# "Let Me Just Interrupt You": Estimating Gender Effects in Supreme Court Oral Arguments

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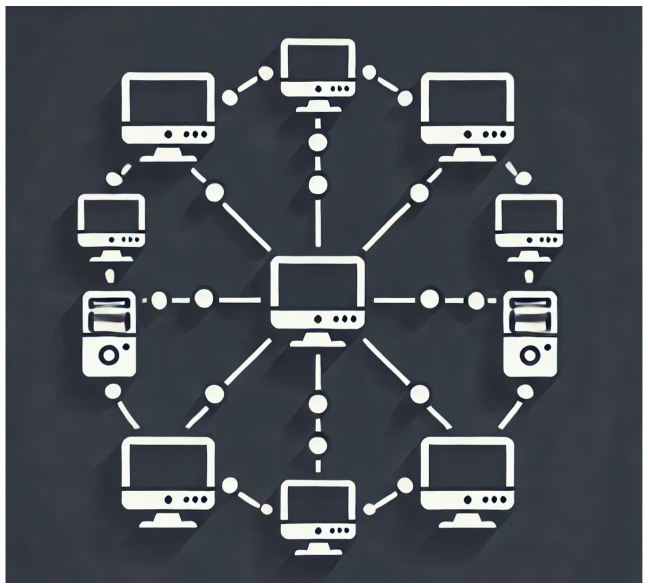
# Outline: Three-part talk

1. Introduction & Background
2. Causal Formalisms & Research Design
3. Findings & Corroboration

I'll pause for questions after each part.

# Through natural language we, as humans, …

## Transmit and gather information

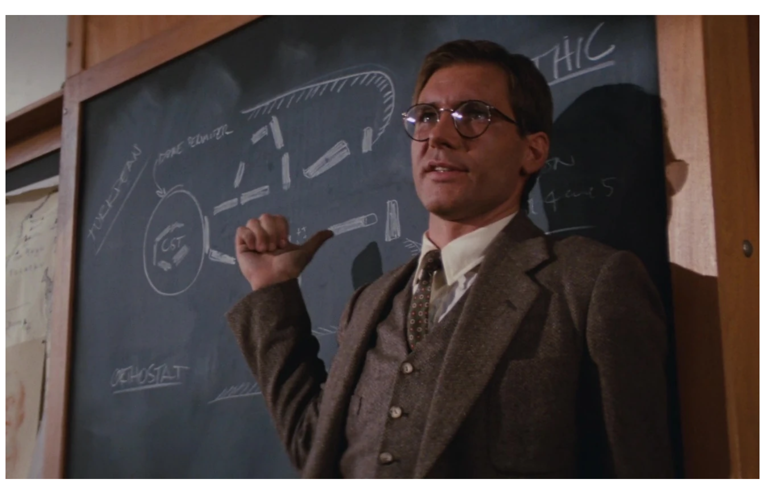


Source: ChatGPT-4o

## Facilitate collaboration

Source: Getty images

## Judge a person's intelligence



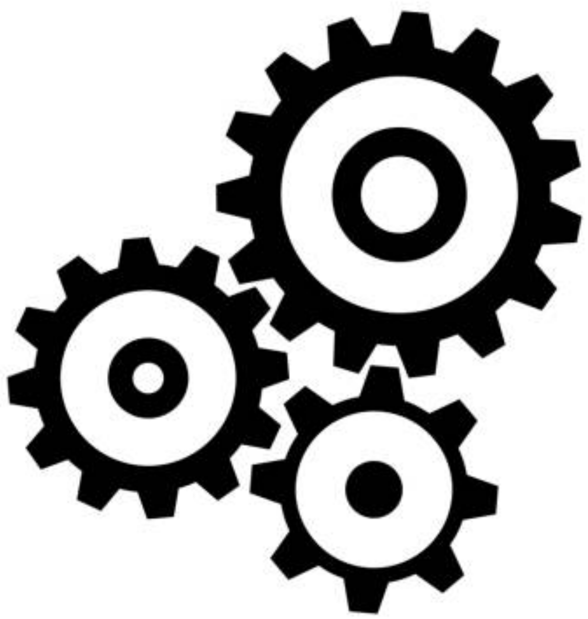
Source: Indiana Jones fandom

## Reinforce social norms and hierarchies

Source: Shutterstock

# Different NLP paradigms, overlapping methods

Downstream-centered



Building computational systems which involve language (engineering)

*Human language technologies

Corpus-centered

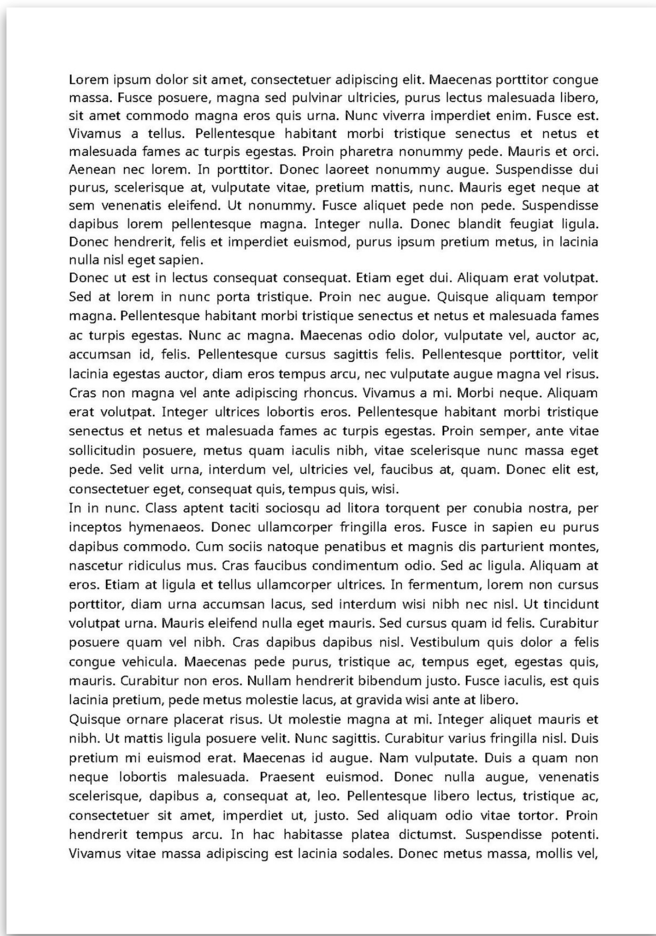
Language as the object of study (science)

*Text-as-data
*Computational social science
*Data Science

Antoniak & Mimno. “Evaluating the stability of embedding-based word similarities.” TACL, 2018.

# Text-as-data prototypical pipeline

Raw text


Lorem ipsum dolor sit amet, consectetuer adipiscing elit. Maecenas porttitor congue massa. Fusce posuere, magna sed pulvinar ultricies, purus lectus malesuada libero, sit amet commodo magna eros quis urna. Nunc viverra imperdiet enim. Fusce est. Vivamus a tellus. Pellentesque habitant morbi tristique senectus et netus et malesuada fames ac turpis egestas. Proin pharetra nonummy pede. Mauris et orci. Aenean nec lorem. In porttitor. Donec laoreet nonummy augue. Suspendisse dui purus, scelerisque at, vulputate vitae, pretium mattis, nunc. Mauris eget neque at sem venenatis eleifend. Ut nonummy. Fusce aliquet pede non pede. Suspendisse dapibus lorem pellentesque magna. Integer nulla. Donec blandit feugiat ligula. Donec hendrerit, felis et imperdiet euismod, purus ipsum pretium metus, in lacinia nulla nisl eget sapien.

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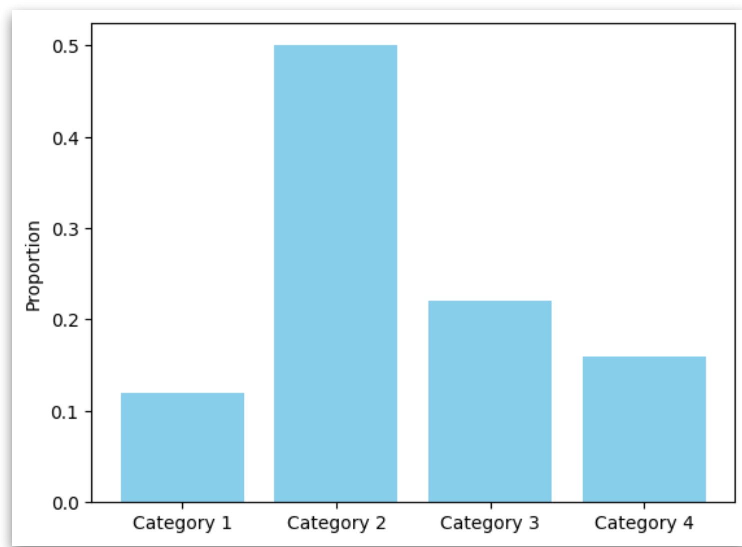
Social Construct Measurement




