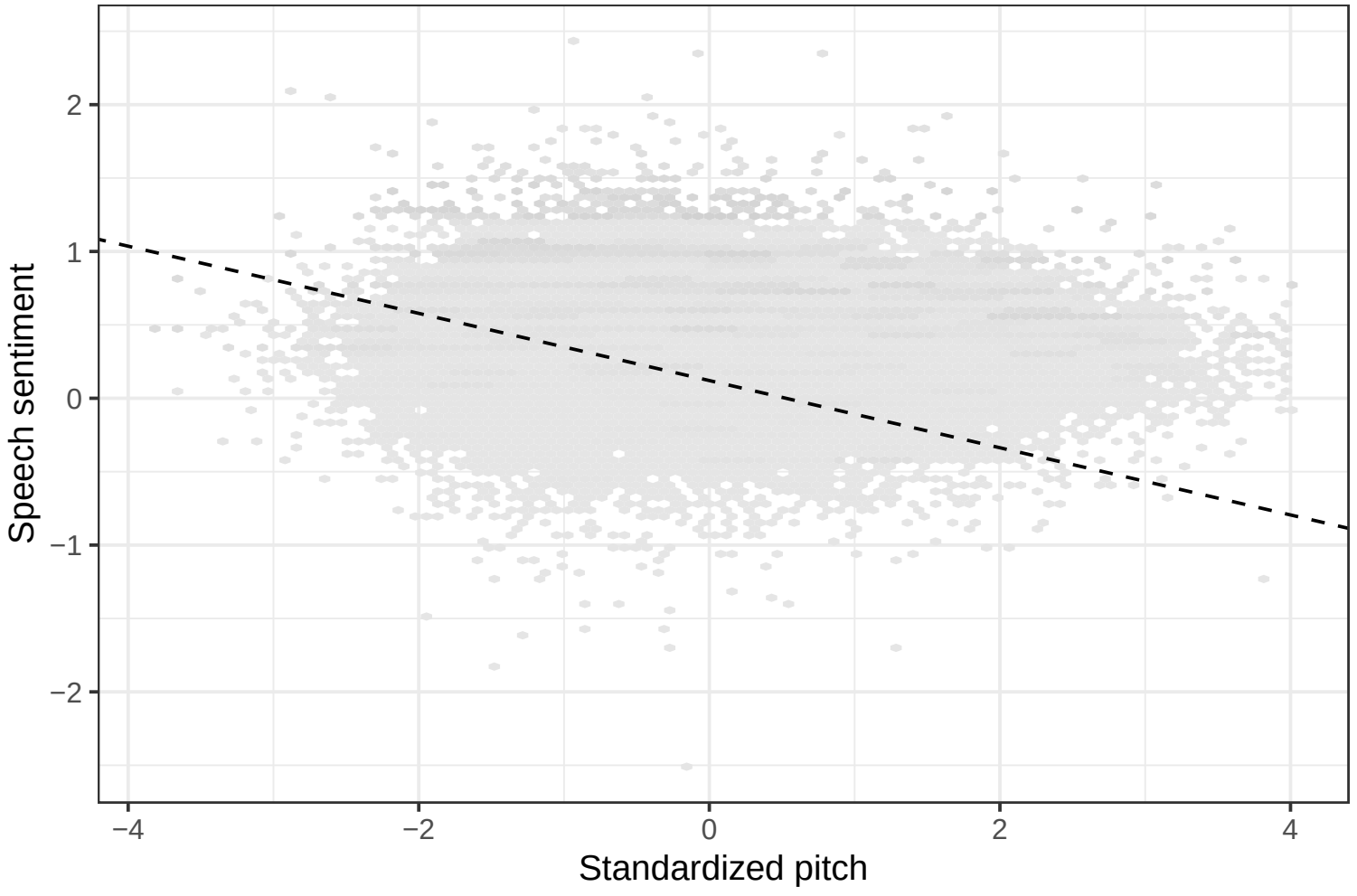

$\rightarrow$ speeches with higher std. pitch are more negative ($t = 19$, $p < .001$), correlation weaker in non-dyadic speeches

