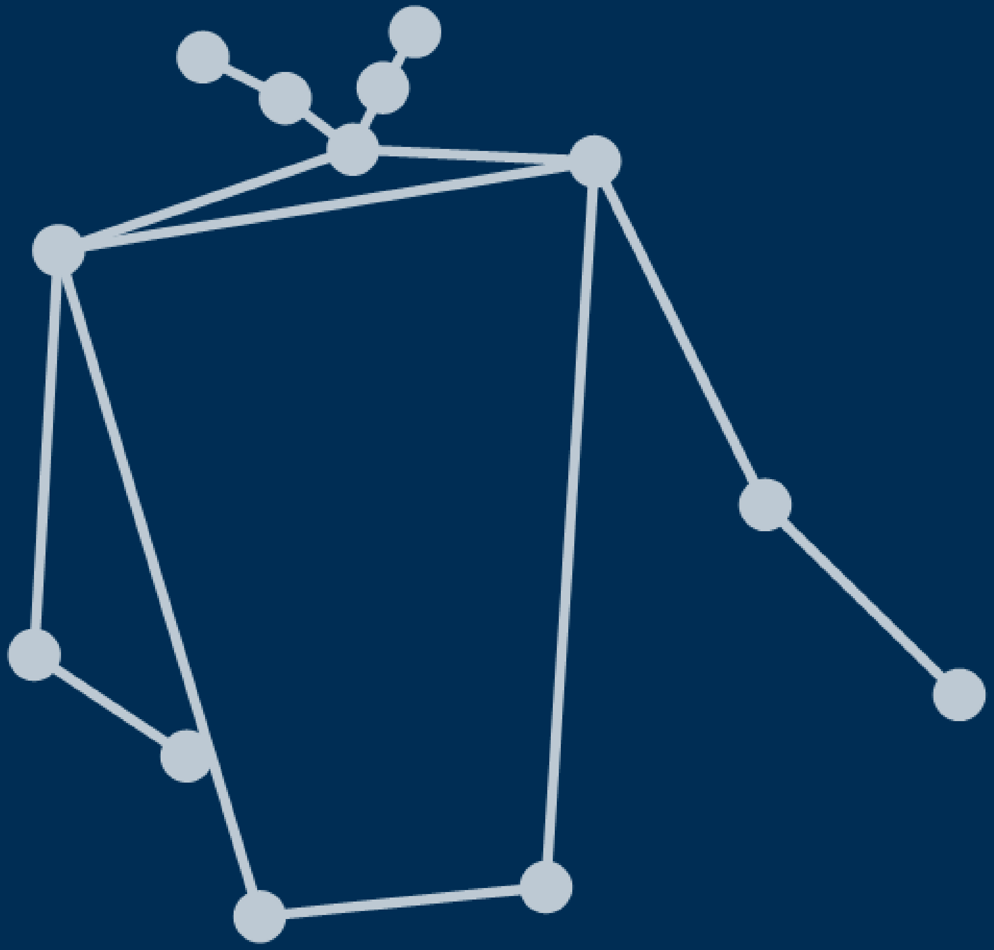


Gendered Patterns of Parliamentary Attention

Using computer vision to uncover behavioural biases among elected politicians

Oliver Rittmann, *University of Mannheim*

Research Talk, *London School of Economics and Political Science*

January 27, 2026

The Telegraph

Male MPs accused of not listening to women and telling them to 'shush'

By Laura Hughes, POLITICAL CORRESPONDENT
1 April 2016 • 1:46pm

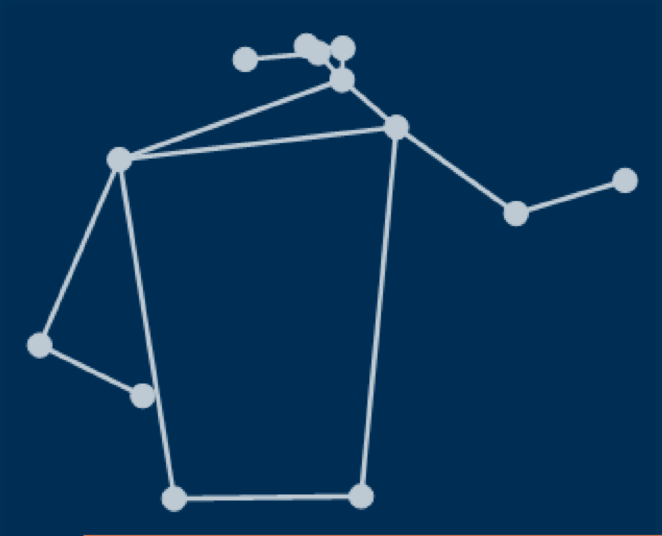
ZEIT ONLINE

Politik · Peter Dausend

Lesezeit: 9 Min.

”When a woman speaks, many men turn around, chat, and stop listening”

Missachtung, Sexismus, Retromänner: Drei Parlamentarierinnen berichten, was sie im Bundestag erleben. Aufgezeichnet von PETER DAUSEND



Research question:

Do parliamentary speeches by women legislators receive less attention than speeches by men legislators?

Underrepresentation of women in politics

Supply:
- Political ambition
  Fox & Lawless (2005)
- Persistence
  Bernhard & de Benediktis-Kessner (2021)

Demand:
- Voter discrimination
  Clayton et al. (2020)
- Party discrimination
  Fujiwara et al. (2025)
- Institutional factors
  Dahlerup & Freidenvall (2005)

Descriptive representation
(numerical representation)

Behaviour within institutions
Anzia & Berry (2011)
Dietrich et al. (2019)

Inequalities within institutions
Erikson & Josefsson (2019)
Krook (2018)
Kerevel & Atkeson (2013)

Substantive representation
(policy outcomes)

Our focus:
Attention inequalities as a barrier to women's equitable participation in parliament

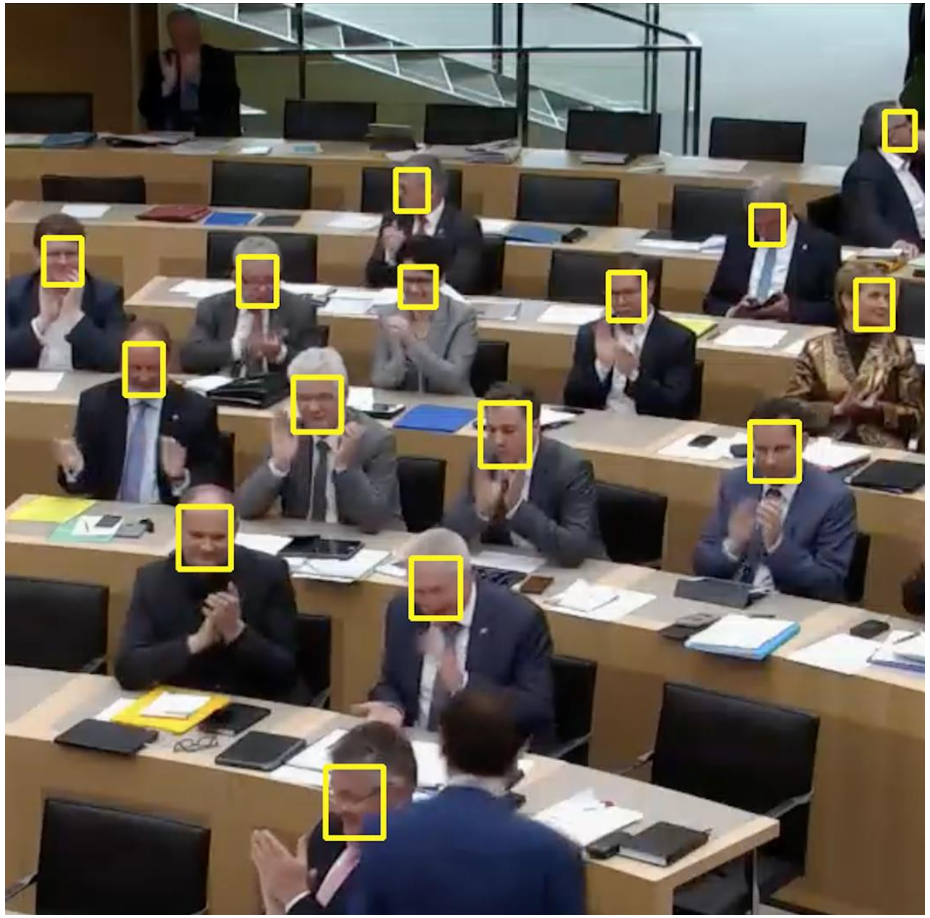
Gender inequalities within parliaments

Attention is difficult to study!