$Y_i$

Downstream Inference

Prevalence

$$E[Y]$$

Association

$$X \sim Y$$

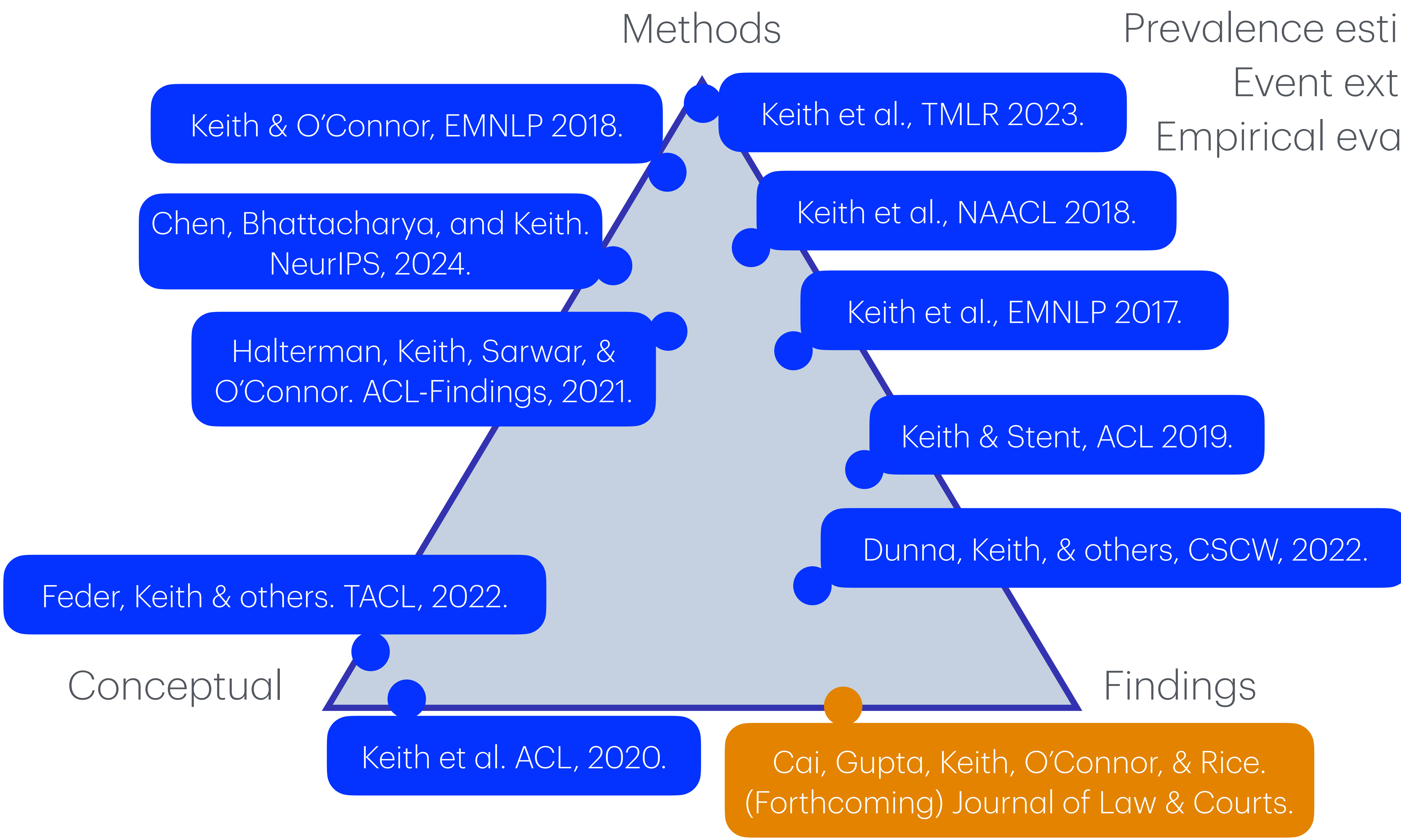
Causal Estimation

$$E[Y|do(X = x)]$$

+ Uncertainty
(Confidence intervals)

# My text-as-data work

Causal estimates with text
Prevalence estimation
Event extraction
Empirical evaluation



# Today’s focus

“Let Me Just Interrupt You”: Estimating Gender Effects in Supreme Court Oral Arguments*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July 29, 2024


**Abstract**

Oral argument is the most public and visible part of the U.S. Supreme Court’s decision-making process. Yet what if some advocates are treated differently before the Court solely because of aspects of their identity? In this work, we leverage a causal inference framework to quantify the effect of an advocate’s gender on interruptions of advocates at both the Court-level and the justice-level. Examining nearly four decades of U.S. Supreme Court oral argument transcript data, we identify a clear and consistent gender effect that dwarfs other influences on justice interruption behavior, with female advocates interrupted more frequently than male advocates.



**Word Count**: 9,868

**Keywords**: U.S. Supreme Court; Oral Argument; Gender Bias; Causal Inference; Text-as-Data


* All data and materials necessary to replicate the results reported in this article are available at https://github.com/kakeith/interruptions-supreme-court

†Authors are in alphabetical order by last name. Authors contributed as follows: implementation of data pipeline by EC, AG, KK, DR; research design by KK, BO, DR; first draft writing of manuscript by KK, DR; editing manuscript by EC, AG, KK, BO, DR. Send correspondence to kak5@williams.edu and drrice@umass.edu.

(Forthcoming) Journal of Law & Courts

Department of Political Science

Light on the NLP methods, but opens avenues for some interesting future NLP work

“Design trumps analysis” in observational causal studies

—Rubin (2008)

# Background: U.S. Supreme Court justices appointed for life


Fig source

# Background: Recent U.S. Supreme Court cases

## In 6-to-3 Ruling, Supreme Court Ends Nearly 50 Years of Abortion Rights

The decision will lead to all but total bans on the procedure in about half of the states.

Share full article

Abortion rights protesters demonstrating in front of the Supreme Court after the decision was released on Friday. Haiyun Jiang/The New York Times

By Adam Liptak

Published June 24, 2022 Updated Nov. 2, 2022

Leer en español

WASHINGTON — The Supreme Court on Friday overturned Roe v. Wade, eliminating the constitutional right to abortion after almost 50 years in a decision that will transform American life, reshape

Dobbs v. Jackson
June 24, 2022
6-3 vote

## Supreme Court Rejects Affirmative Action Programs at Harvard and U.N.C.

In earlier decisions, the court had endorsed taking account of race as one factor among many to promote educational diversity.

Share full article 922


Demonstrators in favor of affirmative action in Washington on Thursday. Kenny Holston/The New York Times

By Adam Liptak
Reporting from Washington

June 29, 2023

The Supreme Court on Thursday rejected affirmative action at colleges and universities around the nation, declaring that the race-conscious admissions programs at Harvard and the University of North Carolina were unlawful and sharply curtailing a policy that had long been a pillar of higher education.

Students v. Harvard
June 29, 2023
6-2 vote

## Here's What the Court's Chevron Ruling Could Mean in Everyday Terms

The decision is expected to prompt a rush of litigation challenging regulations across the entire federal government, from food safety to the environment.

Share full article

The Environmental Protection Agency building in Washington. Stefani Reynolds for The New York Times

By Coral Davenport, Christina Jewett, Alan Rappeport, Margot Sanger-Katz, Noam Scheiber and Noah Weiland

June 28, 2024

The Supreme Court's decision on Friday to limit the broad regulatory authority of federal agencies could lead to the elimination or weakening of thousands of rules on the environment, health care, worker protection, food and drug safety, telecommunications, the financial sector and more.

Loper v. Raimondo
June 28, 2024
6-2 vote

# Oral argument influences court outcomes

- Influences the information justices have (Johnson 2001, 2004)
- Influences the issues discussed in the decisions (Black, Johnson and Weeding 2012)
- Influences the justices’ votes (Johnson, Wahlbeck, and Spriggs 2006)

Fig credit: Wikipedia

# Motivating Example: United States v. Texas (Nov 2021)

"Advocates" are the lawyers arguing either side of the case.
For example, Solicitor General of the DOJ

**General Prelogar**: While I certainly acknowledge, Justice Alito, that an injunction that would bind state court judges is extremely rare, it's not unheard of, and I think, in the unprecedented facts of this case, it's appropriate relief. And —

**Justice Alito**: Well, judges have been enjoined —

**General Prelogar**: —and the reason for that is—

**Justice Alito**: —let me just interrupt you —judges have been enjoined from performing unlawful acts.

# Research question and findings (in plain English)

Do justices interrupt female advocates more simply *because* they are women?

**Our Finding:** They do!

# Why study gender bias in judges interrupting advocates?

- **Allocational harms:** Women less opportunity to speak, cases they argue may be disproportionately affected
- **Representationl harms:** Barocas et al. argue representational harms should be treated as harms in their own right
  - Interruptions assert dominance (Zimmermann and West 1996)
  - Interruptions reinforce status (Mendelberg et al., 2014)
  - Gender disparities on display on a very public and high-stakes stage

Additionally amplified given that **disproportionately few women** are advocates

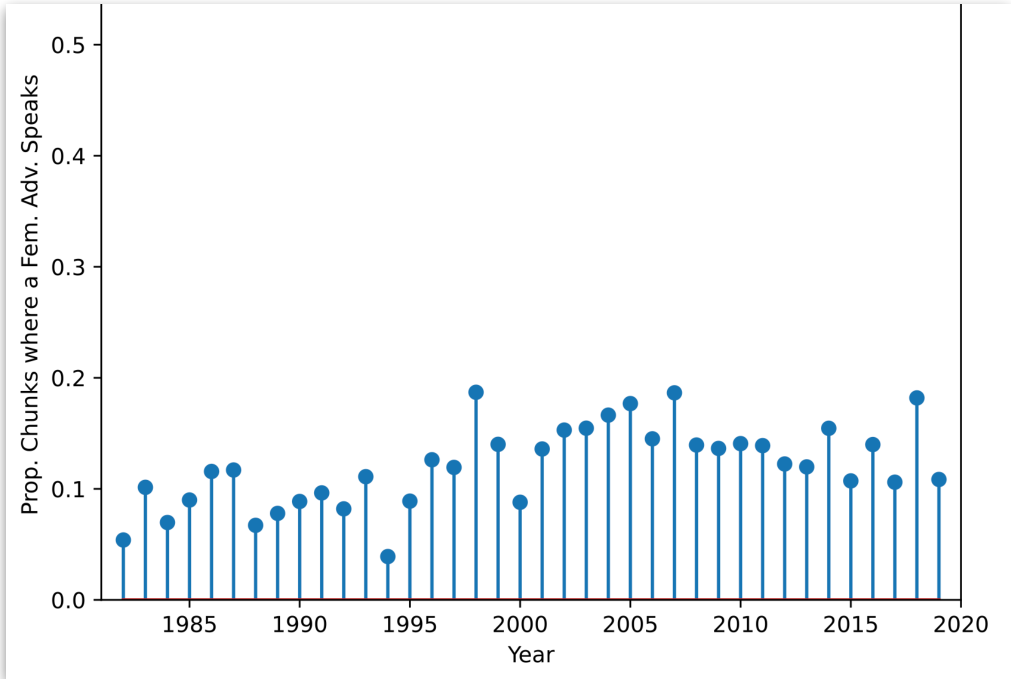


Figure 2 (our paper)

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Common **counterarguments**:

- *Ideological alignment:* Female advocates typically on "liberal" cases and justices interrupt those they disagree with
- *Style:* Women just speak "differently"
- *Experience:* Female advocates less experience
- *Heatedness:* Interruption-heavy part of the arguments

**Our Finding:** Gender effects have greater magnitude

# Previous work on U.S. Supreme Court oral arguments

| Authors | Dependent Variable(s) | Model(s) | Justice-level? |
|---|---|---|---|
| Jacobi and Schweers (2017) | Justice→Justice Interruptions | Many | None |
| Patton and Smith (2017) | Advocate Length of First Speech; Average Length of Speech | Truncated Poisson | None |
| Lindom, Gregory and Johnson (2017) | Advocate Speaking Time; Justice Sentiment; Justice→Advocate Interruptions | OLS and Tobit | None |
| Feldman and Gill (2019) | Justice→Justice Interruptions | Logit | None |
| Jacobi and Sag (2019) | Justice→Advocate Interruption Count Per Case | OLS | None |
| Patton and Smith (2020) | Proportion of Words by Justices | Justice match for Tobit | Partial |
| Hack and Jenkins (2022) | Petitioner Win | Logit | None |
| Gleason and Smart (2022) | Justice Vote | Logit | None |
| **This work** | **Justice→Advocate Interruption Rate, Token-Normalized** | **Non-parametric** | **Yes** |

# Research question and findings (in plain English)

Do justices interrupt female advocates more simply *because* they are women?

