Stereotypes in High-Stakes Decisions

Evidence from U.S. Circuit Courts

Daniel L. Chen
w/ Elliott Ash (EthZ) and Arianna Ornaghi (British Academy)

Lexical slant

- Google translate
  - "he/she is a doctor" (turkish) -> "he is a doctor" (english)
  - "he/she is a nurse" (turkish) -> "she is a nurse" (english)
- A truck driver should plan his route carefully.
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- Does implicit bias exist?
  - Ottaway et al. 2001, Rothermund et al. 2004, Arkes et al. 2004, Blanton et al. 2006
- Does it affect real-world decisions?
  - police (Correll et al. 2002); physicians (Green et al. 2007); resume screening (Bertrand et al. 2005)
- Does it lead to disparate treatment?
  - patients' feelings (Penner et al. 2010); grocery cashiers (Glover et al. 2017); students (Carlana 2018)
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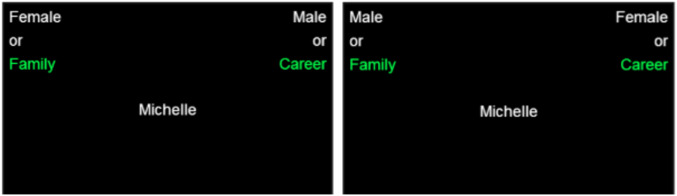

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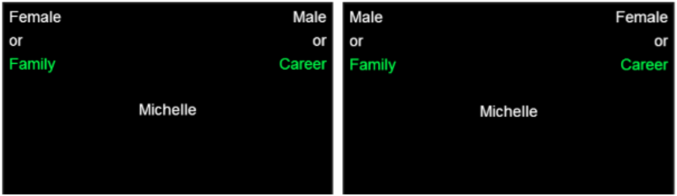

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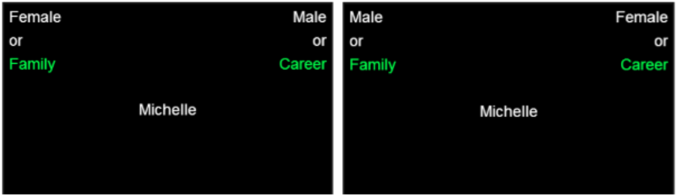

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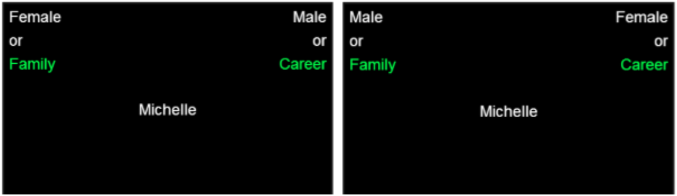

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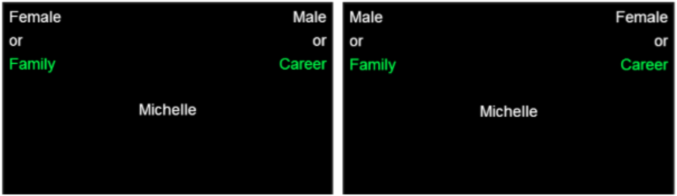

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- Challenge: how can we measure implicit attitudes for the judiciary?
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  - And that judges' decisions are often highly predictable
  - Suggesting that judges' preferences directly affect their decisions..
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- Proposed solution: proxy for IAT using large amounts of written text
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Words closest to female and male dimension

- Migraine, hysterical, morbid, obese, terrified, unemancipated, battered
- Reserve, industrial, honorable, commanding, armed, conscientious, duty

Word-Embedding Association Test: $WEAT = \sum_{x \in X} s(x, A, B) - \sum_{y \in Y} s(y, A, B)$ (Caliskan et al. 2017)

distance between IAT vectors correlate with behavioral delays

- X, Y are **male** (his, he, him, mr, himself) vs. **female** words (her, she, ms, women, woman)
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- 700M tokens, 2B 8-grams, 5M citation edges across cases

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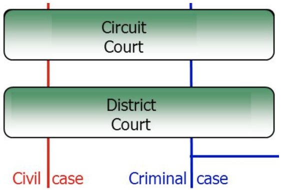
- Link 145K cases to District Court case's judge