- Attention is a subtle non-verbal behaviour
- We are aware of it, but there is no formal documentation

  - ➢Lack of data sources
  - ➢Lack of measurement tools

Making audience attention measurable



Data: Video footage from TV cameras installed in parliament

Measurement of attention: Computational video analysis

Preview of the results:

- Women receive less attention than men, on average
- This difference is driven by men in the audience
- Women pay equal attention to both their men and women colleagues

Progress, but more to learn

Limitations

- Evidence from one specific case, limited time frame
- Democratic deliberation often happens *before* parliamentary debates
- Downstream consequences of the gender attention gap remain unclear

Contributions

- New computational video analysis pipeline to measure audience attention
- First non-anecdotal evidence on the gender attention gap

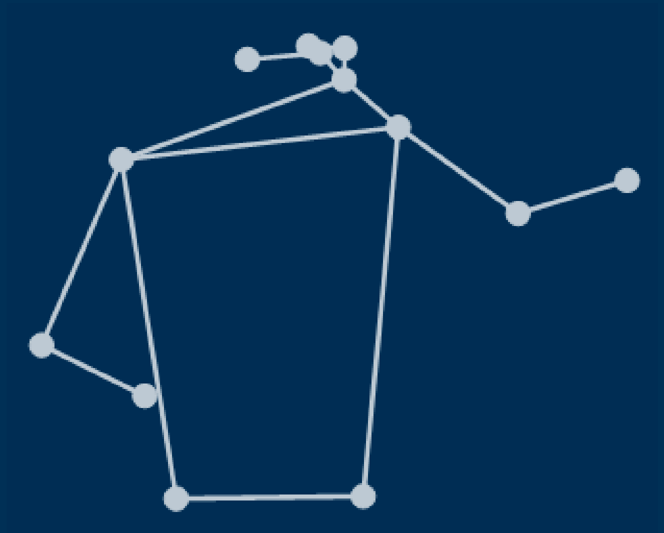
Measuring and analysing parliamentary attention

1. **Data:** Video footage from parliamentary television cameras

2. **Measurement:** Computational video analysis pipeline

3. **Results:** Gender attention gap

4. **Conclusion:** Summary and contributions



Data:

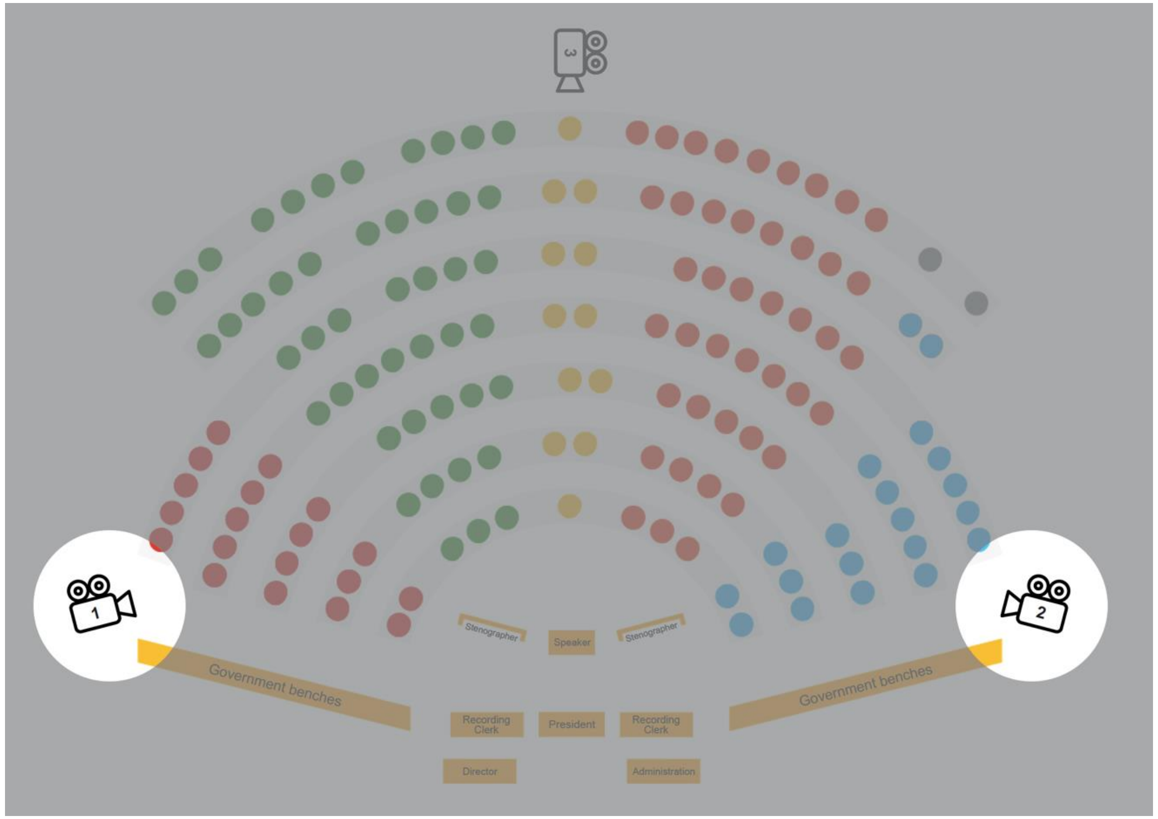
Video footage from parliamentary television cameras

- Parliaments around the world publish video recordings of their parliamentary debates
- **But:** Mostly show the speaker, not the audience
- To study audience attention, we need recordings of the audience

Video footage Landtag Baden-Württemberg

- **Case:**
  Landtag BW, German state-level parliament

Video footage Landtag Baden-Württemberg



Video footage Landtag Baden-Württemberg

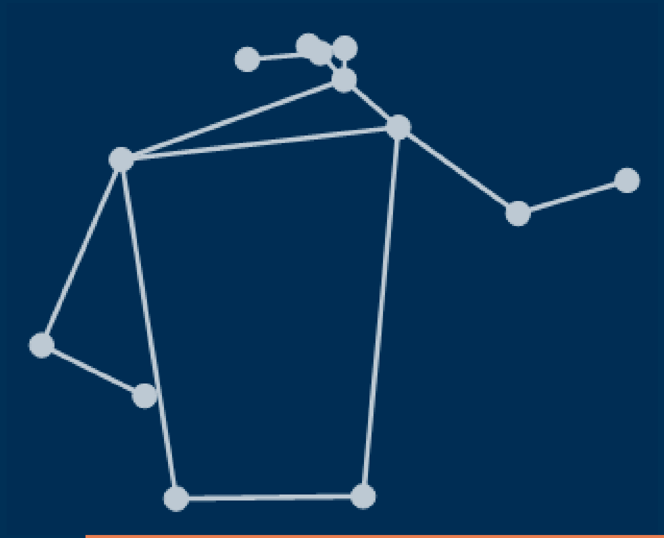
- **Case:**
  Landtag BW, German state-level parliament
- **Unedited video data:** Cooperation with local broadcaster *SWR*
- **Video corpus:** one year of plenary sessions (July 2018 to July 2019)
  - 30 session days
  - 142 debates
  - 1,003 speeches

Case: Landtag Baden-Württemberg 2018/19

- **143 seats**
- **Five party groups**:
  - Green Party (47 seats, 32.9%)
  - Christian Democrats (43 seats, 31.1%)
  - AfD (20 seats, 14.0%)
  - Social Democrats (19 seats, 13.3%)
  - Liberals (12 seats, 8.4%)
- **Governing coalition**:
  Greens and Christian Democrats

Case: Landtag Baden-Württemberg 2018/19

- **Share of women: 25.8%,**
- But highly unequal between parties:
  - Green Party: 22/47 (46.8%)
  - Christian Democrats: 10/43 (23.3%)
  - AfD: 2/20 (10.0%)
  - Social Democrats 2/19 (10.5%)
  - Liberals: 1/12 (8.3%)

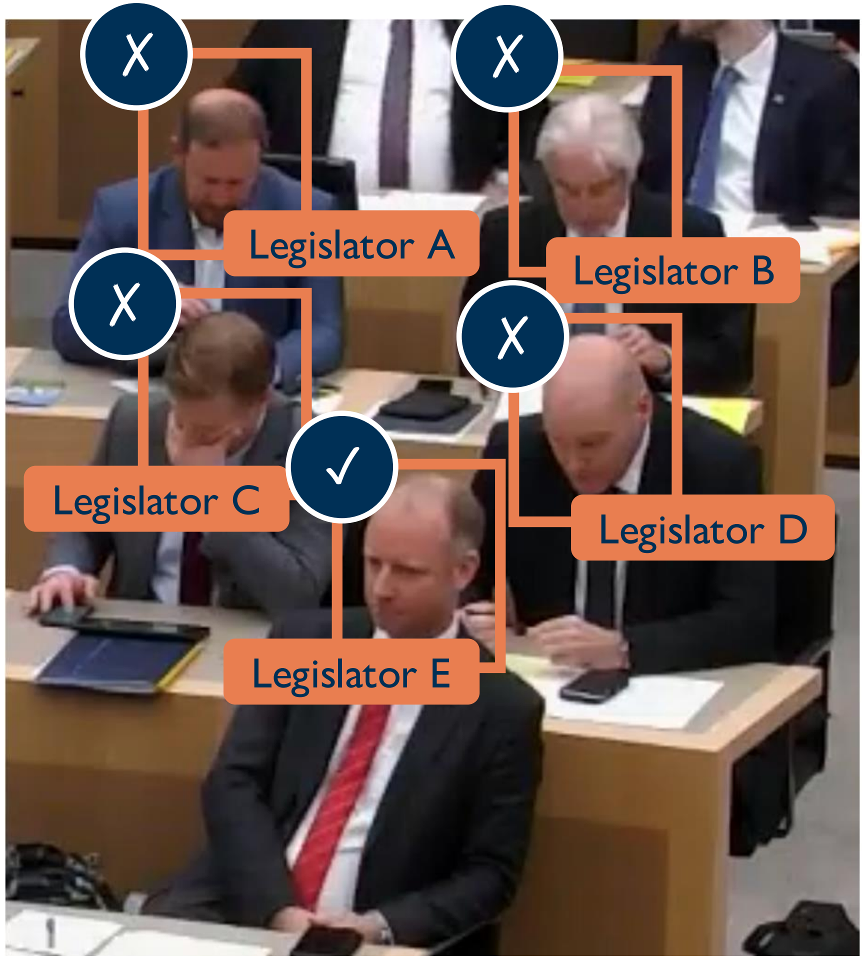


Measurement:

Using computer vision to measure attention in parliament

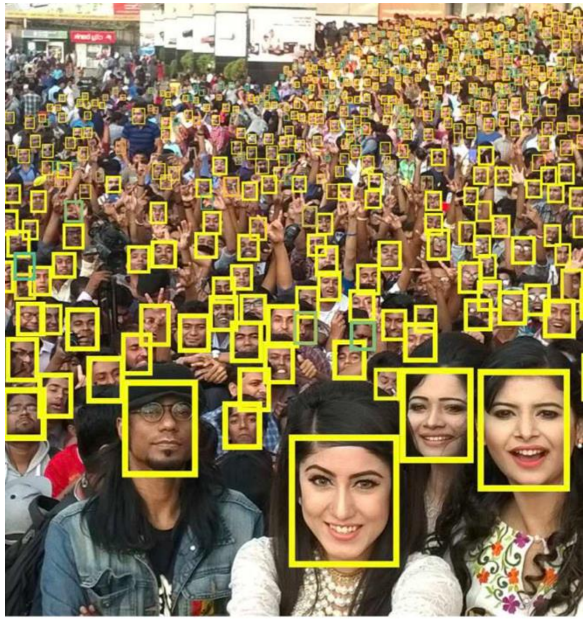
Three goals of measurement

1. Face detection
2. Face recognition
3. Attention classification

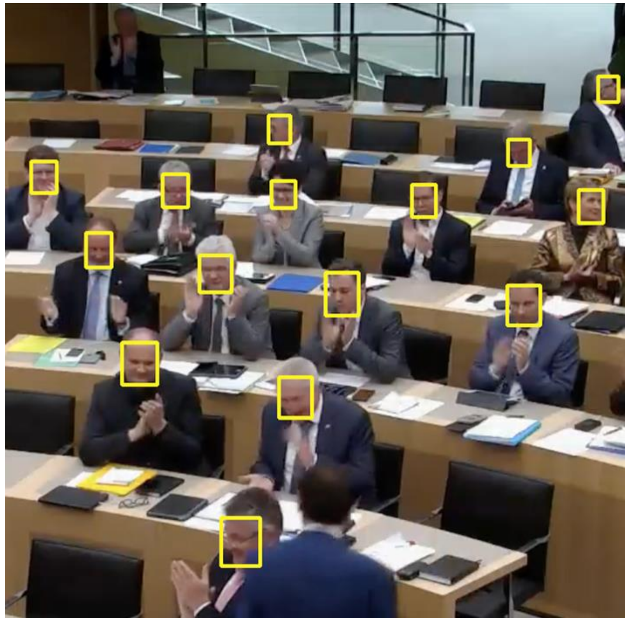


Measuring attention in parliament

1. **Face detection**: Detect faces in the video
   - *TinyFace* architecture (Hu and Ramanan, 2017)



TinyFace application
(Hu and Ramanan, 2017)



TinyFace application
Landtag BW

Measuring attention in parliament

1. **Face detection**: Detect faces in the video
2. **Face recognition:** Identify legislators based on their face
   - One of the most deeply studied areas in computer vision in the past decades
   - **Convolutional Neural Network (CNN)** to predict the **identity of legislators based on detected faces**

Measuring attention in parliament

1. **Face detection**: Detect faces in the video
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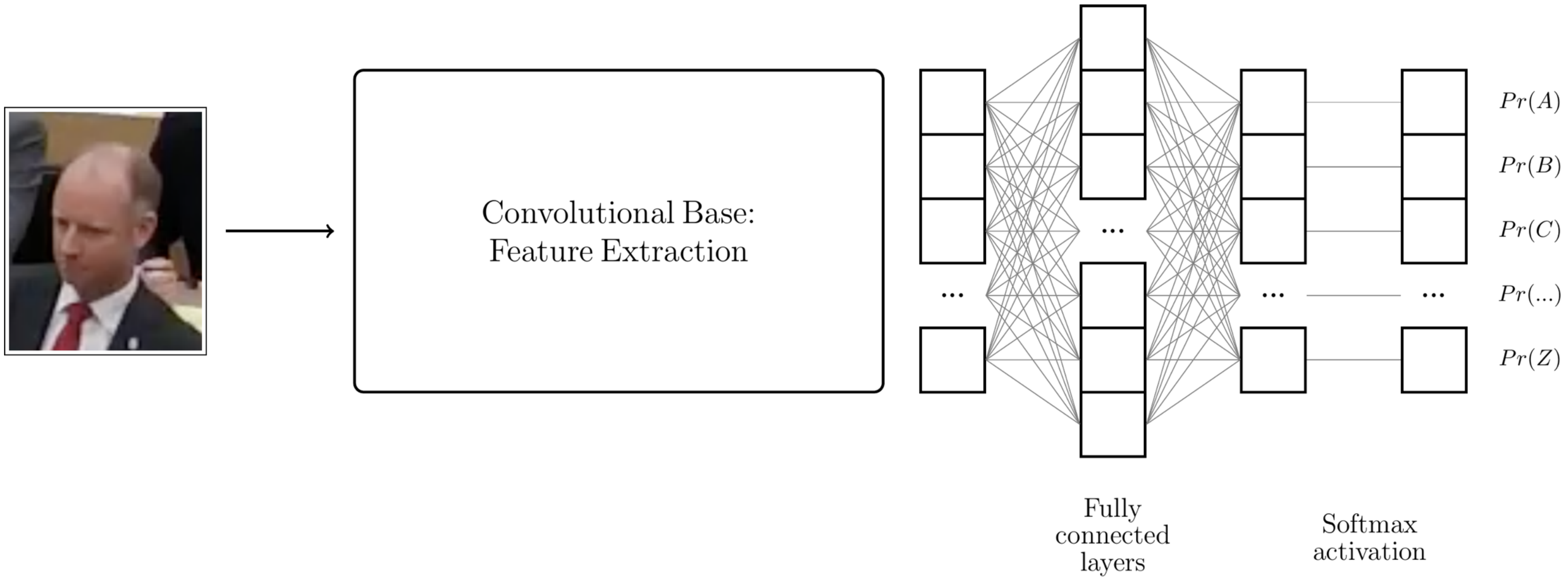


Measuring attention in parliament

1. **Face detection**: Detect faces in the video
2. **Face recognition:** Identify legislators based on their face
   - One of the most deeply studied areas in computer vision in the past decades
   - **Convolutional Neural Network (CNN)** to predict the **identity of legislators based on detected faces**
   - **Training data** set based on both **photos and video clips of all legislators in the *Landtag***
   - Transfer learning approach:
     ResNet-18 pre-trained on ***ImageNet*** data set and **fine-tuned** with the **legislator data** set (He et al., 2016; Deng et al., 2009)
   - Performance: **99.7% correct classification** on test set (true-positive rate)
     [details]

Measuring attention in parliament

1. **Face detection**: Detect faces in the video
2. **Face recognition:** Identify legislators based on their face
3. **Attention classification:** Classify faces as attentive or not attentive
   - **Training data: ~46.000 images** annotated by four coders

Measuring attention in parliament

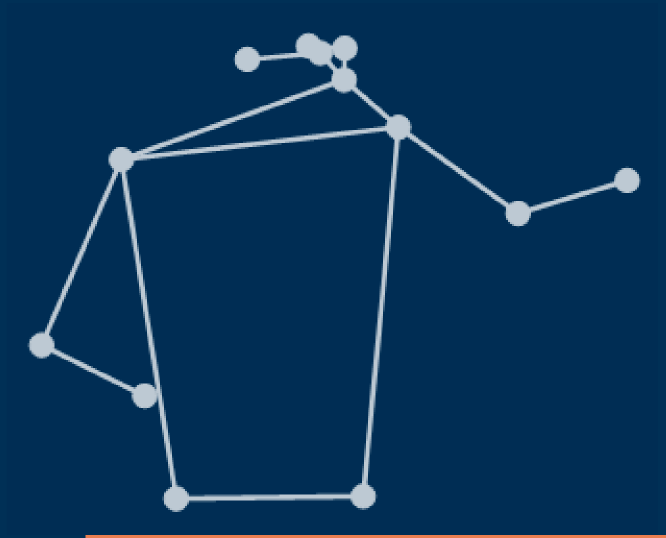
1. **Face detection**: Detect faces in the video
2. **Face recognition:** Identify legislators based on their face
3. **Attention classification:** Classify faces as attentive or not attentive
   - **Training data: ~46.000 images** annotated by four coders
   - ***ResNet-34*** pre-trained ***ImageNet*** data set and fine-tuned with labelled training data to classify images as attentive or not attentive (He et al, 2016; Deng et al., 2009)
   - Performance: **88.6%** (13 out of 15) image frames correctly classified [details]

Measuring attention in parliament

- Analysis of **one year of plenary sessions** (July 2018 to July 2019)
- Unit of observation: Speaker-listener dyad
  - > 25,000 observation
- For each speech and each listening legislator:

Dependent Variable = Share of attentive frames during a speech

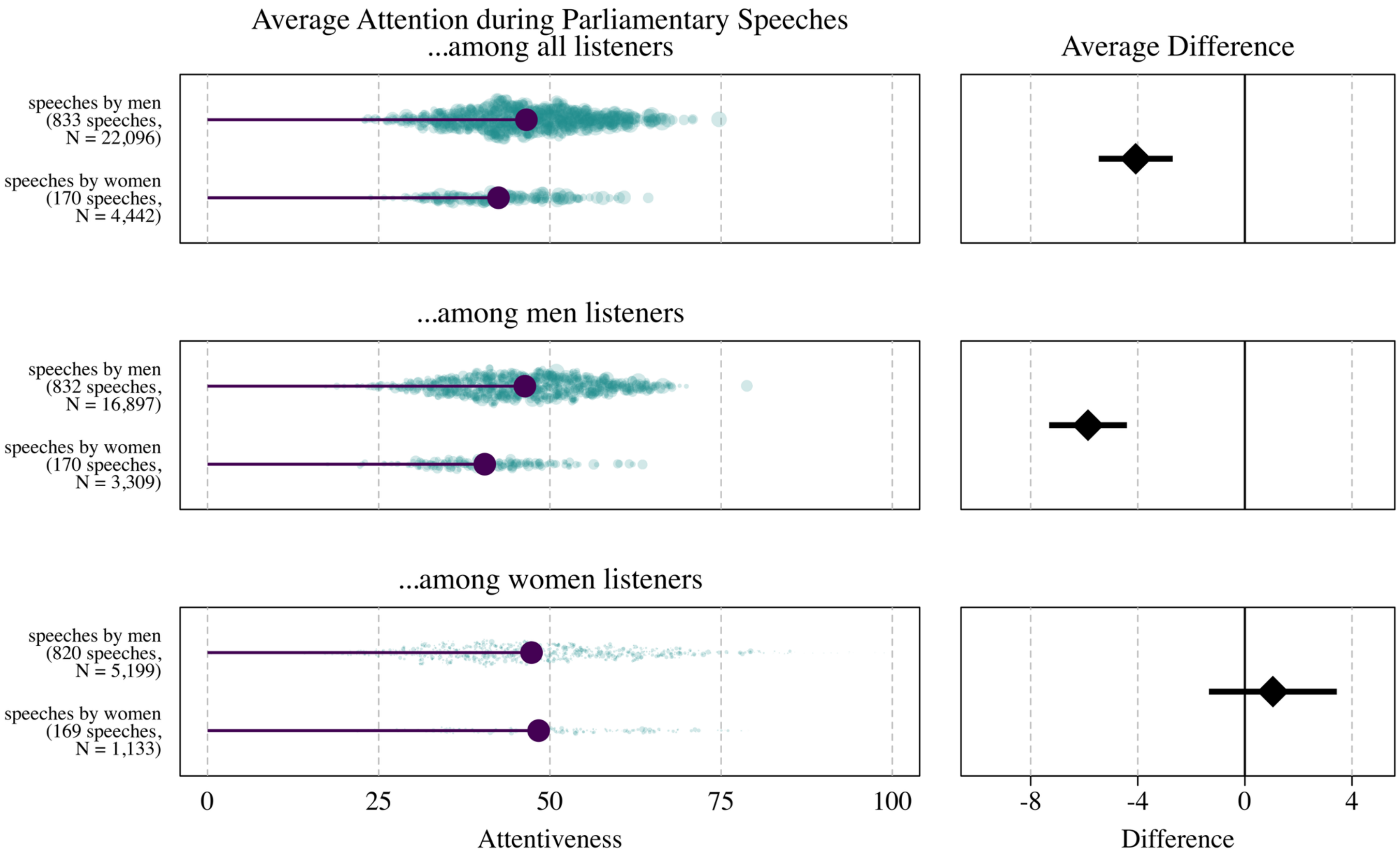
[details]



Results:

Do women receive less attention than men?

Average attention gap



Average attention gap

- **Main result:**
  - Women in the Landtag BW receive less attention than men, on average
  - This difference is driven by men in the audience
  - Women pay equal attention to both their men and women colleagues

Additional analyses

Open questions:

1. Is the average attention gap a **byproduct of other structural inequalities** between men and women in parliament?

Byproduct of other structural inequalities?

Examples:

- ➢Women speak later in the day, when attention is lower
- ➢Women hold less prestigious positions and, thus, receive less attention
- ➢...

Byproduct of other structural inequalities?

- **Refined estimand:**
  - Average *within-listener* difference of attention,
  - conditional on *observable covariates*
- **Estimation strategy:**
  - Linear regression models with legislator fixed effects (listener)
  - Entropy balancing weights (Hainmueller, 2012)

Same party group	Cabinet member (speaker)	Type of debate
Same government/opposition status	Committee chair (speaker)	Morning vs. afternoon
Shared committee membership	Topic expertise (speaker)	Length of prev. speeches in session
Same electoral district	Seniority (speaker)	#N speeches during debate
Neighboring electoral district	Front/mid/back-bencher (speaker)	Length of speech
Same *Regierungsbezirk*	Topic expertise (listener)	Voice pitch
	Party (listener)	Detected frames per second

Byproduct of other structural inequalities?

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Byproduct of other structural inequalities?

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Same party group
Same government/opposition status
Shared committee membership
Same electoral district
Neighboring electoral district
Same *Regierungsbezirk*

Cabinet member (speaker)
Committee chair (speaker)
Topic expertise (speaker)
Seniority (speaker)
Front/mid/back-bencher (speaker)
Topic expertise (listener)
Party (listener)

Type of debate
Morning vs. afternoon
Length of prev. speeches in session
#N speeches during debate
Length of speech
Voice pitch
Detected frames per second

Byproduct of other structural inequalities?

Attention gap, all listener

• Mean comparison:	- 4.08 pp (0.71)
• + listener fixed effects:	- 3.24 pp (0.68)
• + entropy balancing weights:	- 3.45 pp (0.77)
• + exclude party leader speeches:	- 2.94 pp (0.79)

Attention gap, only men listener

• Mean comparison:	- 5.86 pp (0.74)
• + listener fixed effects:	- 5.01 pp (0.68)
• + entropy balancing weights:	- 4.65 pp (0.76)
• + exclude party leader speeches:	- 4.29 pp (0.77)

[details]

Additional analyses

Open questions:

1. Is the average attention gap a **byproduct of other structural inequalities** between men and women in parliament?
   →Observable contextual factors explain the attention gap only partially

2. Is the **size** of the gender attention gap **substantively meaningful**?

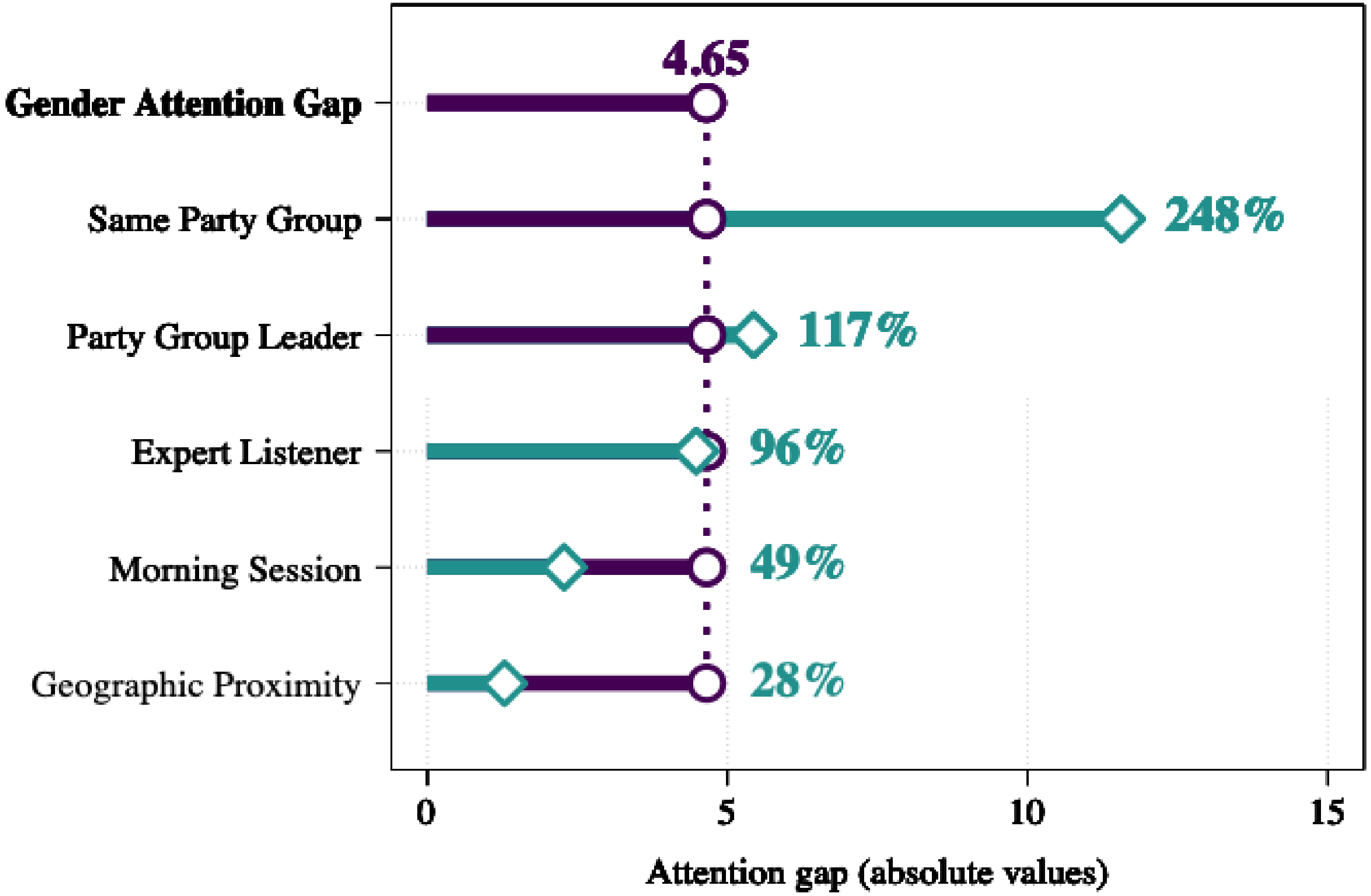
Is the attention gap substantively meaningful?

- Difficult to specify a threshold above which the attention gap is "important"

- **Ideally:** Study of the downstream consequences of the attention gap
  - **But:** Limited time frame makes this difficult

- To still make progress:
  Benchmarking against other attention disparities
  → Is the attention gap rather a product of *explicit hostility* or *implicit bias*?

Is the attention gap substantively meaningful?