**Our Finding:** They do!

*Causal* question!

# Causal experiments on identity-based bias

- Experiments are the "gold standard" in causal inference because they directly address confounding
- I'll show you three different experiments in three different "domains"
- All follow roughly this causal DAG

**Intervene:**
Identity signal → Outcome

# Causal experiments on identity-based bias, #1

**Domain:** help-wanted ads in Boston and Chicago newspapers (Bertrand & Mullainathan. AER, 2004)

**Intervene:**
Race-aligned and gender-aligned written names

**Outcome:**
Employer Call-back

**Intervene:**
Resume content

TABLE 1—MEAN CALLBACK RATES BY RACIAL SOUNDINGNESS OF NAMES

| | Percent callback for White names | Percent callback for African-American names | Ratio | Percent difference (*p*-value) |
|---|---|---|---|---|
| Sample: | | | | |
| All sent resumes | 9.65 | 6.45 | 1.50 | 3.20 |
| | [2,435] | [2,435] | | (0.0000) |
| Chicago | 8.06 | 5.40 | 1.49 | 2.66 |
| | [1,352] | [1,352] | | (0.0057) |
| Boston | 11.63 | 7.76 | 1.50 | 4.05 |
| | [1,083] | [1,083] | | (0.0023) |
| Females | 9.89 | 6.63 | 1.49 | 3.26 |
| | [1,860] | [1,886] | | (0.0003) |
| Females in administrative jobs | 10.46 | 6.55 | 1.60 | 3.91 |
| | [1,358] | [1,359] | | (0.0003) |
| Females in sales jobs | 8.37 | 6.83 | 1.22 | 1.54 |
| | [502] | [527] | | (0.3523) |
| Males | 8.87 | 5.83 | 1.52 | 3.04 |
| | [575] | [549] | | (0.0513) |

**Finding:** White-aligned names receive 50% more callbacks

Bertrand & Mullainathan. "Are Emily and Greg More Employable Than Lakisha and Jamal? A Field Experiment on Labor Market Discrimination." AER, 2004

# Causal experiments on identity-based bias, #2

- **Domain:** Entrepreneurial pitches (Brooks et al. PNAS, 2014)
- **Intervention:** Dubbed in male or female voice
- **Intervention:** Different pictures of the (fake) speaker at the start of the pitch

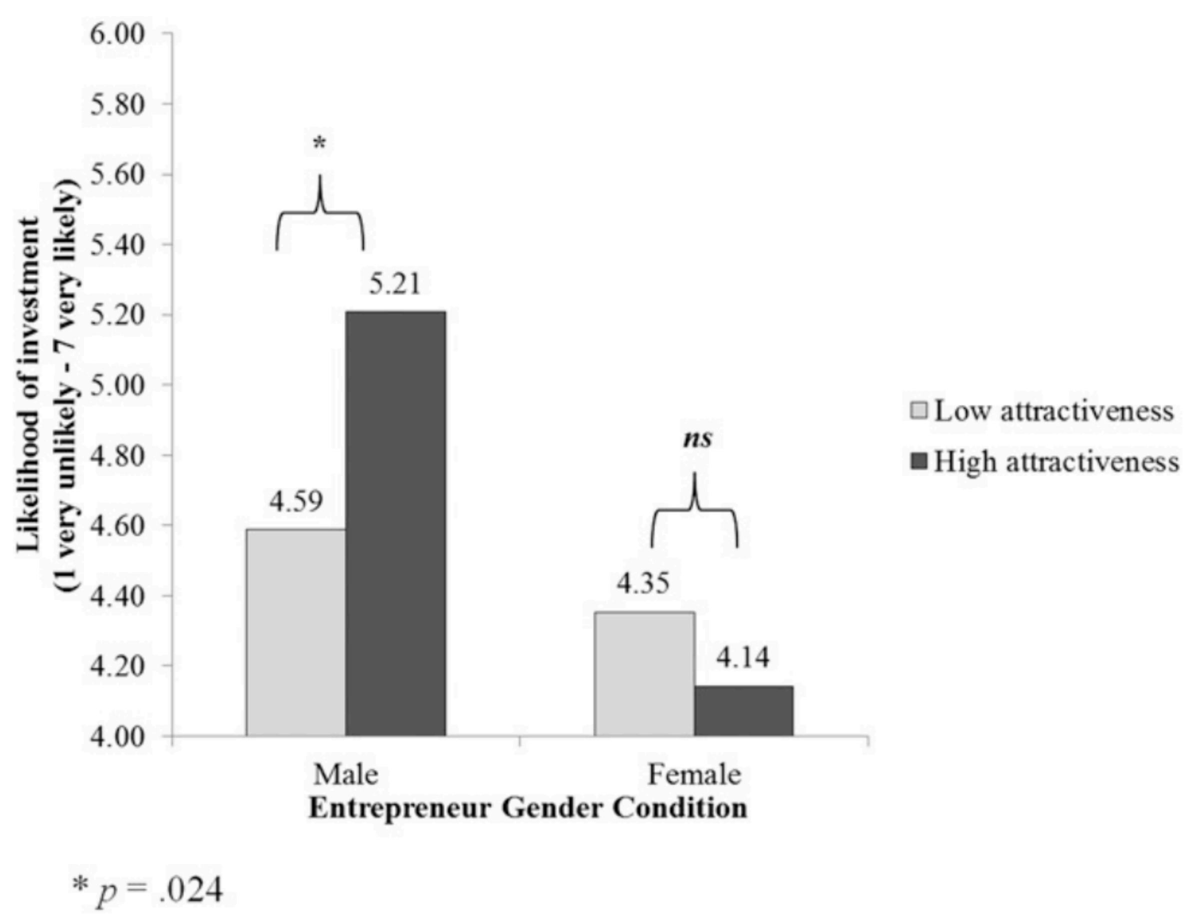


**Fig. 2.** The effect of entrepreneur gender and physical attractiveness on ratings of investment likelihood in an experimental setting ($n = 520$). ns, not significant.

**Finding:** Attractive men judged as more likable of investment.

More attractive women judged as *less likely* of investment

# Causal experiments on identity-based bias, #3

- **Domain:** Social media, Twitter (Munger, 2017)
- Examining responding to racial slurs
- **Intervention:** The race of the profile avatar and the number of follower counts


**Fig. 3** Treatments. **a** The treatment—black bot. **b** The bot applying the treatment—white bot

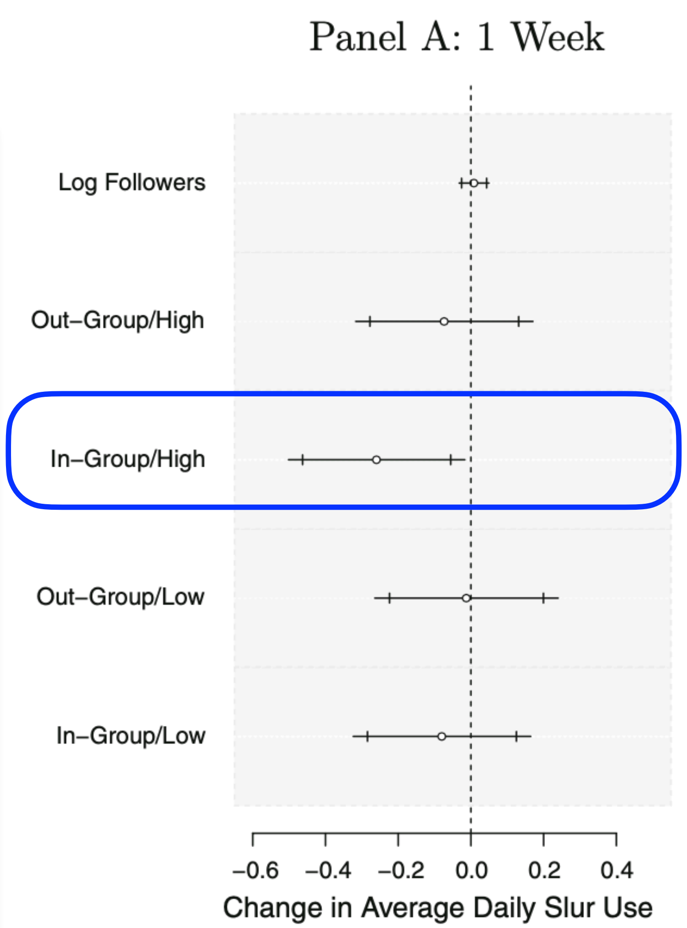


Fig. 5

Intervention from the white avatar with a high follower count reduced slur use the most

# Research question and findings (in plain English)

Do justices interrupt female advocates more simply *because* they are women?

**Our Finding:** They do!

*Causal* question!

... but we can't run experiments ...

# Outline

1. Introduction & Background
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# Potential outcomes

- "Neyman-Rubin potential outcomes" is one (of a few) causal inference formalisms (Neyman, 1923; Rubin, 1974; Holland, 1988)
- Notation:

$$Y(0) \qquad\qquad Y(1)$$

Counterfactual outcome if the individual received the "control"

Counterfactual outcome if the individual received the "treatment"

- "Fundamental problem of causal inference" is that it is typically impossible to have *both* individual counterfactuals (Holland, 1986).
  - Thus, we shift to estimands that are averages over target populations.
- Causal inference formalisms very useful for observational (non-experiment) causal questions:
  - Does smoking cause lung cancer?
  - Do more firearms in homes cause more firearms deaths?