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- method: latent semantic scaling [12]
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- we scale speeches based on first and second dimension seed word lists (e.g. `taxes`, `financial` vs. `immigration`, `moral`)

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- in H3, compare to voter dyadic affect measured in election surveys

Results

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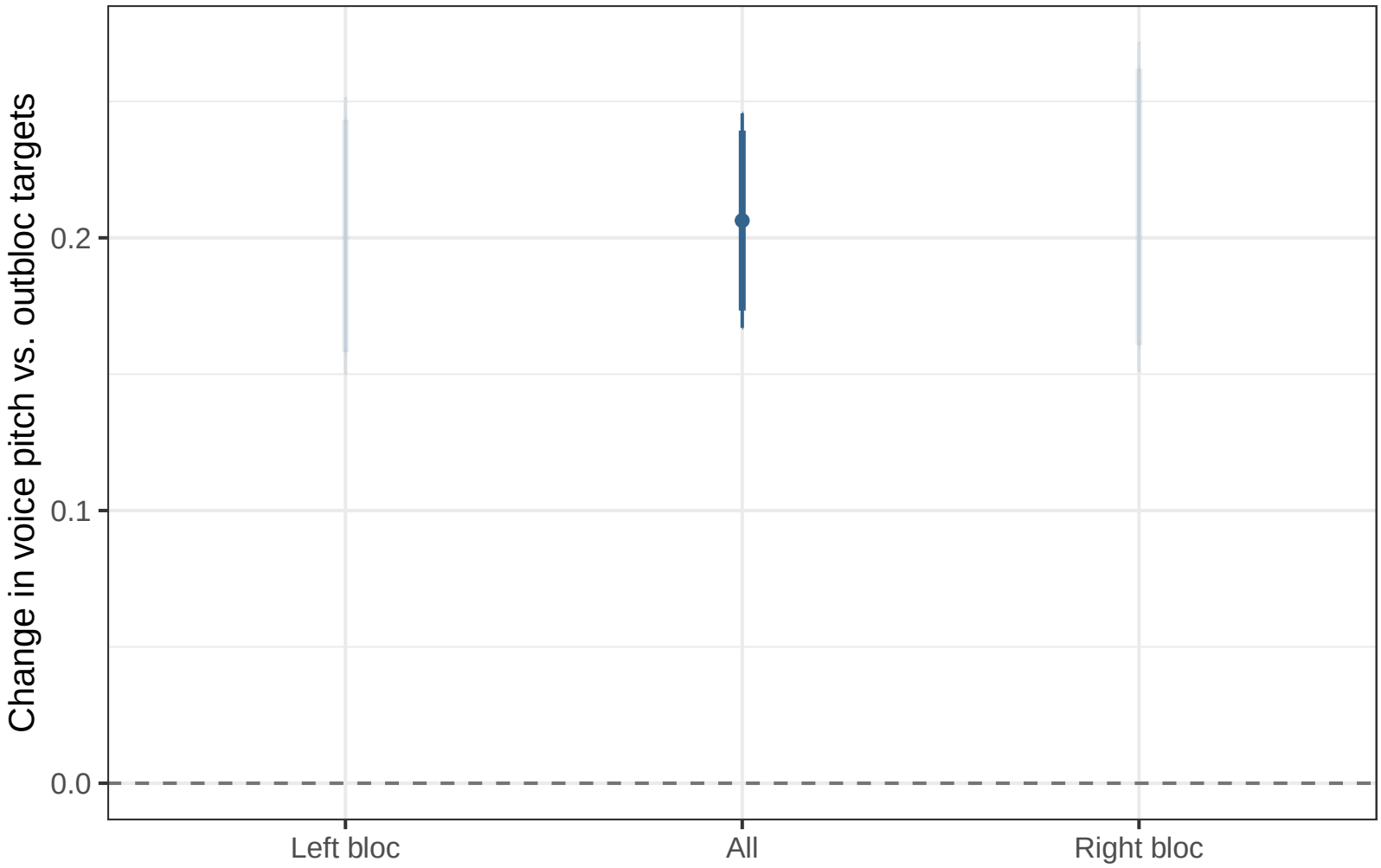