[details]

Additional analyses

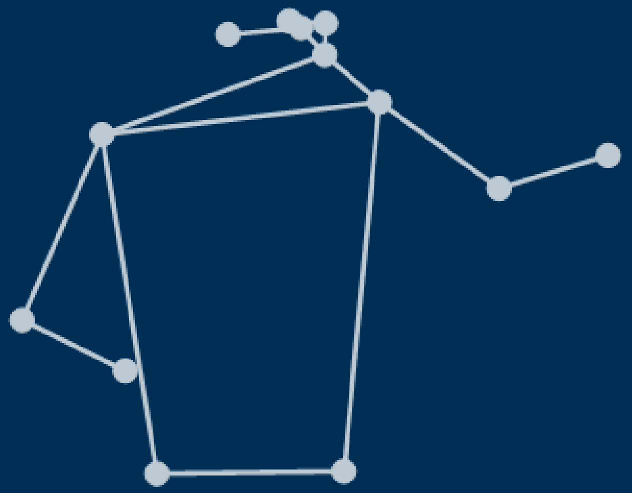
Open questions:

1. Is the average attention gap a **byproduct of other structural inequalities** between men and women in parliament?
   →Observable contextual factors explain the attention gap only partially

2. Is the **size** of the gender attention gap **substantively meaningful**?
   →No definite answer
   →Partisanship is more important for attention than gender
   →Implicit biases is a more plausible explanation than explicit hostility

Additional analyses

- Is the attention gap driven by **dyadic dependencies**?
  → Network analysis model: No [details ⎘]
- Is the average attention gap **driven by only a few listeners**?
  → Multilevel random-effects model: There is individual-level variation, but gap is not driven by a few outliers [details ⎘]
- Is the attention gap driven by **data-preprocessing choices**?
  → Specification curve analysis: No [details ⎘]
- Does the attention gap vary conditional on the debated topic?
  → Text analysis to measure stereotypically feminine/masculine issues: No robust evidence after accounting for partisanship [details ⎘]



Conclusion:
Summary and contributions

Summary and contributions

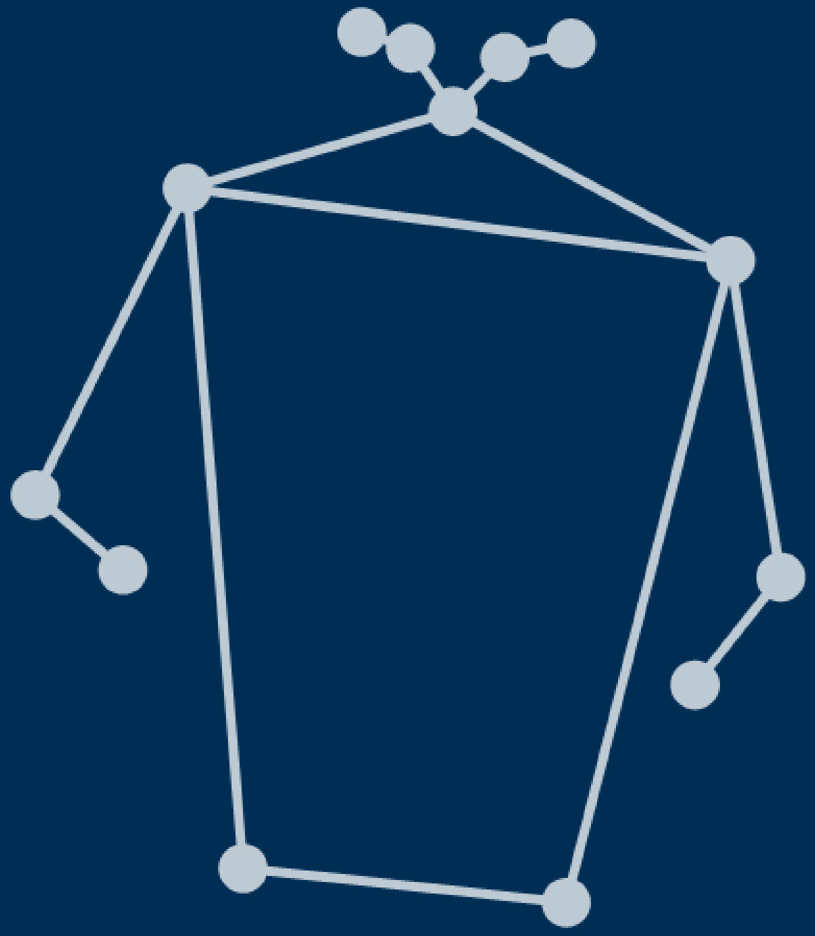
- **RQ:** Do legislators pay less attention to their women colleagues during parliamentary meetings?
- **Methodological contribution:** Computer vision in political science
  Computer vision techniques to **analyse video footage** capturing **legislators while attending parliamentary meetings**
  [previous research using computer vision for video analysis in political science]
- **Substantive contribution:**
  First non-anecdotal evidence on the gender attention gap
  - **Women receive less attention than men** in the *Landtag BW*
  - This **difference is driven by men** who listen less to women
  - **Women pay equal attention** to men and women

Thank you!

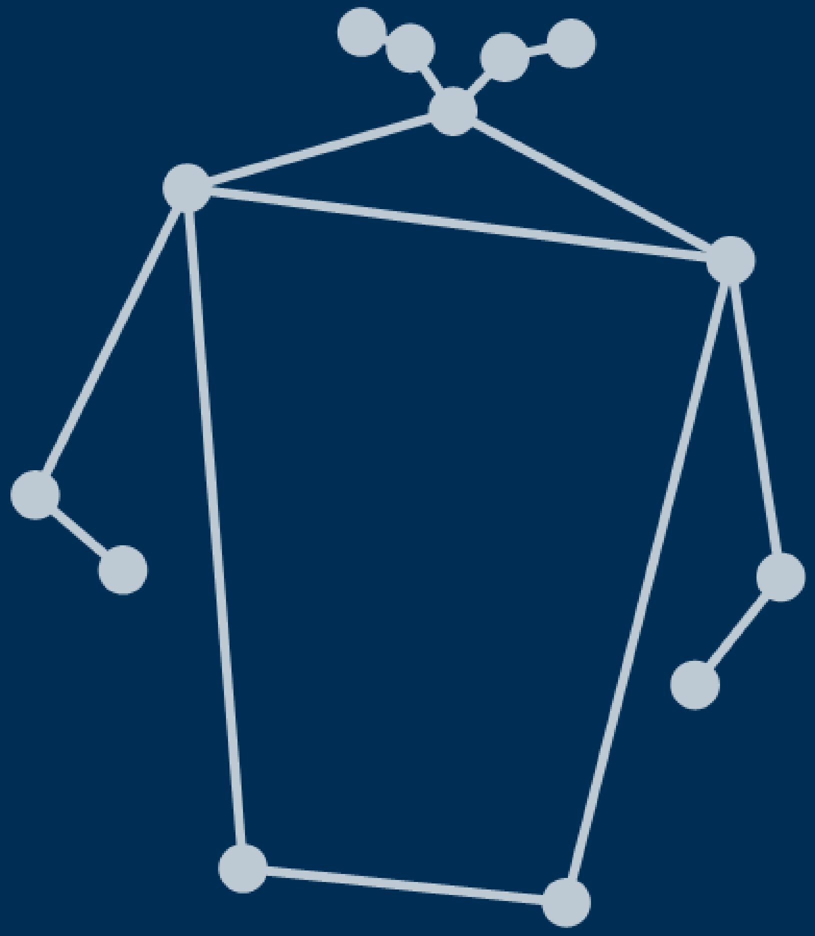
Oliver Rittmann

oliver.rittmann@uni-mannheim.de

Rittmann, Oliver, Dominic Nyhuis, and Tobias Ringwald. Forthcoming. "Gendered Patterns of Parliamentary Attention." Online first: *The Journal of Politics*.



Appendix



Appendix: Face recognition

Validation

- Test set: 30 randomly sampled images per legislator
- Classification accuracy: 99.7%

[back to presentation]
[back to appendix]

Appendix: Attention classification

Codebook instructions

- Attentive
  - The legislator looks forward (orthogonal to shoulder axis)
  - If eyes closed: attentive only if the chin is raised (blinking)
- Not attentive
  - The legislator does not look forward (looks down, to the left/right, or backwards)
  - If eyes closed: not attentive if lowered or supported head
- Unclear

- 46,000 labeled images
  - 90% train set, 10% test set
  - 500 images labeled by all four coders to monitor inter-coder reliability

Appendix: Attention classification

(1) Percentage Agreement					
	Model Prediction	*1*	*2*	*3*	*4*
Human Annotation	**0.866**				
Coder 1		1.00	0.93	0.90	0.94
Coder 2			1.00	0.89	0.91
Coder 3				1.00	0.91
Coder 4					1.00

(2) Cohen's Kappa					
	Model Prediction	*1*	*2*	*3*	*4*
Human Annotation	**0.729**				
Coder 1		1.00	0.85	0.80	0.88
Coder 2			1.00	0.77	0.82
Coder 3				1.00	0.83
Coder 4					1.00

[back to presentation]
[back to appendix]

Appendix: Dependent variable

$$Y_{ij} = \frac{\overbrace{\sum a_{ij}}^{\text{Sum of all frames during speech } i \text{ in which legislator } j \text{ is detected and classified as attentive}}}{\underbrace{\sum a_{ij} + a'_{ij}}_{\text{Sum of all frames during speech } i \text{ in which legislator } j \text{ is detected}}}$$

- $a_{ij} = 1$ for all frames during speech i in which legislator j was detected in the audience and **classified as attentive**, and zero otherwise
- $a'_{ij} = 1$ for all frames during speech i in which legislator j was detected in the audience and **classified as inattentive**, and zero otherwise

[back to presentation]
[back to appendix]

Appendix: Within-listener comparison

- Concerns about simple mean comparison:
  - Camera does usually not capture the full audience
  - Women in the audience are concentrated in few party groups
  - ➢ The result may be confounded by selection mechanism

- Does the attention gap persist when tracing legislators over time?
  - ➢ **Legislator fixed-effect models**

Appendix: Within-listener comparison

	Full Data			Men			Women		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Woman Speaker	−3.24	−3.45	−2.94	−5.01	−4.65	−4.29	2.05	0.97	1.69
	(0.68)	(0.77)	(0.79)	(0.68)	(0.76)	(0.77)	(1.18)	(1.50)	(1.55)
Listener Fixed Effects	✓	✓	✓	✓	✓	✓	✓	✓	✓
Entropy Balancing Weights		✓	✓		✓	✓		✓	✓
Without Party Group Leader Speeches			✓			✓			✓
N	26,417	26,417	23,002	20,157	20,157	17,476	6,260	6,260	5,526
R^2	0.24	0.27	0.26	0.27	0.30	0.30	0.15	0.18	0.18
N(Listeners)	126	126	126	96	96	96	30	30	30

The dependent variable is attention during a speech.