# Lundberg et al.'s Quantitative Framework

- Recommend stating **theoretical estimand** (the target quantity) outside of any statistical model
- Framework:

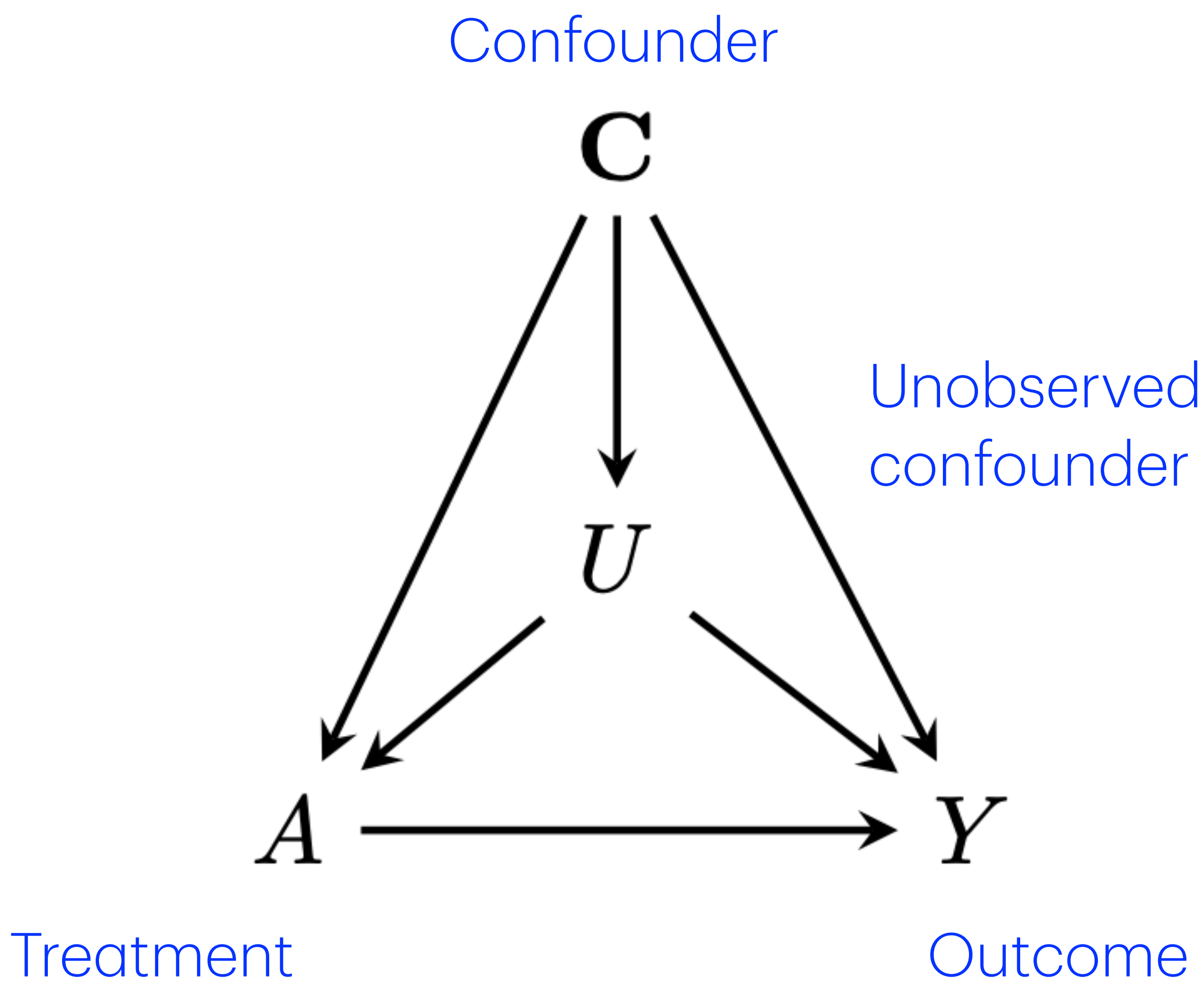
1. State theoretical estimand
2. Specify unit-specific quantity
3. Define target population
4. List identification assumptions
5. Choose estimation strategy

- Use **Causal DAGs** because they are **non-parametric** and delay choices on statistical "functional form", e.g., "linear"

Lundberg et al. "What Is Your Estimand? Defining the Target Quantity Connects Statistical Evidence to Theory." ASR, 2021.

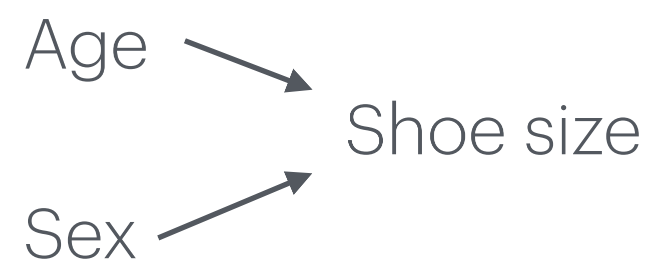
# Causal Directed Acyclic Graphs (Causal DAGs)

In a causal DAG, nodes are causal variables and edges denote direct causal relationships (Pearl 2000)



# Aside: Causal DAGs help clarify misleading conclusions!

**Collider bias:** Conditioning on the collider creates a spurious association between the two original variables




Lundberg et al.'s examples of misleading social science conclusions due to collider bias

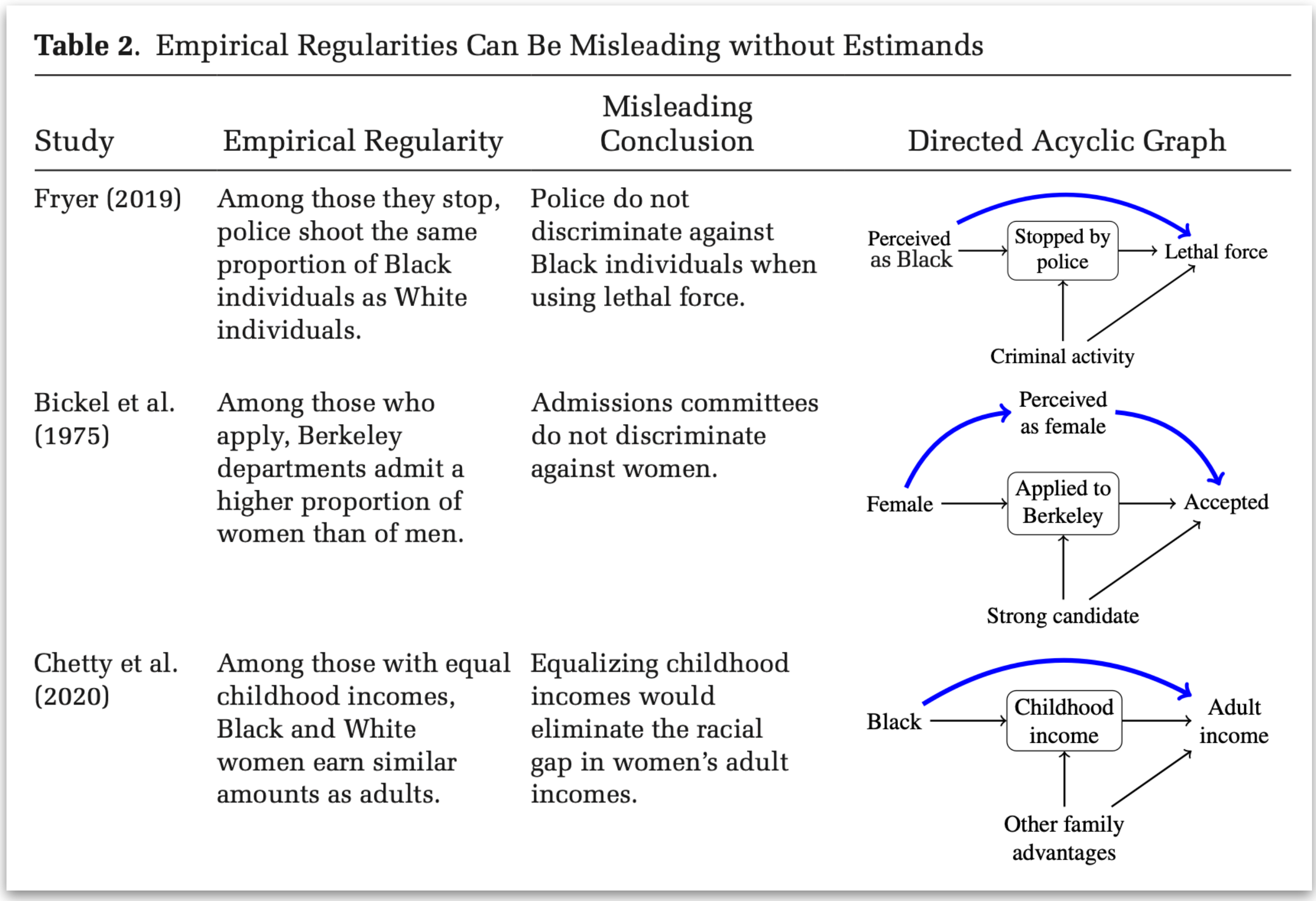


**Table 2.** Empirical Regularities Can Be Misleading without Estimands

| Study | Empirical Regularity | Misleading Conclusion | Directed Acyclic Graph |
|---|---|---|---|
| Fryer (2019) | Among those they stop, police shoot the same proportion of Black individuals as White individuals. | Police do not discriminate against Black individuals when using lethal force. | Perceived as Black; Stopped by police; Lethal force; Criminal activity |
| Bickel et al. (1975) | Among those who apply, Berkeley departments admit a higher proportion of women than of men. | Admissions committees do not discriminate against women. | Perceived as female; Female; Applied to Berkeley; Accepted; Strong candidate |
| Chetty et al. (2020) | Among those with equal childhood incomes, Black and White women earn similar amounts as adults. | Equalizing childhood incomes would eliminate the racial gap in women's adult incomes. | Black; Childhood income; Adult income; Other family advantages |

# Research question and findings (in plain English)

Do justices interrupt female advocates more simply *because* they are women?

**Our Finding:** They do!

*Causal* question!

... but we can't run experiments ...

... so we use potential outcomes, causal DAGs, Lundberg's framework, and very careful research design...

# Lundberg framework applied to our Supreme Court questions

2. Specify unit-specific quantity

For a specific justice (j) in a specific "chunk" of an oral argument (i), how would the interruption rate (Y) change if the advocate in that "chunk" (T) had their gender signal changed from male (M) to female (F)?

$$Y_{i|j}(T_i = F) - Y_{i|j}(T_i = M)$$

# Unit of analysis is a two-speaker discourse "chunk"

We define a **valid chunk** as:

- Four or more contiguous utterances
- With exactly two speakers—a single justice and a single advocate
- Where the advocate makes the first utterance
- Each speaker has two or more utterances

Greedy algorithm to segment

Valid chunk

**General Prelogar**: While I certainly acknowledge, Justice Alito, that an injunction that would bind state court judges is extremely rare, it's not unheard of, and I think, in the unprecedented facts of this case, it's appropriate relief. And —

**Justice Alito**: Well, judges have been enjoined —

**General Prelogar**: —and the reason for that is—

**Justice Alito**: —let me just interrupt you —judges have been enjoined from performing unlawful acts.

# Conceptualization versus operationalization

- **Conceptualization:** How does one define a variable theoretically?
- **Operationalization:** Given the theoretical concept, how does one measure the variable from data in practice?