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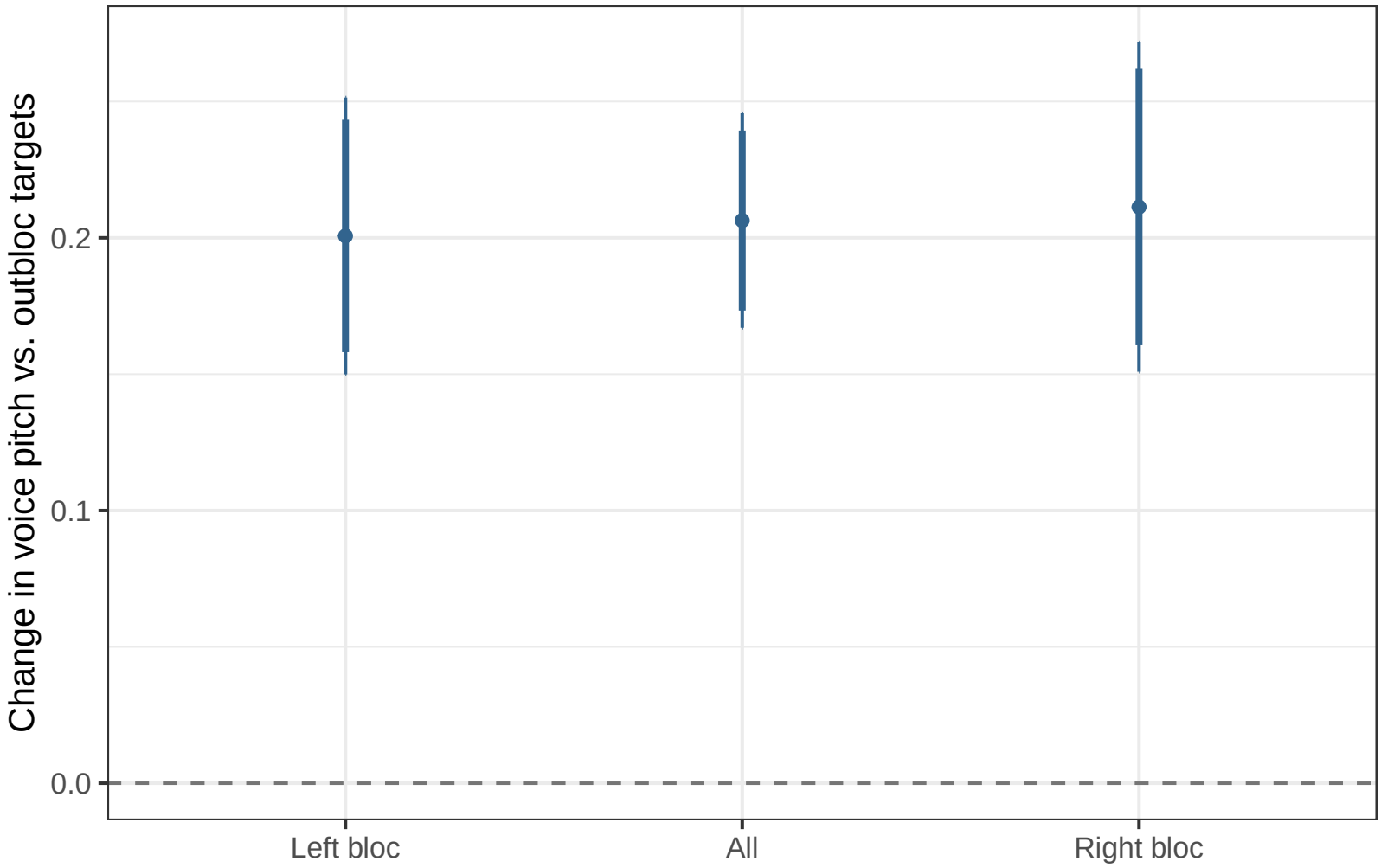