Parentheses report cluster-robust standard errors, clustered by speeches.

[back to appendix]

Appendix: Network model analysis

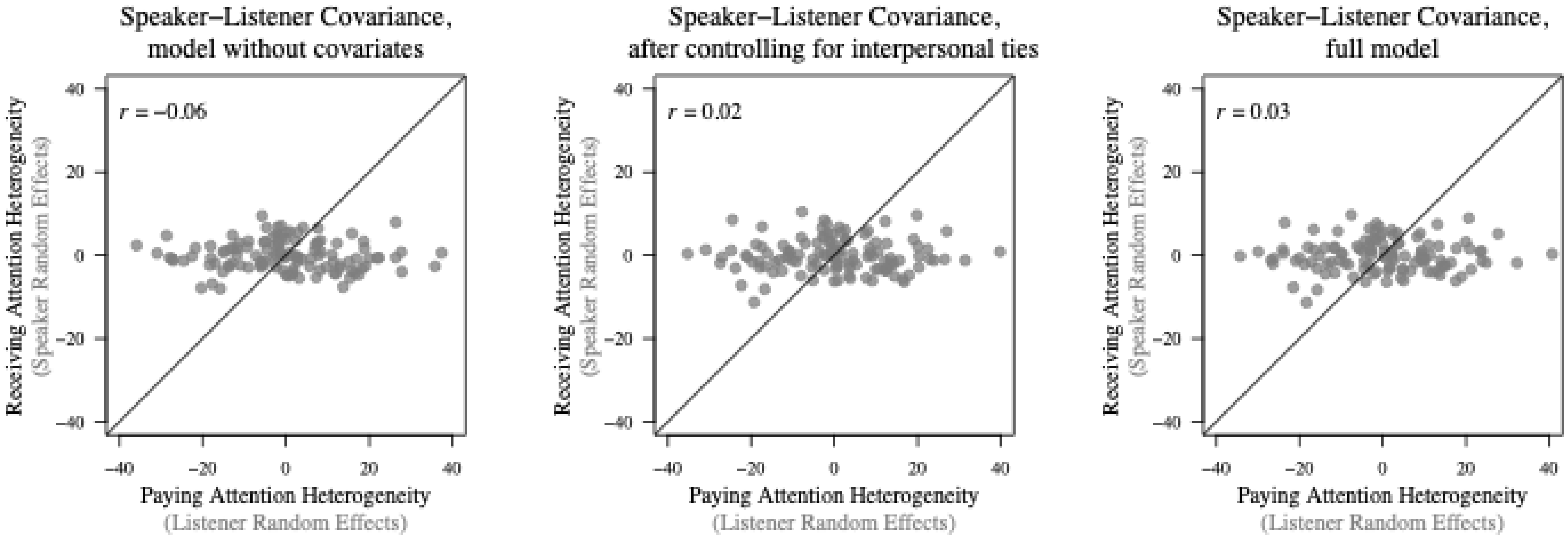
- Dyadic dependencies may violate the conditional independence assumption underlying conventional regression models
- Types of (potential) dyadic dependencies:
  - Listener heterogeneity (some listeners generally are more attentive than others)
  - Speaker heterogeneity (some speakers receive generally more attention than others)
  - Speaker-listener covariance (those who are more attentive also receive more attention)
  - Reciprocity (pairs of legislators who are reciprocally attentive to one another)

- Network analysis to model such dependencies

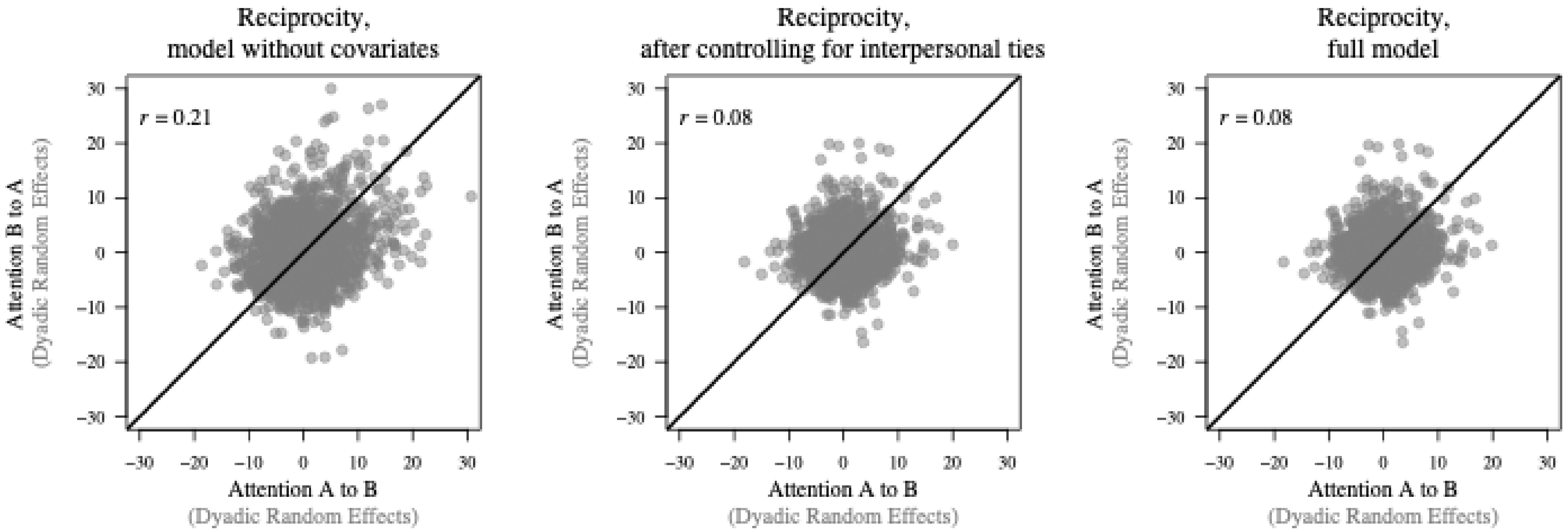
Appendix: Network model analysis

	(1)	(2)	(3)
Intercept	46.87	40.86	40.85
	(1.40)	(1.42)	(1.62)
Same Party		12.12	12.09
		(0.54)	(0.54)
Same Committee		4.63	4.60
		(0.47)	(0.47)
Same Gov./Opp. Status		−0.12	−0.18
		(0.49)	(0.49)
Geographic Proximity		1.44	1.47
		(0.67)	(0.67)
Woman Speaker			−4.01
			(1.10)
Woman Listener			3.12
			(3.07)
Woman Speaker × Woman Listener			4.15
			(1.10)
AIC	248,734.98	248,004.73	247,979.44
BIC	248,775.91	248,078.41	248,077.68
Log Likelihood	−124,362.49	−123,993.36	−123,977.72
N	26,538	26,538	26,538
N(Speaker-Listener Dyads)	8,987	8,987	8,987
N(Listeners)	134	134	134
N(Speakers)	130	130	130
Var(Speaker-Listener Dyads)	97.40	67.43	66.99
Var(Listeners)	228.52	221.35	220.42
Var(Speakers)	17.91	21.35	19.64
Var(Residuals)	595.70	596.91	596.94

Appendix: Network model analysis



Appendix: Network model analysis



[back to presentation]
[back to appendix]

Appendix: Entropy balancing

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Listener Fixed Effects	✓	✓	✓	✓	✓	✓	✓	✓	✓
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The dependent variable is attention during a speech.

Parentheses report cluster-robust standard errors, clustered by speeches.

[back to presentation]
[back to appendix]

Appendix: Benchmarking the attention gap

	Full Data					Men				
	$\hat{\beta}_{\text{women}}$	/	$\hat{\beta}_{\text{benchmark}}$	=	**Ratio**	$\hat{\beta}_{\text{women}}$	/	$\hat{\beta}_{\text{benchmark}}$	=	**Ratio**
Same Party	−3.45		12.23		**0.28**	−4.65		11.56		**0.40**
Party Group Leader (Speaker)	−3.45		5.52		**0.63**	−4.65		5.44		**0.86**
Expert Listener	−3.45		5.45		**0.63**	−4.65		4.48		**1.04**
Morning Session	−3.45		2.91		**1.19**	−4.65		2.28		**2.04**
Geographic Proximity	−3.45		1.24		**2.79**	−4.65		1.29		**3.62**

[back to presentation]
[back to appendix]