# Conceptualization of "gender" as a causal variable

What does it mean theoretically to "intervene" on "gender"?

| | Conceptualization | Critique |
|---|---|---|
| 1 | Gender | Social, institutional, and cultural forces shape gender and gender perceptions (Deaux, 1985; West and Zimmerman, 1987), |
| 2 | Biological sex assigned at birth | Assigned at birth is an "immutable characteristic" and "no causation without manipulation" (Berk et al. 2005; Holland, 2008) |
| 3 | Perceived gender | Researchers cannot actually manipulate the internal psychological state of decision-makers (Hu and Kohler-Hausmann, 2020) |
| 4 | Gender signal | Gender is made of many constituent components (Sen and Wash, 2016) |
| 5 | Gender signal as defined by (hypothetical) manipulations of the advocate's clothes, hair, name, and voice pitch | * Our choice * |
| 6 | Gender signal by setting their physical appearance, facial features, name, and voice pitch to specific values (e.g. all facial features set to that of the same 40-year-old, white female and clothes set to a black blazer and pants). | Causal inference requires "sufficiently well-defined interventions" but "sufficiently" is subjective and can be taken too far and lose generalizability (Hernan, 2016) |

# Operationalizing "gender signal"

Two-stage deterministic algorithm

- **First stage:** Measure "gender signal" by the gendered title used by the Chief Justice to introduce the advocate, e.g., Mr. or Ms.
  - We use "binary gender" (even though there are more than two genders) because the Court never uses an explicitly non-binary gender title like 'Mx.'
- **Second Stage:** (only 0.75% of advocates) Look-up advocate first name in the World Gender Name Dictionary (Raffo and Lax-Martinez 2018), compiled via government admin data

99.8% of advocates assigned to a gender

# Outcome: Token-normalized interruption rate

**Intuition:** If an advocate is attempting to say 1,000 words during an oral argument, how many interruptions from a justice would the advocate endure (on average) by the time they got to 1,000 words?

$$Y_{i|j} = \frac{\text{number of advocate utterances interrupted by justice } j \text{ in chunk } i}{(\text{number of advocate tokens in chunk } i)/1000}$$

Interruptions come deterministically from markers in the manually-transcribed transcripts (largely double-dashes)

# Lundberg framework applied to our Supreme Court questions

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$$Y_{i|j}(T_i = F) - Y_{i|j}(T_i = M)$$

3. Define target population

Over whom or what do we aggregate [the] unit-specific quantity?

- Justices with >1000 chunks
- Target population: All advocates a justice had (or would potentially) encounter

# Research question and findings (in plain English)

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**Our Finding:** They do!

**Common counterarguments:**

- *Ideological alignment:* Female advocates are typically on more "liberal" cases and justices interrupt those they disagree with
- *Style:* Women just speak "differently"
- *Experience:* Female advocates just have less experience
- *Heatedness:* Interruption-heavy part of the arguments

**Our Finding:** The gender effects dwarfs these other effects

# Operationalization of “ideological alignment”

Binarized ideology: “liberal” or “conservative”

$$A_i = \begin{cases} 1 & \text{if advocate } a_i \text{ and justice } j_i\text{'s ideological preferences match} \\ 0 & \text{otherwise} \end{cases}$$

**Advocates:**
Supreme Court Database’s manual coding of ideological direction of court decision and whether the advocate’s side won

**Judges:**
Binarized average of time-varying Martin-Quinn score

**Example**

L

C

**General Prelogar**: […] in the unprecedented facts of this case, it’s appropriate relief. And —

**Justice Alito**: Well, judges have been enjoined —

**[…]**

A=0

# Justice ideology scores from Martin & Quinn (2002)

Dynamic Item Response Model for a Uni-dimensional Issue Space

Observed votes

$$v_{tkj} = \begin{cases} 1 \text{ if } z_{tkj} > 0 \\ 0 \text{ else} \end{cases}$$

Term

Case

Justice

$$z_{tkj} = \alpha_k + \beta_k \theta_{tj} + \epsilon_{tkj}$$

"Ideal point" (inference goal)

Assume "random walk" for each justice

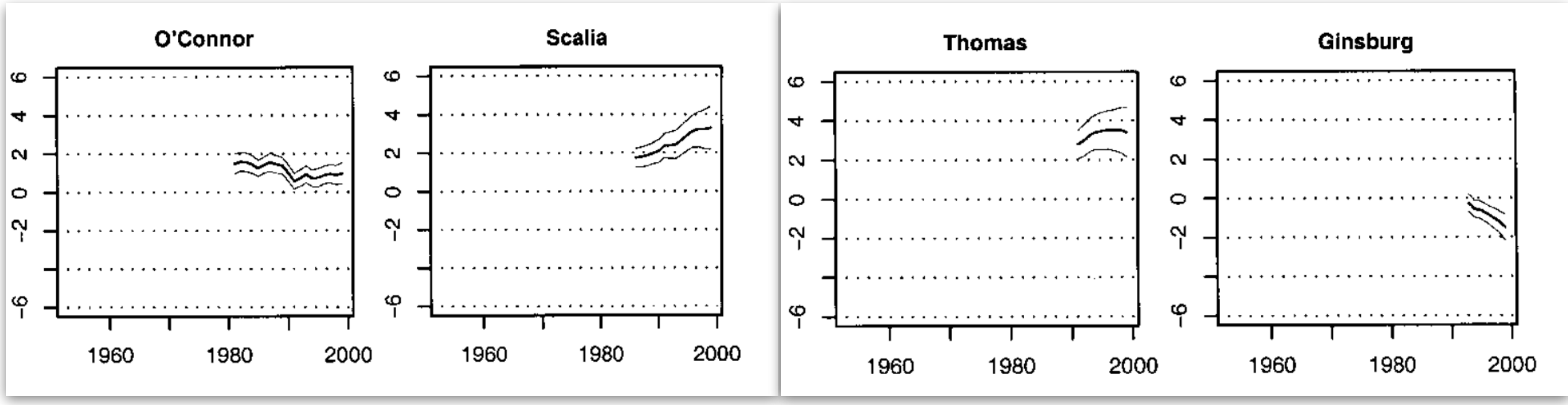
$$\theta_{t,j} \sim \mathcal{N}(\theta_{t-1,j}, \Delta_{\theta_{t,j}})$$

Estimation of posterior via Gibbs sampling

$$P(\alpha, \beta, \theta | \mathbf{V})$$

Positive = "Conservative"

Negative = "Liberal"




Subset from Figure 1, Martin & Quinn, 2002

# Causal identification assumptions

4. List identification assumptions

- Causal inference typically relies on **assumptions** that cannot be empirically tested.
- A powerful aspect of causal inference formalisms is that one makes all assumptions explicit before moving onto causal estimation.

1. **Markov assumption for conversational chunks:** Conversational dynamics between a justice and an advocate in one chunk do not influence the conversational dynamics in a subsequent chunk. (Very strong but necessary assumption!)

2. **No unmeasured confounding** or mediating variables.

# Estimation

Per-justice differences in means

$$\theta^j_{\text{Gender}} := \left( \frac{1}{n_{j,T_i=F}} \sum_{i:j_i=j,\mathbf{T_i=F}} Y_{i|j} \right) - \left( \frac{1}{n_{j,T_i=M}} \sum_{i:j_i=j,\mathbf{T_i=M}} Y_{i|j} \right)$$

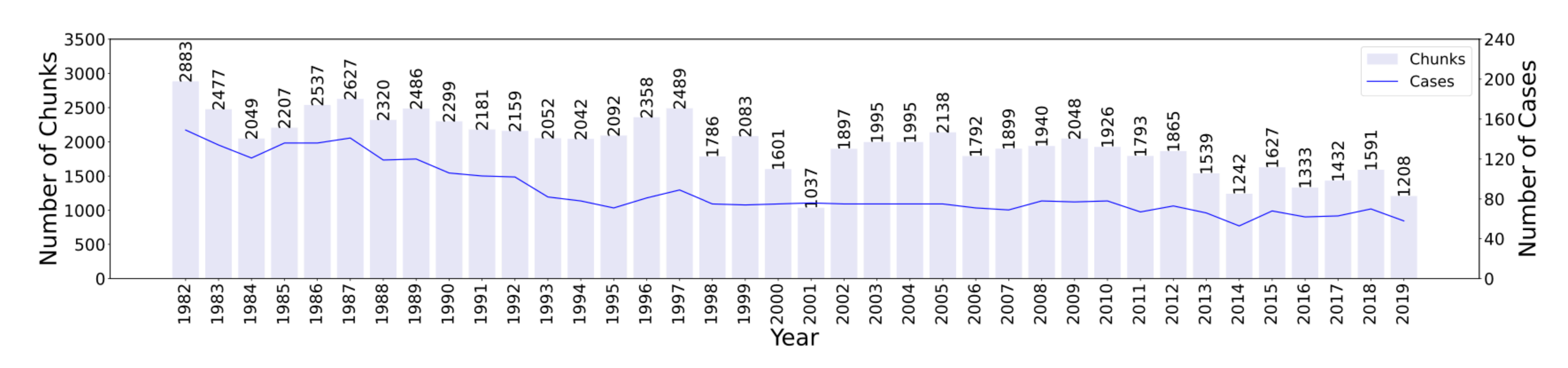
$$\theta^j_{\text{Ideological Alignment}} := \left( \frac{1}{n_{j,A_i=1}} \sum_{i:j_i=j,\mathbf{A_i=1}} Y_{i|j} \right) - \left( \frac{1}{n_{j,A_i=0}} \sum_{i:j_i=j,\mathbf{A_i=0}} Y_{i|j} \right)$$

# Data

Data sources: ConvoKit, Oyez, Supreme Court Data Base

| **Corpus Details** | |
|---|---|
| Years | 1982-2019 |
| Cases | 3,424 |
| Unique advocates | 4,025 |
| Unique female advocates | 551 |

| **Chunk Details** | All Data | Valid Chunks |
|---|---|---|
| Count | – | 64,164 |
| Number of Tokens | 37,880,545 | 23,065,962 |
| Number of Utterances | 776,193 | 508,189 |
| Prop. Advocate Utterances Interrupted | 0.25 | 0.21 |
| Median Num. Tokens Per Chunk | – | 296 |
| Median Num. Utterances Per Chunk | – | 6 |