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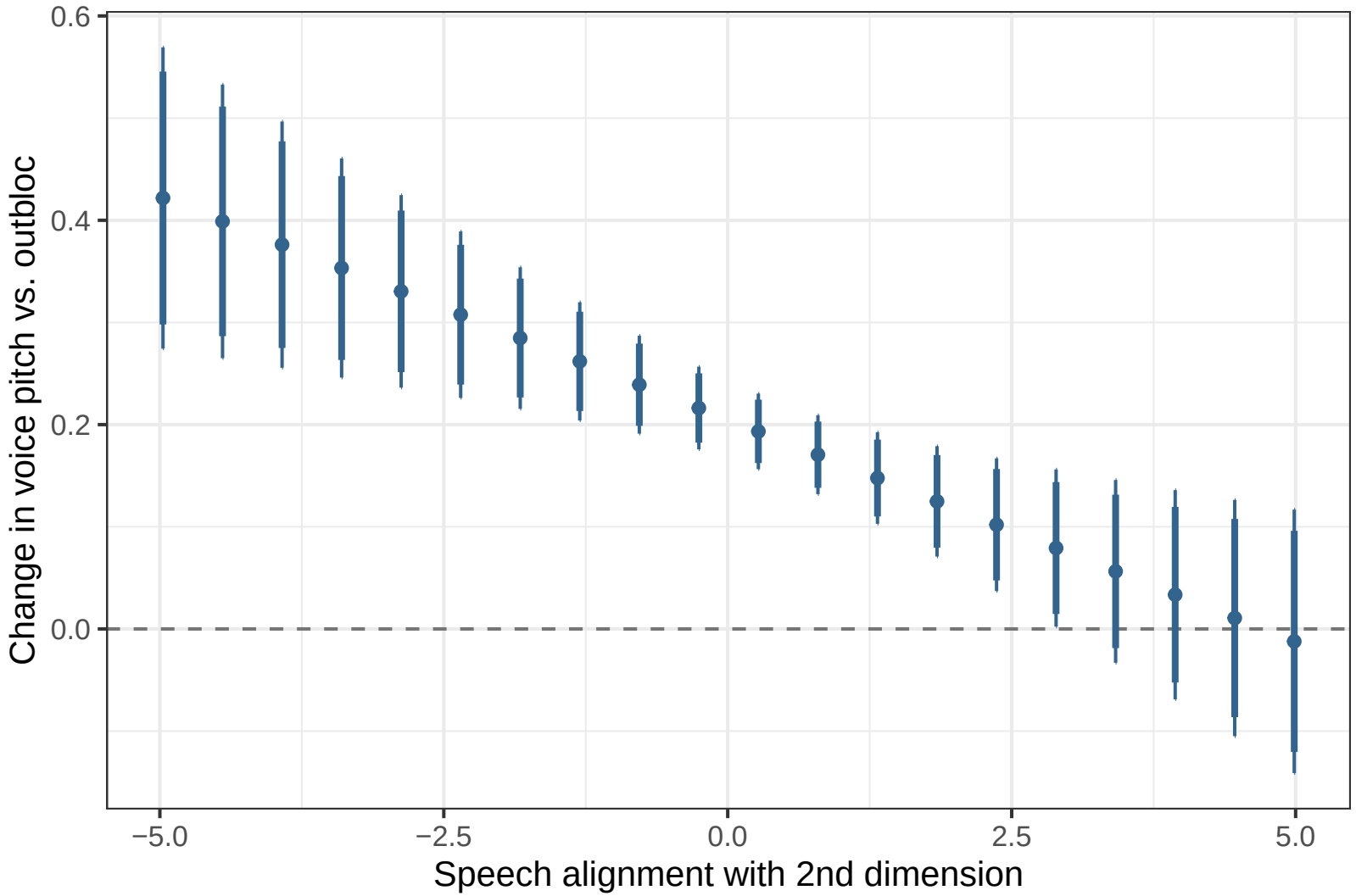