- Civil case writings linked to sentencing and defendant characteristics in 94 D



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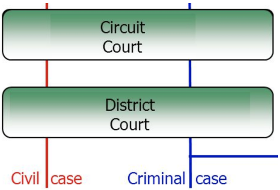

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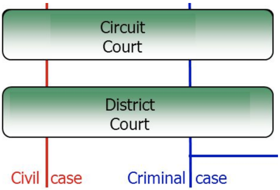

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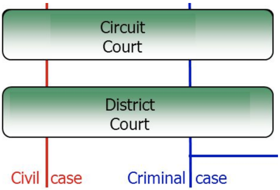

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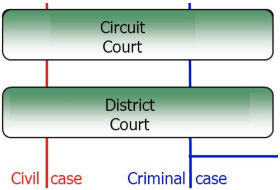
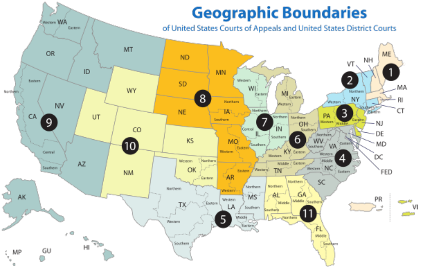


US Federal Courts as Natural Laboratory



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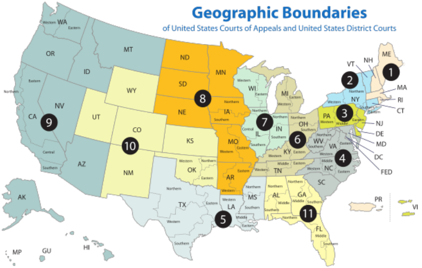

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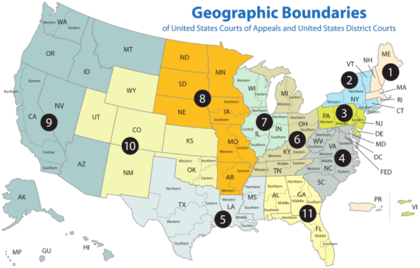

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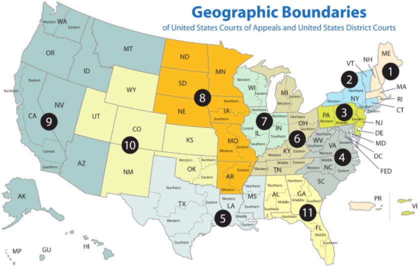

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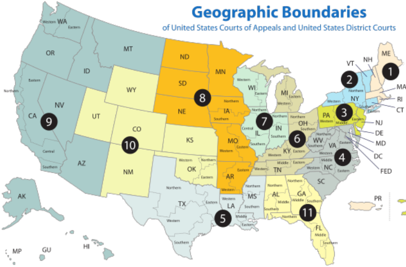

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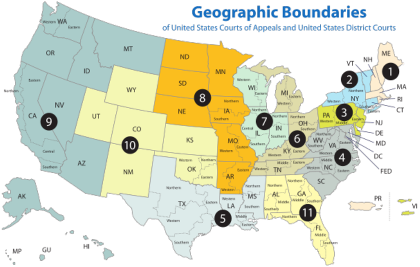
- 327K cases/yr in the 94 D $\Rightarrow$ 67K cases/yr in 12 C $\Rightarrow$ 100 cases/yr in Supreme Ct

US Federal Courts as Natural Laboratory



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Introduce theories:

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- (obama speaks media illinois) is orthogonal to (president greets press chicago) according to **cosine similarity**
- But **word embeddings** capture contextual similarities between words

1. Finding the degree of similarity between two words.

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model.similarity('woman','man')
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2. Finding odd one out.

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3. Amazing things like woman+king-man =queen

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queen: 0.508
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4. Probability of a text under the model

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- Each word is mapped to one vector, often hundreds of dimensions
  - Contrast to 2B N-grams for sparse word representations
- If we know the words having similar meanings in different languages, word embeddings can be used to (Google) translate!