# Outline

1. Introduction & Background
2. Causal Formalisms & Research Design
3. Findings & Corroboration

# Main findings

Bootstrap 95% confidence intervals (resampling chunks)

| Justices | $\theta_{\text{Gender}}$ | $\theta_{\text{Ideological Alignment}}$ | $\frac{\theta_{\text{Gender}}}{\theta_{\text{Ideological Alignment}}}$ |
|---|---|---|---|
| All | 0.89±0.36 | -0.25±0.23 | 3.59 |
| Male | 1.06±0.43 | -0.20±0.26 | 5.34 |
| Female | 0.43±0.71 | -0.39±0.45 | 1.12 |

*Positive values:* Interrupt women more

*Negative values:* Ideologies do not align

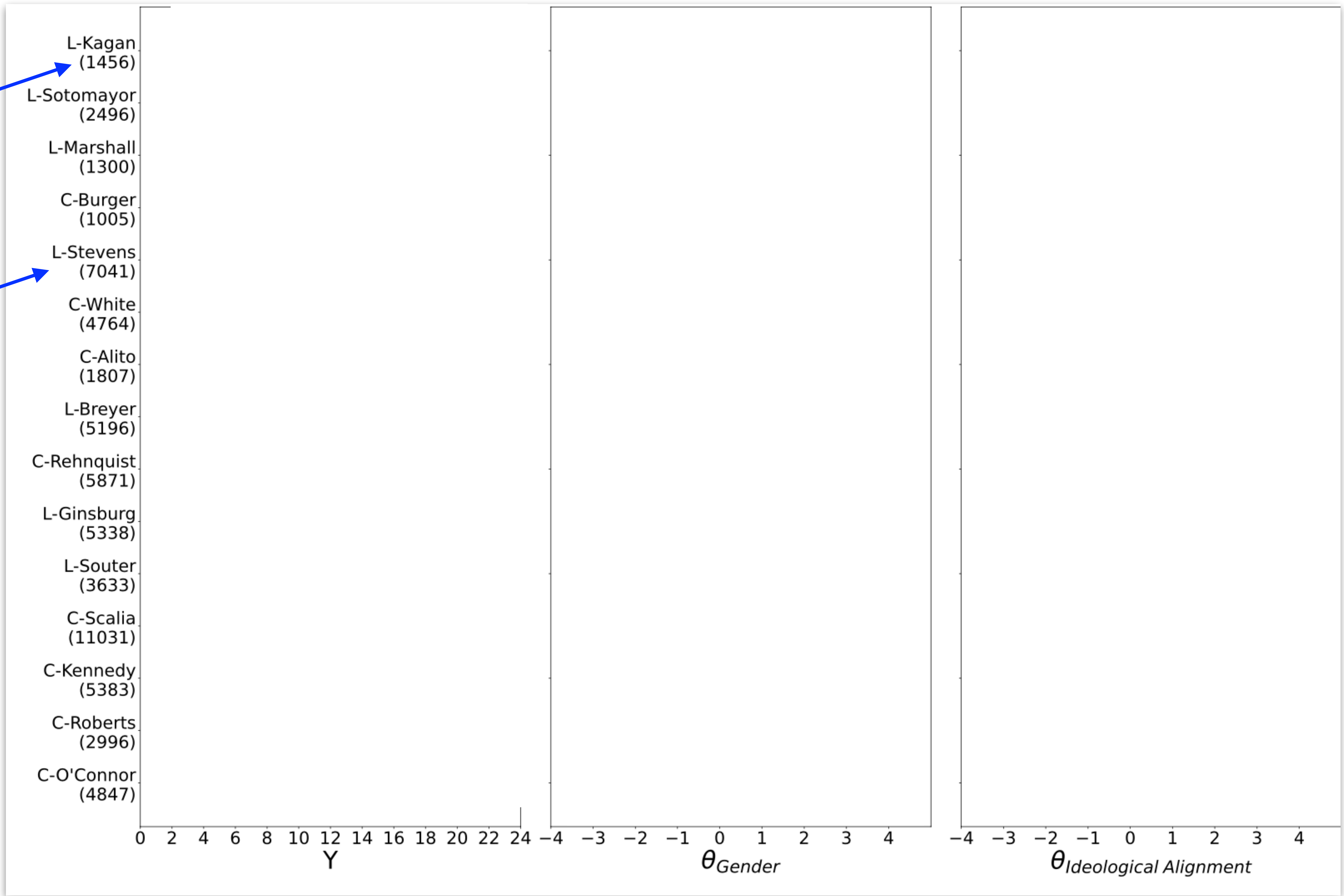
**Main takeaway:** The magnitude of gendered interruption disparities is over **3 times** of that in differences in interruptions due to ideological-alignment

# Justice-level effects

Num chunks
(Our threshold >1000)

L = Liberal (ave. M&Q scores)

C = Conservative (ave. M&Q scores




Overall Token-normalized interruption rate

**Male** ⟷ **Female**

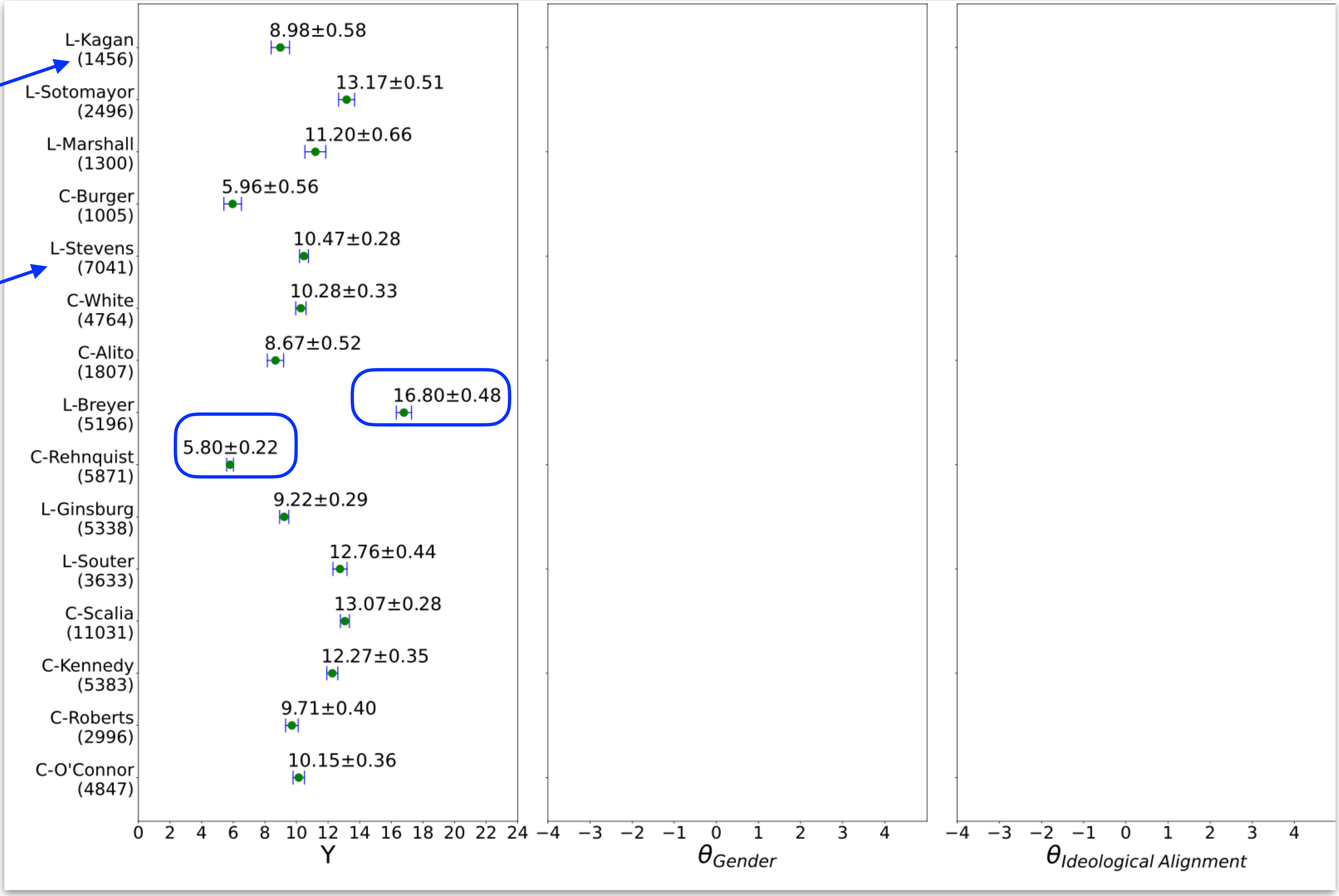
**Does not align** with the justice's ⟷ **Aligns** with the justice's

# Justice-level effects

Num chunks
(Our threshold >1000)

L = Liberal (ave. M&Q scores)

C = Conservative (ave. M&Q scores

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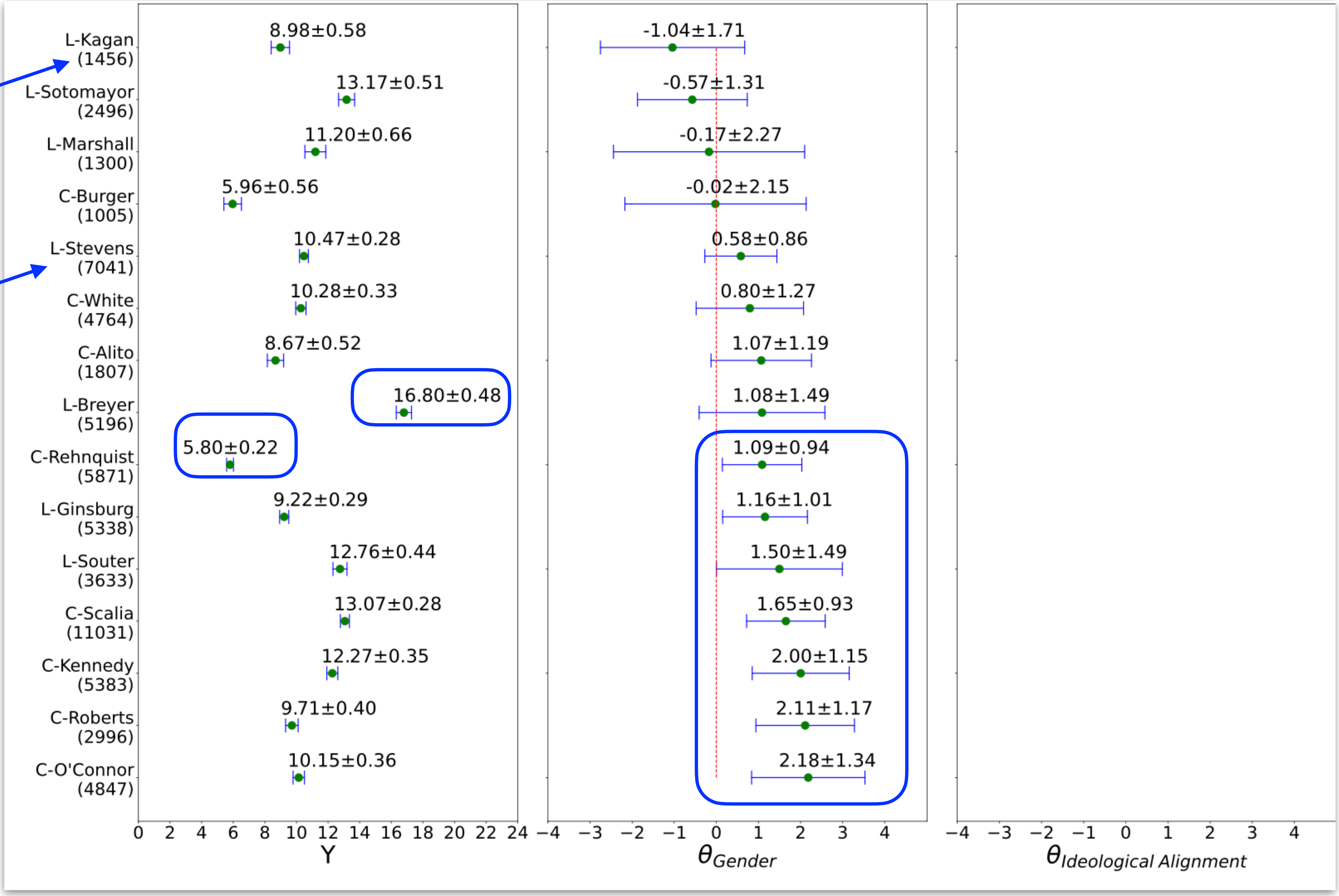