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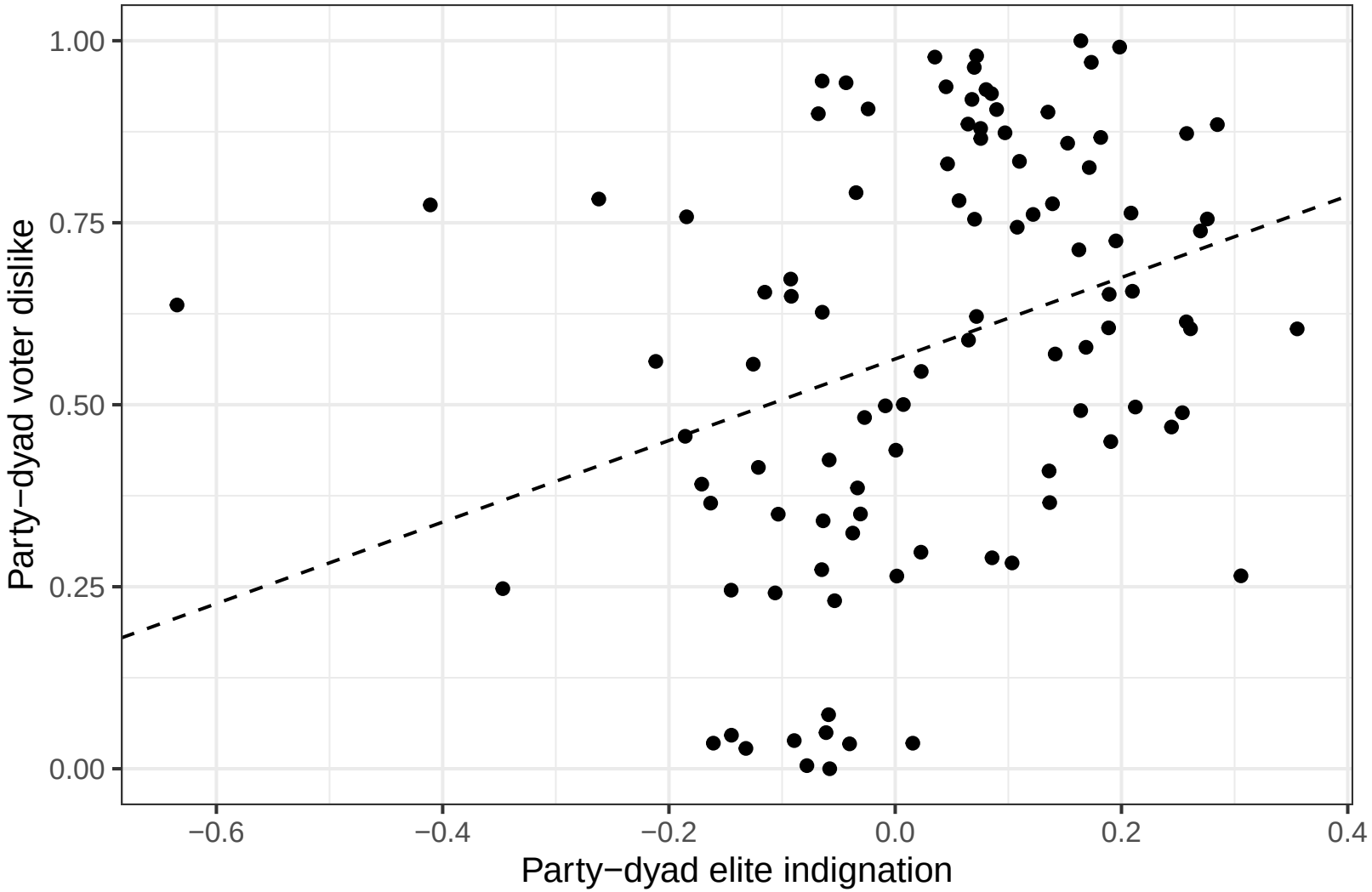