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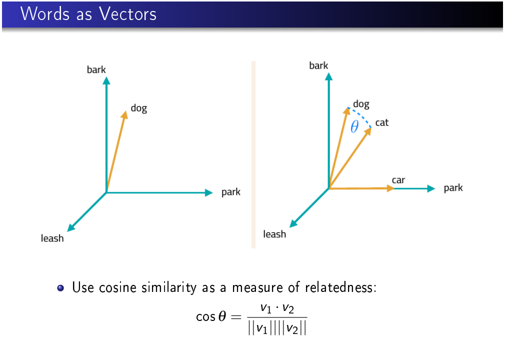
How it works: Predict surrounding words given current word



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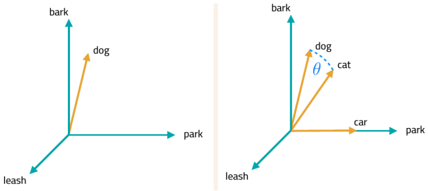

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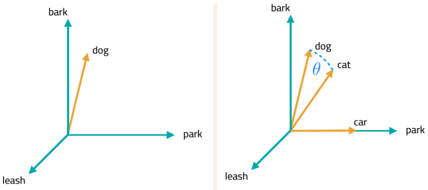

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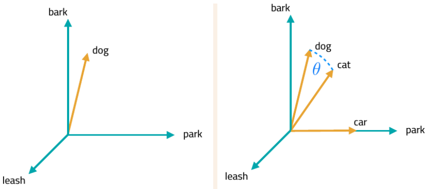

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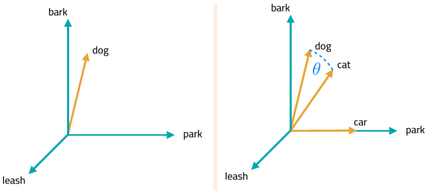

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Distance encodes semantic similarity between words

- GloVe (Global Vectors)
  - Based on intuition that co-occurrence probabilities convey meaning
  - Begins by contructing a co-occurence matrix using a fixed window
  - Obtains word vectors $w_i \in (-1, 1)^{300}$ that minimize

$$J(\boldsymbol{w}) = \sum_{i,j} f\left(X_{ij}\right)\left(w_i^T w_j - \log\left(X_{ij}\right)\right)^2$$

  - X_{ij} is the co-occurrence count between words i and j
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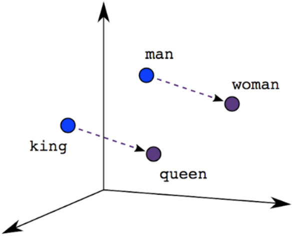
  - Minimize $J(\cdot)$ by stochastic gradient descent (Pennington et al. 2014)
    - ★ 300-dimensional vectors, 50K vocabulary, window of 10 words, 0.05 learning rate, 20 epochs

Word embeddings identify cultural dimensions

- Identify cultural dimension by taking difference between pairs of words



- $\overrightarrow{man} - \overrightarrow{woman}$ identifies a step in masculine direction

$$\overrightarrow{male} - \overrightarrow{female} = \frac{\sum_n \overrightarrow{male\ word_n}}{|N_{male}|} - \frac{\sum_n \overrightarrow{female\ word_n}}{|N_{female}|}$$

where $|N_{male}|$ is number of words used to identify the male dimension, e.g. $\overrightarrow{boy} - \overrightarrow{girl}$, $\overrightarrow{he} - \overrightarrow{she}$, etc.

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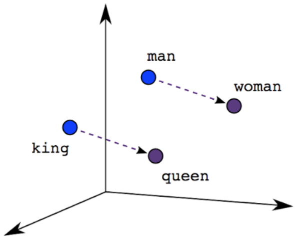

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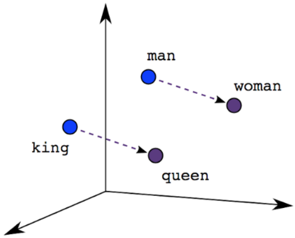
Words meaningfully project onto cultural dimensions

- **Validation**: Correctly identifies 96.5% of names as male or female



- Understand connotation of words along gender dimension by looking at cosine of angle between vector representing word and the dimension itself

$$sim\left(\vec{x}, \vec{y}\right) = cos\left(\theta\right) = \frac{\vec{x} \cdot \vec{y}}{\|\vec{x}\| \, \|\vec{y}\|} = \frac{\sum x_i y_i}{\sqrt{\sum x_i^2}\sqrt{\sum y_i^2}}$$