Overall Token-normalized interruption rate

**Male** ⟷ **Female**

**Does not align** with the justice's ⟷ **Aligns** with the justice's

# Justice-level effects

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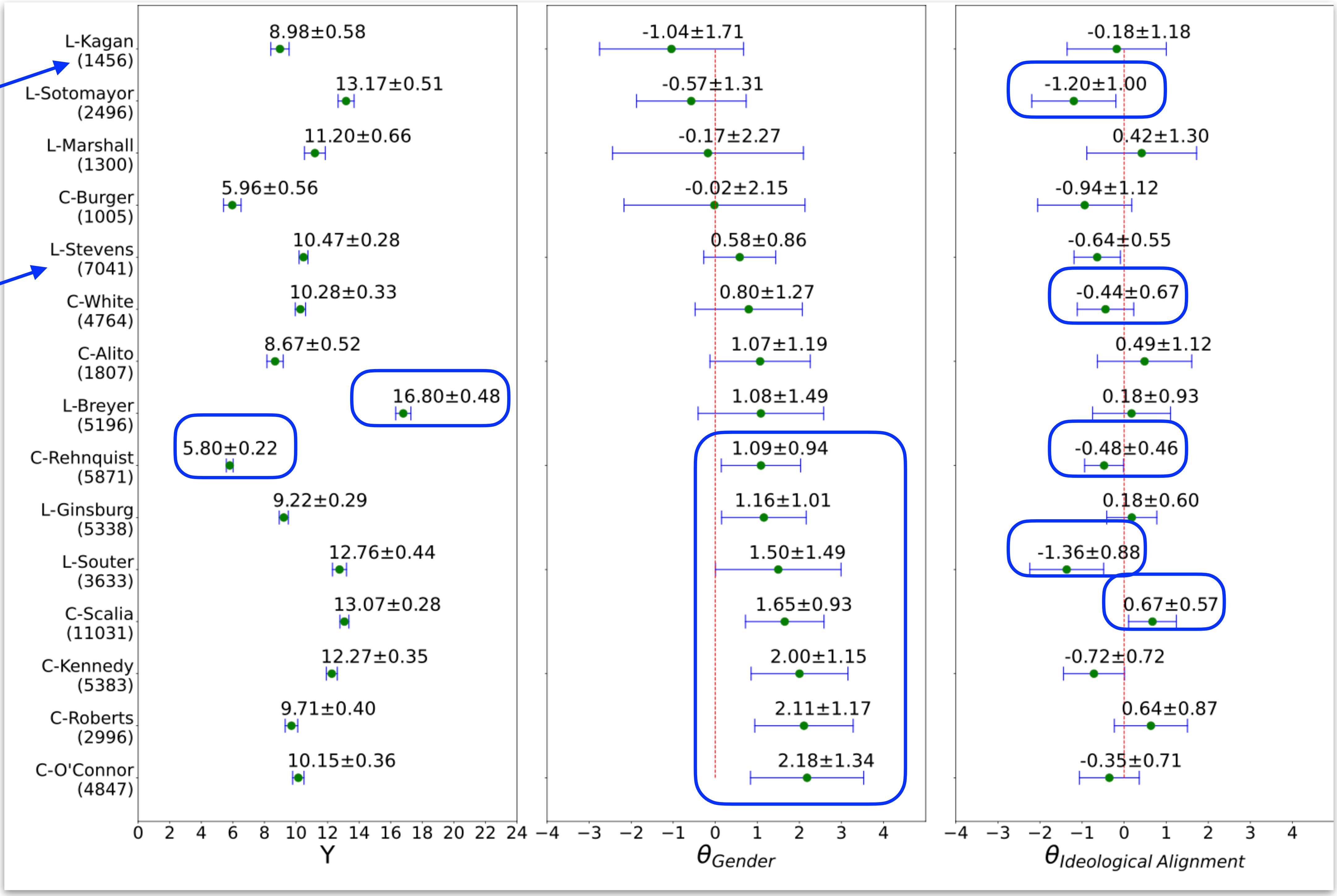



Overall Token-normalized interruption rate

**Male** ↔ **Female**

**Does not align** with the justice's ↔ **Aligns** with the justice's

# Research question and findings (in plain English)

Do justices interrupt female advocates more simply *because* they are women?

**Finding:** They do!

**Common counterarguments:**

- *Ideological alignment:* Female advocates are typically on more "liberal" cases and justices interrupt those they disagree with
- *Style:* Women just speak "differently"
- *Experience:* Female advocates just have less experience
- *Heatedness:* Interruption-heavy part of the arguments

**Finding:** The gender effects dwarfs these other effects

# Detail: Removed chunks involving gender issues

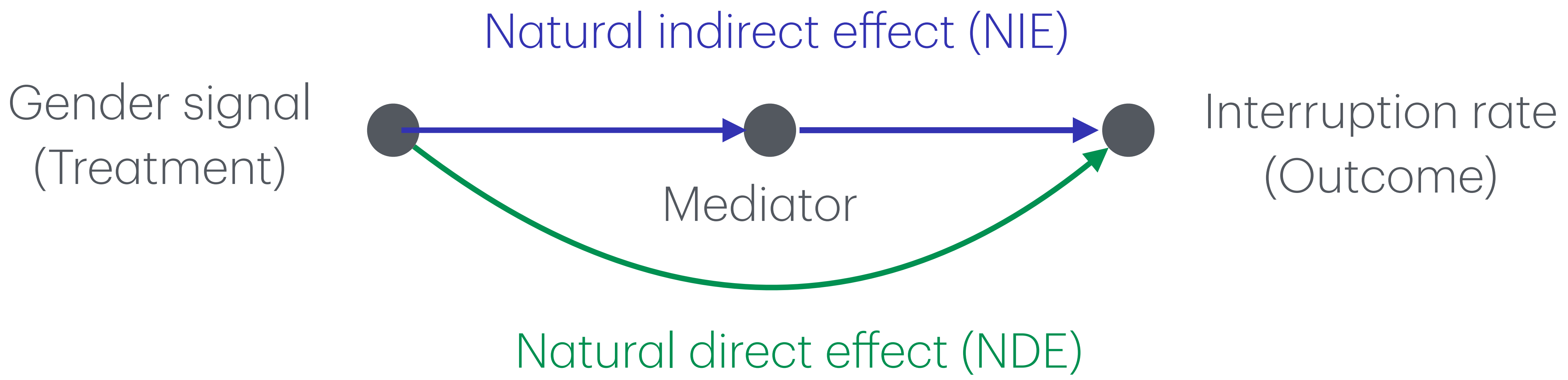
- Confounding variable: Substantive issue of the case
- Female advocates on cases with "women's issue" likely to be perceived as having "position of authority" (Miller and Sutherland 2022; Patton and Smith 2017)
- Gendered case issues: sex discrimination, abortion, and privacy (manually annotated by Supreme Court Database)
- Valid chunks from cases with gendered issues are 1,591 out of 65,768 (2.4%)

| | |
|---|---|
| $E[Y\|C = \text{Other issue}, T = M]$ | 10.90 |
| $E[Y\|C = \text{Gender issue}, T = M]$ | 12.47 |
| $E[Y\|C = \text{Other issue}, T = F]$ | 12.35 |
| $E[Y\|C = \text{Gender issue}, T = F]$ | 10.82 |

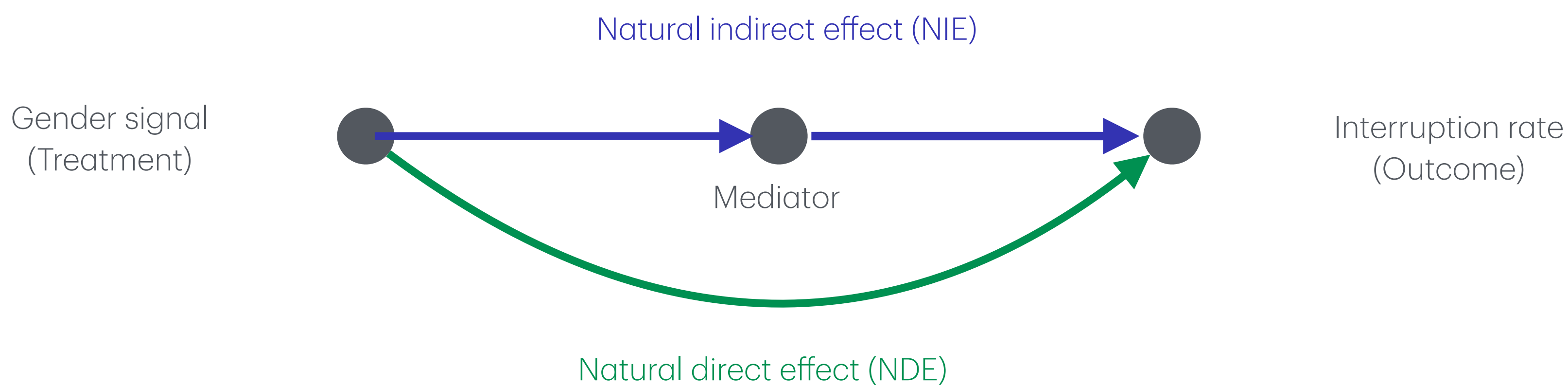
Table A1 (our paper)