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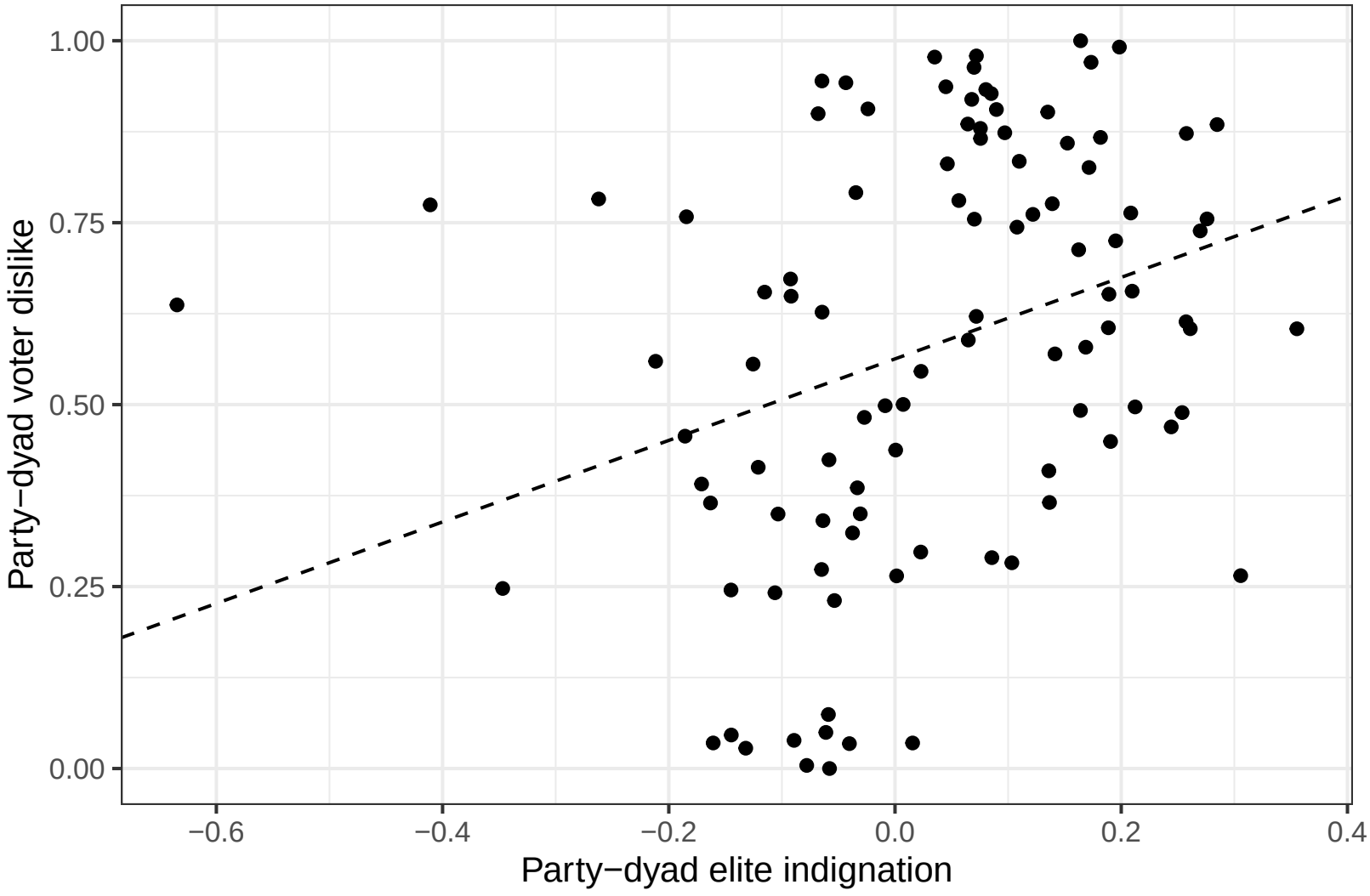

☞ robust to speaker party FEs, exclusion of radical right targets

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- demonstrates elites use vocal style to signal partisan dislike
- implies content-only approaches underestimate expressed partisan hostility
- consistent with role of elite social interaction in sustaining mass affective polarization

Thanks for your attention!