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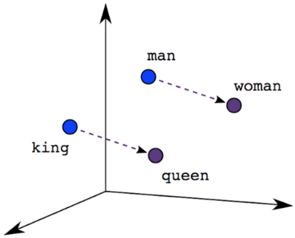

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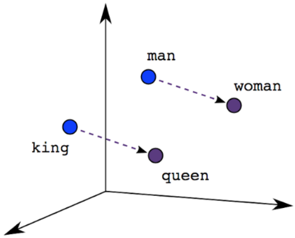

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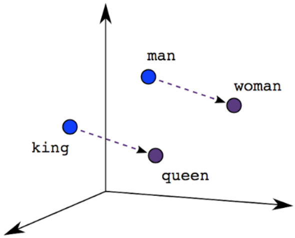

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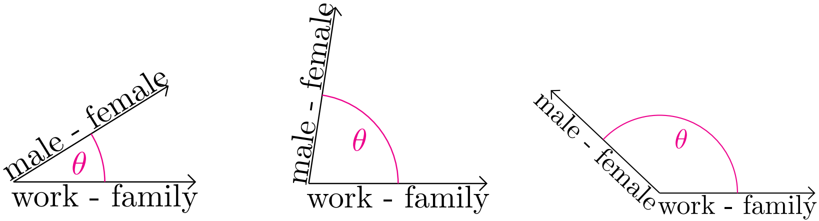
Figure: Measuring Gender Stereotypes using Cosine Similarity



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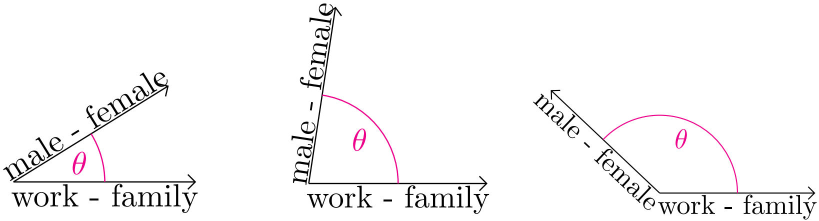

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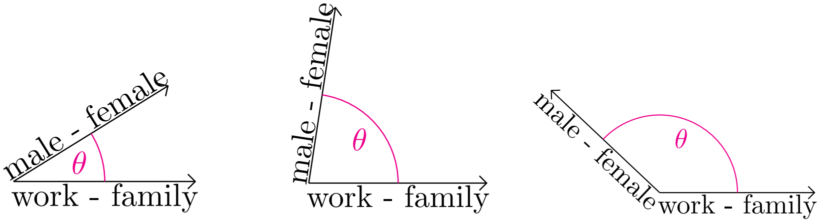

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Reinterpreting NLP as Discrete Choice

- Utility for judge i at year t:

$$u_{it} = \widetilde{\boldsymbol{\alpha}}_t + \boldsymbol{x}'_{it}\widetilde{\gamma}_t + \sum_{(c,c')\in c_j \times c_j : c \neq c'} \widetilde{\boldsymbol{\nu}}_{c,c',t} \mathbf{1}_{i \in R_t},$$

See also *Athey et al. SHOPPER model*

- Arbitrary pattern of complements/substitution across phrases
  - $\Rightarrow$ word embeddings

Constructing judge specific gender lexical slant measure

- We consider opinions authored by a certain judge as a separate corpus
- We train embeddings using bootstrap approach (Antoniak and Minmo 2018)
  - 10 bootstrapped samples of size N_j
  - N_j is number of sentences written by judge j
- Lexical slant of judge j = median slant across bootstrap samples
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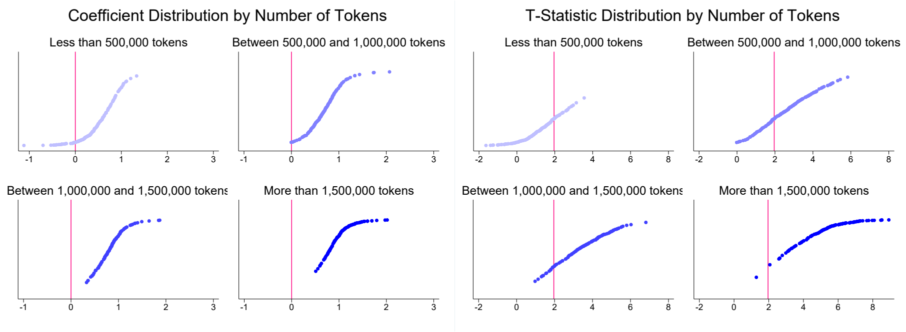