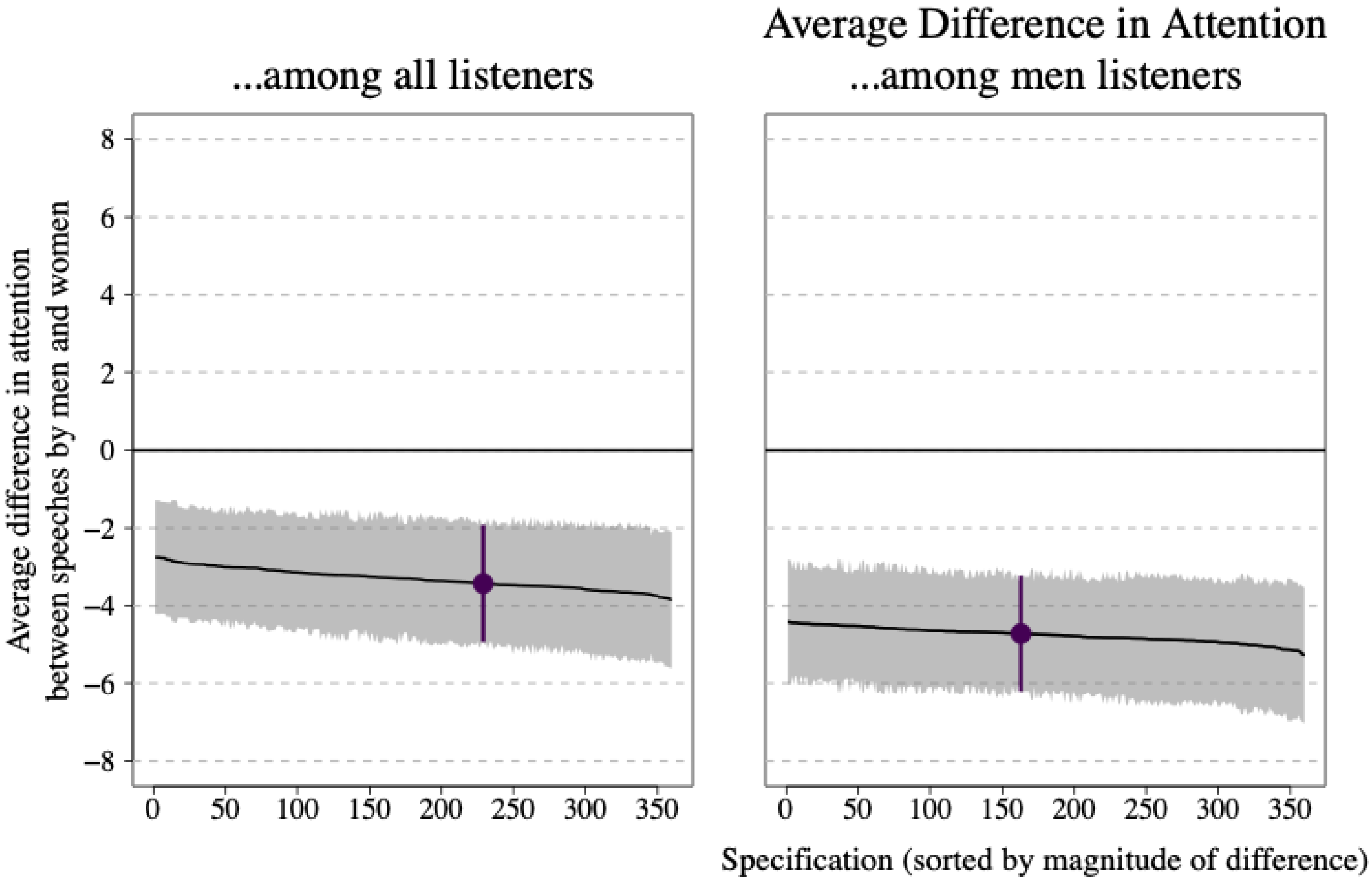
Appendix: Specification curve analysis

- A series of preprocessing decisions precede the analysis
  - Minimum and maximum length of a speech to be included in the analysis
  - Minimum share of frames in which a legislator must be detected during one speech
  - How often a legislator must be observed in both conditions (listening to women and men)
  - Whether to refine entropy balancing weights or not

- We do not want our results to depend on these decisions

➢ Specification curve analysis (Simonsohn et al., 2020)
  - 360 analyses based on varying preprocessing decisions

Appendix: Specification curve analysis



[back to presentation]
[back to appendix]

Appendix: Attention gap driven by few listener?

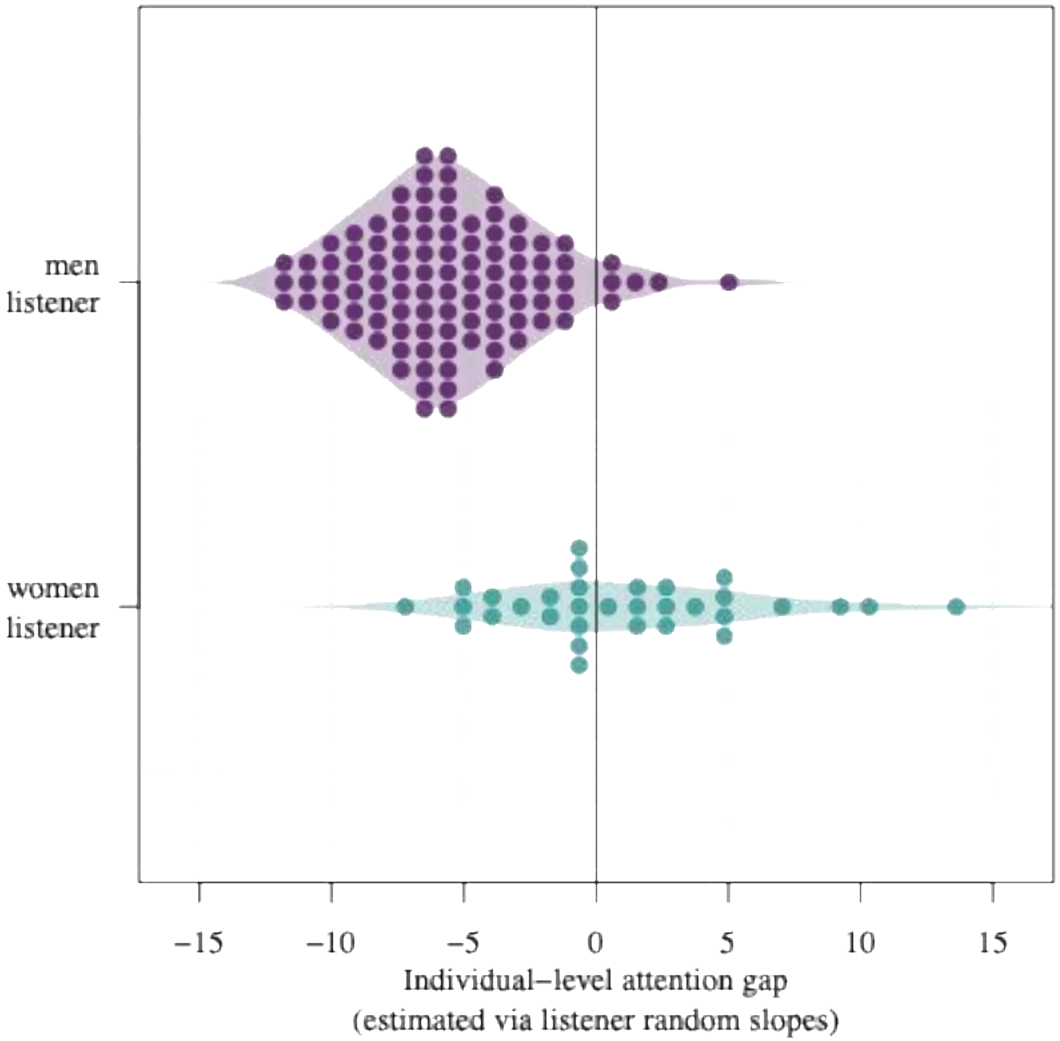
The average attention gap may be driven by a **few high-discrimination legislators**, whereas the majority shows no discrimination

Estimation of individual-level attention gap:

→Multilevel model

→Random-effects:
Intercepts and slopes vary by listener

[back to presentation]
[back to appendix]



Appendix: Topic moderation?

- **Role congruity theory** suggests that gender bias depends on issue context (Eagly & Karau, 2002)

  Issues **incongruent** with **feminine stereotypes** → **less attention**
  Issues **congruent** with **feminine stereotypes** → **more attention**

- **Computational text analysis** to measure the **substantive incongruity of a speech with stereotypically feminine issues**

Appendix: Measurement of issue incongruity

- **Goal:**
  Measure the congruity of a speech with stereotypically feminine and masculine issues

- **Measurement approach:**
  Combine word-embeddings and dictionaries to scale the text of speeches between two semantic poles (Gennaro & Ash, 2022)

Appendix: Measurement of issue incongruity

Components of the measure

Dictionary to represent stereotypically **masculine issue areas**

[military, weapons delivery, armed, forces, trade, export, import, taxes, economy, economic growth, security, police]*

Dictionary to represent stereotypically **feminine issue areas**

[education, family, pregnancy, care, poverty, wage inequality, health, support, social work, children, parenting]*

*translated from German

Appendix: Measurement of issue incongruity

Calculation of the measure

- $\boldsymbol{M}$ = centroid of embedding vectors of the stereotypically **masculine word list**
- $\boldsymbol{F}$ = centroid of embedding vectors of the stereotypically **feminine word list**
- $\boldsymbol{d_i}$ = centroid of embedding vectors of all terms in speech i