Elite Vocal Style and Mass Affective Polarization

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New method and Python software developed in separate working paper (Rask, 2023): `polannote`

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- Output: A list of annotations (for each recording)

Tidying audio: Annotation II

Back to presentation

Data preprocessing and requirements

- Audio: Divide recording into K batches

$$K = \left\lceil \frac{\text{number of samples/sampling rate}}{60 \times \text{batch duration}} \right\rceil$$

  - Done to lower computational cost
- Transcript: Ordered collection of speeches contained in the audio (e.g. ParlSpeech V2). Three needs:
  - Ordering: $i < i + 1$
  - Speaker names
  - Text

$\longrightarrow$ Method requires the existence of a corresponding transcript

Tidying audio: Annotation III

Method: Two steps

- Step 1: Speaker diarization
- Step 2: Speaker and speech recognition

Tidying audio: Annotation IV

Step 1: Speaker diarization

- Segments a recording into N individual speeches using unsupervised learning
- State-of-the-art software: `pyannote.audio` [2, 1] using neural network building blocks
- Output: A list of speech segments each with corresponding sets of timestamps and generic speaker labels (e.g. A, B, C, etc.).
    - Due to batching, speaker A in batch k is generally not the same as speaker A in batch $k + 1$

Tidying audio: Annotation V

Step 2: Speaker and speech recognition

- Due to the transcript, we know the target speaker and text *ex ante*
  $\longrightarrow$ Weak supervision!
- Construct supervisory signals from each segment from step 1
  - Text signal: Automatic Speech Recognition (ASR) on each segment to generate hypothesis text
  - Audio signal: Generate 512-dimensional embeddings (last layer of a x-vector TDNN-based architecture [11]) for each segment. Embeddings encode the speaker identity.
- Match supervisory signals to targets using fuzzy linkages
  - Cosine similarity for text signal – text target (match on words) and for audio signal – audio target (match on speaker)
  - Assign to target if above threshold(s)

Tidying audio: Annotation VI

Analyze validity of method by manually annotating a recording with ground-truth timestamps.

Evaluation metric: Diarization Error Metric (DER)

$$\text{DER} = \frac{\text{false alarm} + \text{missed detection} + \text{confusion}}{\text{total}}$$

- Total: Total duration of ground-truth speaker time
- False alarm: total duration of speech not within the ground-truth timestamps
- Missed detection: total duration of ground-truth speech falsely assigned as non-speech (non-speech: timestamps that fall outside ground-truth)
- Confusion: total duration of speech assigned to a wrong speaker.

The false alarm and missed detection capture the quality of the diarization in step 1 and confusion capture the quality of the speaker and speech recognition in step 2.

Tidying audio: Annotation VII

Ground-truth: Recording from Danish parliament on December 6 2012 with 478 speeches

- DER: 1.6%
- Using official timestamps (provided in metadata): 17.6%

Measurement II: Measuring indignation

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Standardized vocal pitch as a proxy for indignation:

- estimate pitch for all speeches using open-source software `communication` (R package by [6])
  - estimates are computed on 25 ms windows with 12.5 ms overlap (= 800 estimates on 10 seconds of audio)
  - pitch is tracked by two algorithms: We consider a window as valid if both algorithms return estimates > 0
  - compute mean of valid pitch estimates for each speech to obtain a speech-level measure
- standardize pitch within each speaker to remove speaker heterogeneity (e.g. gender)