Women interrupted **less on** cases with gendered issues

# Corroborative Analysis 1: Causal mediation analysis



# Corroborative Analysis 1: Causal mediation analysis




Years 2007-2019 (for consistent manual transcripts)

**Disfluencies:** Deterministically marked in transcripts

**Experience:** 0 or 1, have argued before

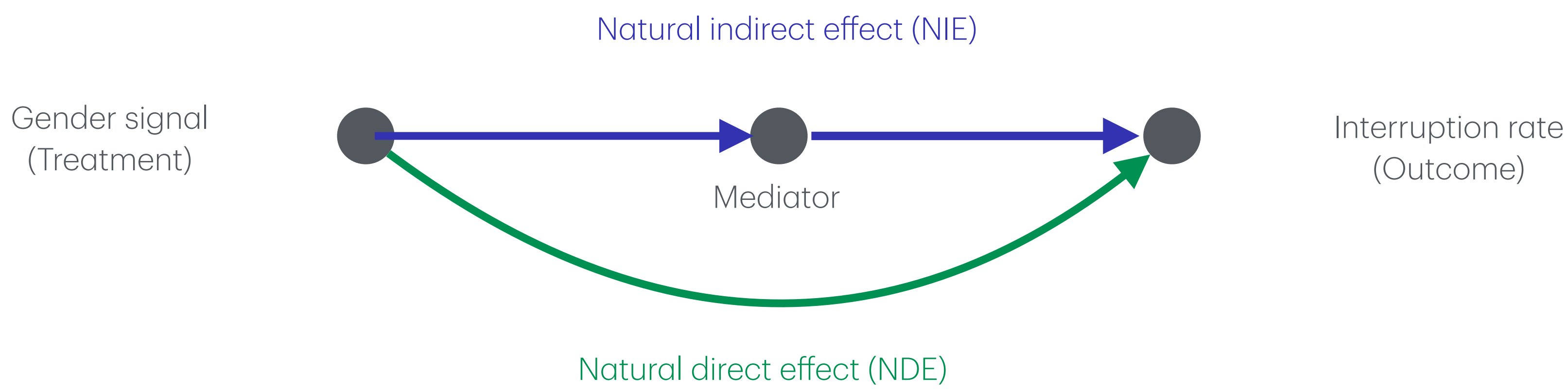
| **All justices** (n=17,801) | NDE | NIE |
|---|---|---|

| **Male justices** (n=11,821) | NDE | NIE |
|---|---|---|

| **Female justices** (n=5,980) | NDE | NIE |
|---|---|---|

(Pearl, 2001; Imai et al., 2010; VanderWeele, 2016)

# Corroborative Analysis 1: Causal mediation analysis




Years 2007-2019 (for consistent manual transcripts)

**Disfluencies:** Deterministically marked in transcripts

**Experience:** 0 or 1, have argued before

| **All justices** (n=17,801) | NDE | NIE |
|---|---|---|
| Speech disfluencies as mediator | 0.73±0.60 | -0.07±0.29 |
| Ideological alignment as mediator | 0.83±0.69 | 0.04±0.05 |
| Advocate experience as mediator | 0.68±0.70 | -0.03±0.08 |
| **Male justices** (n=11,821) | NDE | NIE |
| Speech disfluencies as mediator | 1.20±0.78 | 0.12±0.41 |
| Ideological alignment as mediator | 1.36±0.92 | 0.06±0.08 |
| Advocate experience as mediator | 1.18±0.91 | 0.00±0.11 |
| **Female justices** (n=5,980) | NDE | NIE |
| Speech disfluencies as mediator | -0.38±0.84 | -0.03±0.26 |
| Ideological alignment as mediator | -0.38±0.87 | -0.01±0.04 |
| Advocate experience as mediator | -0.48±0.86 | -0.10±0.10 |

NIE's all very small and CIs all cross zero

(Pearl, 2001; Imai et al., 2010; VanderWeele, 2016)

# Corroborative Analysis 2: “Heatedness” of discussions

Relationship between justice interrupting advocate (x-axis) and advocate interrupting justice (y-axis) **not significant**

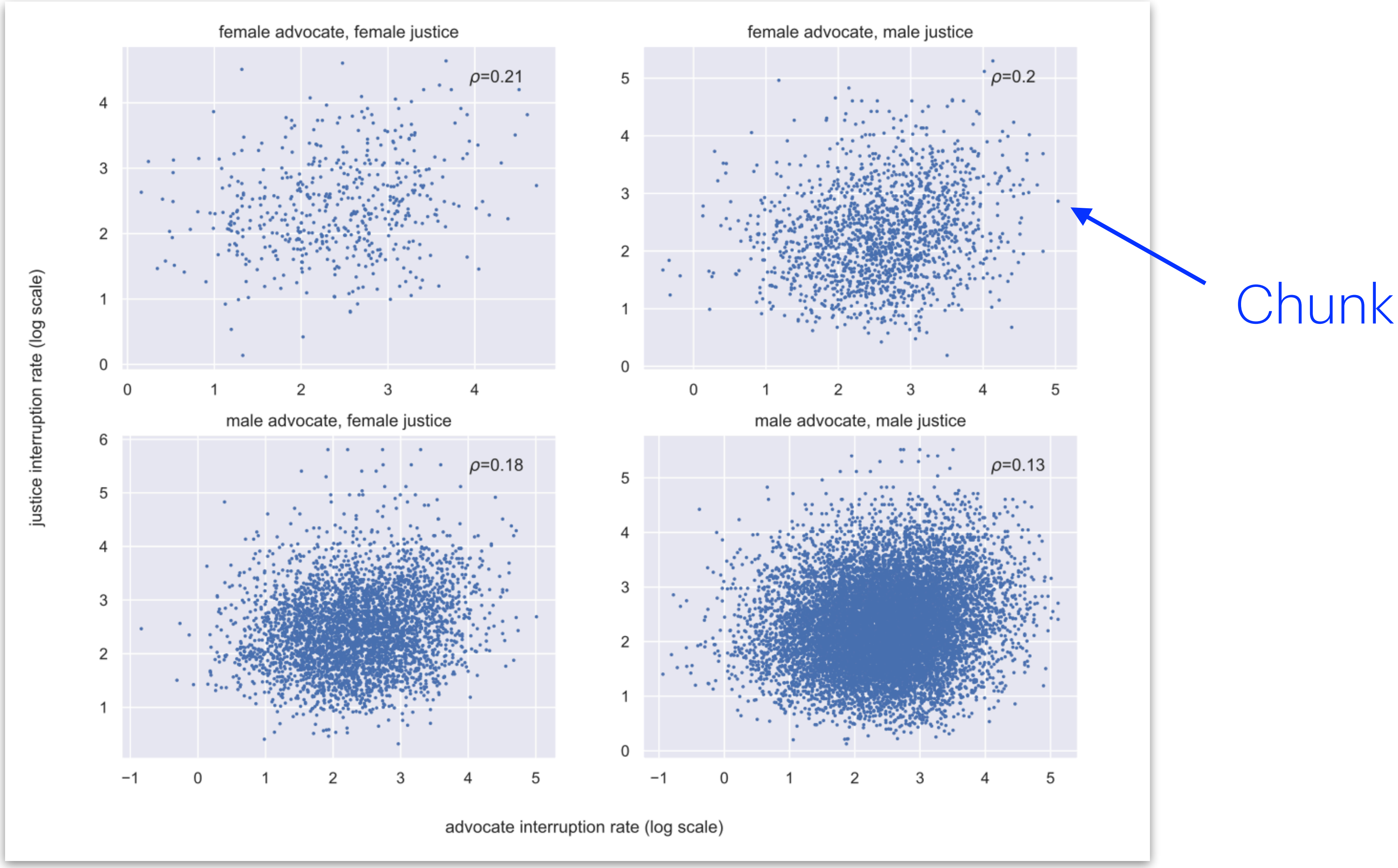



Figure A1 (our paper)

# Corroborative Analysis 3: Remove "Backchannel cues"

- Phrasal **backchannel cues** (e.g., right, yes, uh-huh, go on) are a form of conversational maintenance (Gravano and Hirschberg 2009) and interruptions via backchannel cues may be substantively different
- Discard utterances with any of 18 phrasal **backchannel cues**
- Re-run chunking greedy algorithm
- Results:

| Justices | $\theta_{\text{Gender}}$ | $\theta_{\text{Ideological Alignment}}$ | $\frac{\theta_{\text{Gender}}}{\theta_{\text{Ideological Alignment}}}$ |
|---|---|---|---|
| All | 0.89±0.36 | -0.25±0.23 | 3.59 |
| Male | 1.06±0.43 | -0.20±0.26 | 5.34 |
| Female | 0.43±0.71 | -0.39±0.45 | 1.12 |

Table A3: *Effects on advocate interruption rate, aggregated by justice gender* **including** utterances with back channel cues (same as in main paper).

| Justices | $\theta_{\text{Gender}}$ | $\theta_{\text{Ideological Alignment}}$ | $\frac{\theta_{\text{Gender}}}{\theta_{\text{Ideological Alignment}}}$ |
|---|---|---|---|
| All | 0.96±0.36 | -0.24±0.23 | 3.99 |
| Male | 1.12±0.43 | -0.21±0.26 | 5.22 |
| Female | 0.54±0.68 | -0.32±0.46 | 1.70 |

Table A4: *Effects on advocate interruption rate, aggregated by justice gender* **excluding** utterances with back channel cues.

Very similar magnitudes of effects

# Research question and findings (in plain English)

Do justices interrupt female advocates more simply *because* they are women?

**Our Finding:** They do!

Common **counterarguments**:

- *Ideological alignment:* Female advocates typically on “liberal” cases and justices interrupt those they disagree with
- *Style:* Women just speak “differently”
- *Experience:* Female advocates less experience
- *Heatedness:* Interruption-heavy part of the arguments

**Our Finding:** Gender effects have greater magnitude

# Future work

- Classifying “friendly” versus “non-friendly” interruptions
- Fine-grained classification of issues at the chunk or utterance level
- Real-valued ideological inference of justices from both votes (via IRT) and text
- Using conceptual framework for identity-based bias in other settings

# Data & code publicly available

`https://github.com/kakeith/interruptions-supreme-court`

Thanks! Questions?

Do justices interrupt female advocates more simply *because* they are women?

**Finding:** They do!