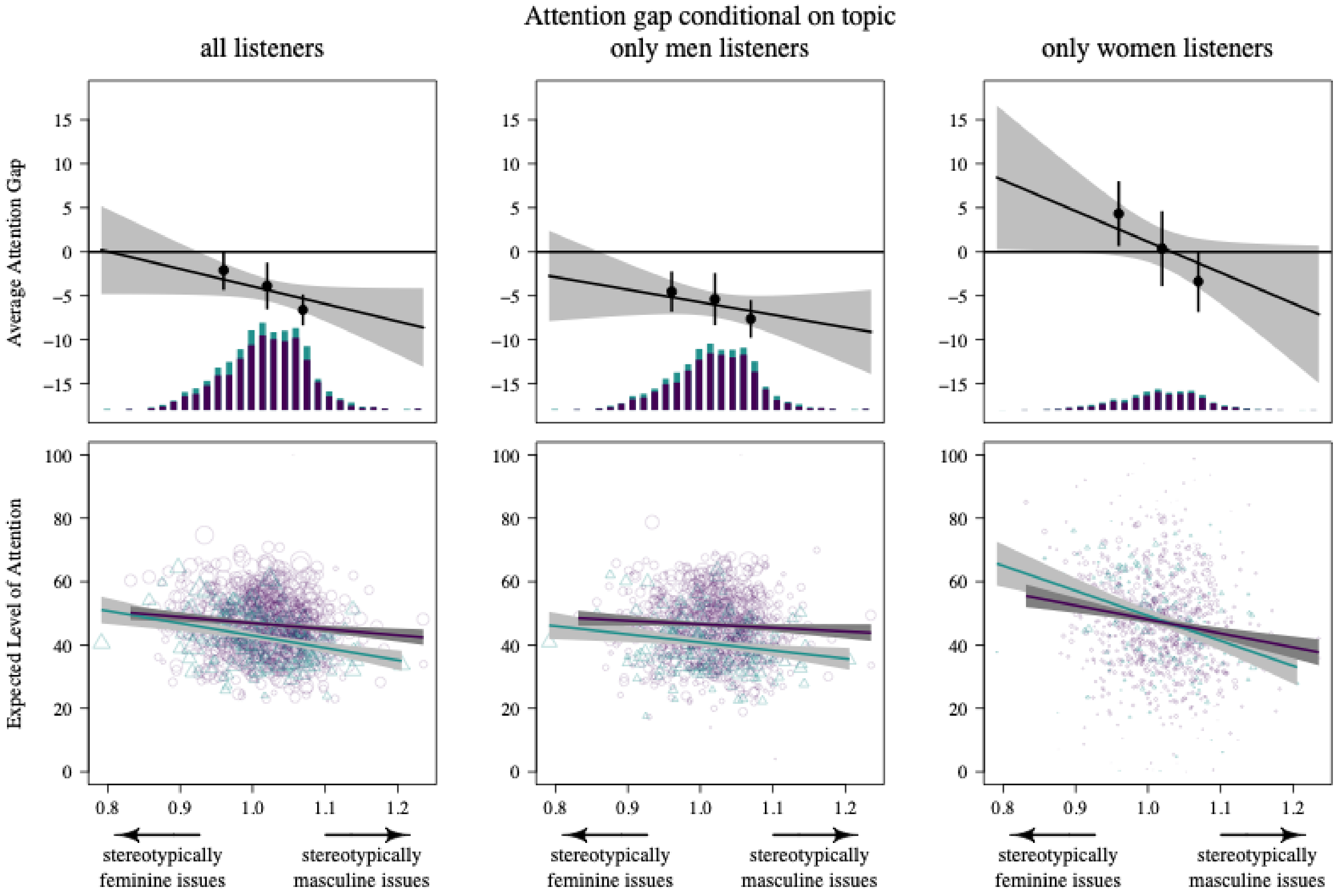
$$S_i = \frac{\overbrace{\mathrm{sim}(\boldsymbol{d_i}, \boldsymbol{M}) + b}^{\text{Cosine similarity between speech } i \text{ and masculine pole}}}{\underbrace{\mathrm{sim}(\boldsymbol{d_i}, \boldsymbol{F}) + b}_{\text{Cosine similarity between speech } i \text{ and feminine pole}}}$$

Interpretation

- $S_i = 1$ when speech is equally semantically similar to feminine and masculine pole
- $S_i > 1$ when speech is more semantically similar to masculine pole
- $S_i < 1$ when speech is more semantically similar to feminine pole

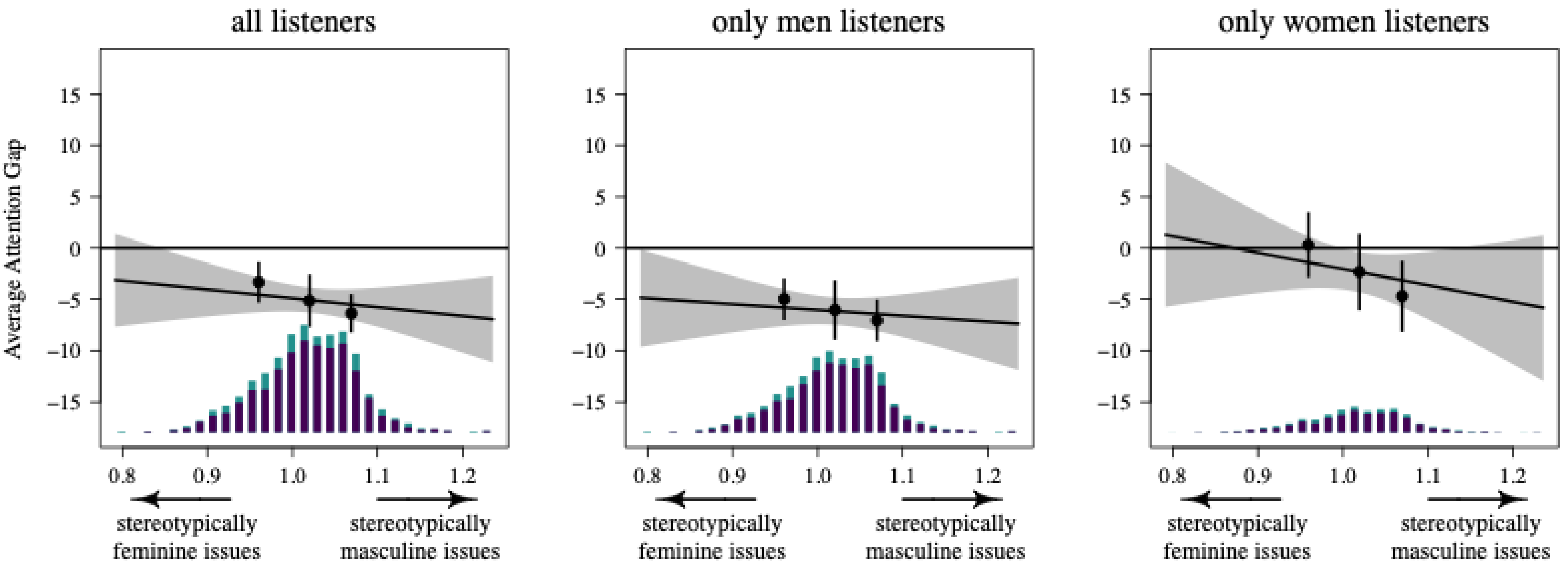
[back to presentation]
[back to appendix]

Appendix: Interaction models, detailed



Appendix: Interaction models, detailed

With control for shared party affiliation



[back to presentation]
[back to appendix]

Appendix: Interaction models

	Full Data			Men			Women		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Woman Speaker × Incongruity	−19.84	−18.33	−8.57	−14.32	−13.35	−5.65	−34.99	−32.14	−16.05
	(10.45)	(10.43)	(9.64)	(10.90)	(10.49)	(10.18)	(17.65)	(17.06)	(15.58)
Listener Fixed Effects		✓	✓		✓	✓		✓	✓
Control for same party group			✓			✓			✓
N	26,538	26,538	26,538	20,206	20,206	20,206	6,332	6,332	6,332

The dependent variable is attention during a speech. Parentheses report cluster-robust standard errors, clustered by speeches.

The intercepts and the coefficients of the constitutive terms of the interaction and the control variables are omitted.

[back to presentation]
[back to appendix]

Appendix: Interaction models, detailed

	Full Data			Men			Women		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Intercept	65.98			57.85			92.16		
	(5.76)			(6.17)			(9.41)		
Women Speaker	15.90	15.21	3.64	8.58	8.44	−0.41	36.13	34.26	14.00
	(10.75)	(10.71)	(9.88)	(11.16)	(10.74)	(10.41)	(18.03)	(17.44)	(15.81)
Incongruity	−19.07	−20.71	−28.21	−11.31	−12.79	−20.02	−44.08	−46.40	−53.66
	(5.63)	(5.28)	(5.37)	(6.03)	(5.48)	(5.65)	(9.22)	(8.87)	(8.15)
Woman Speaker × Incongruity	−19.84	−18.33	−8.57	−14.32	−13.35	−5.65	−34.99	−32.14	−16.05
	(10.45)	(10.43)	(9.64)	(10.90)	(10.49)	(10.18)	(17.65)	(17.06)	(15.58)
Same Party			11.44			10.38			13.98
			(0.48)			(0.51)			(0.94)
Listener Fixed Effects		✓	✓		✓	✓		✓	✓
Control for same party group			✓			✓			✓
N	26,538	26,538	26,538	20,206	20,206	20,206	6,332	6,332	6,332

The dependent variable is attention during speech. Parentheses report cluster-robust standard errors, clustered by speeches.

[back to presentation]
[back to appendix]

Appendix: Computer vision in political science

- **Televised presidential debates**
  - US Presidential elections: Boussalis et al. (2021, APSR)
  - German Federal elections: Boussalis & Coan (2020, PolCom)
- **Campaign ads:** Tarr et al. (2022, PA), Neumann et al. (2022, CCR)
- **Parliamentary debates**
  - US House of Representatives:
    Rittmann et al. (2025, BJPolS), Dietrich (2021, PA)
- **Traffic cameras to study political behaviour**
  - Racial avoidance on city streets:
    Dietrich & Sands (2024, Nature Human Behaviour)
  - Turnout: Dietrich et al. (2024, R&P)

[back to presentation]
[back to appendix]

Ongoing work and broader research agenda

Ongoing work and broader research agenda

Published research

- **Oliver Rittmann**. 2024.
  "Legislators' Emotional Engagement with Women's Issues: Gendered Patterns of Vocal Pitch in the German Bundestag."
  British Journal of Political Science.
- **Oliver Rittmann**, Tobias Ringwald, and Dominic Nyhuis. 2025.
  "Public Opinion and Emphatic Legislative Speech: Evidence from an Automated Video Analysis."
  British Journal of Political Science.
- **Oliver Rittmann**, Dominic Nyhuis, and Tobias Ringwald. 2025.
  "Gendered Patterns of Parliamentary Attention."
  The Journal of Politics.

Working papers

- **Oliver Rittmann. 2025.**
  "A Measurement Framework for Computationally Analyzing Politicians' Body Language."
  OSF Working Paper.

[back to presentation]
[back to appendix]

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[back to appendix]