Other dimensions

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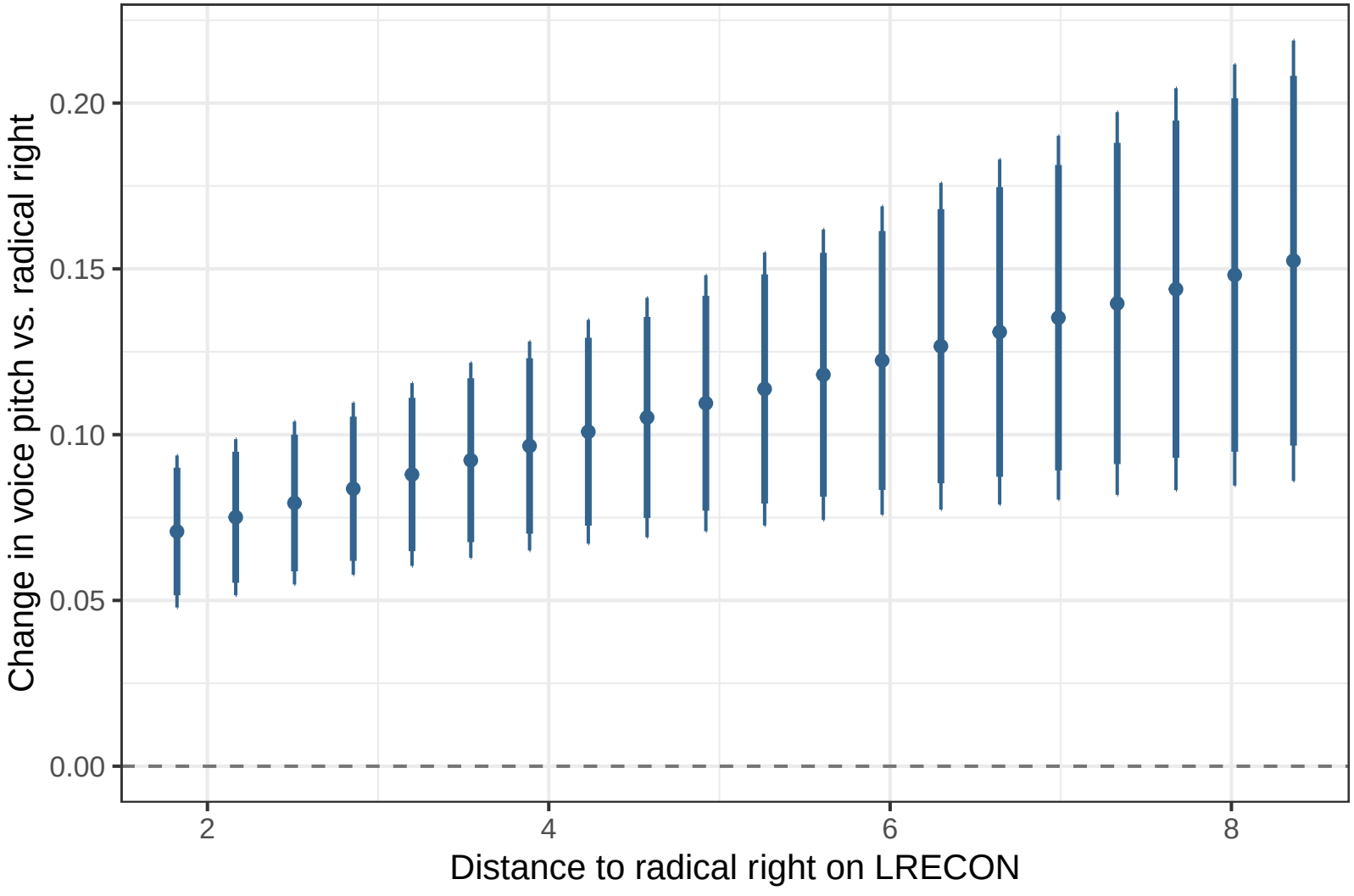

Other dimensions

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