Notes: The graphs show the distribution of the coefficient and the t-statistic resulting from a regressions of a dummy for whether the name is male on the median cosine similarity between the vector representing the name and the gender dimension across bootstrap samples, for sets of judges with different number of tokens. Each observation corresponds to a different judge.

- For sufficiently large corpus, judge-specific embeddings capture M-F dimension in names.
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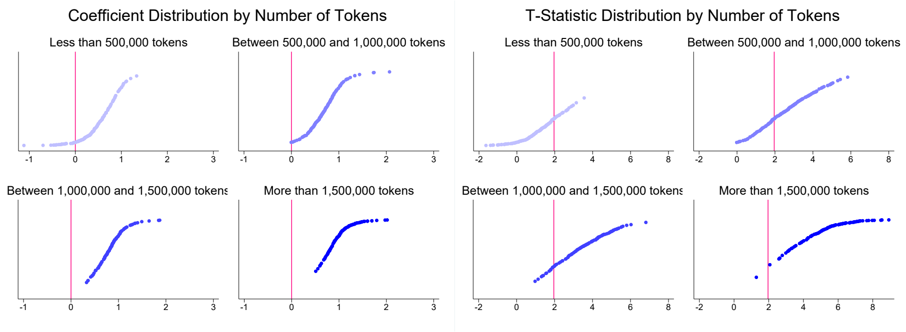

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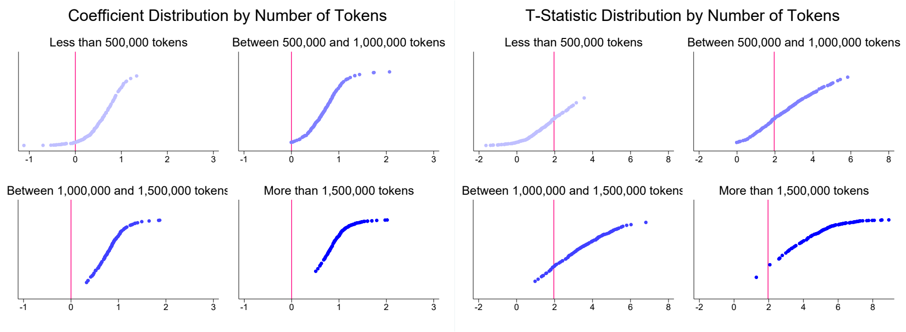

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Judge Randomization

- For interpreting as a judge's lexical slant, judges must be randomly assigned
- **Interviews** of courts and **orthogonality checks** of observables
  - (1) 2-3 weeks before oral argument, computer:
    - randomly assigns available judges including visiting judges
    - ensures judges are not sitting together repeatedly
    - senior judges reduced frequency entered into the program
  - (2) randomly assign panels on yearly basis, then randomly assign cases
    - judges can occasionally recuse
    - panel sees case again on remand
    - exceptions for specialized cases like death penalty
- **Omnibus test**: how similar string of panel assignments is to random strings
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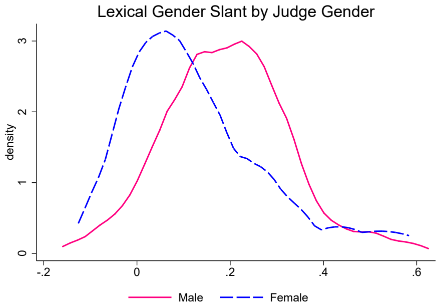
Figure: Gender Slant, by Demographic Characteristics



Notes: The graphs show the distribution of the slant measure (cosine similarity between the gender and career-family dimensions), by judge gender. (p=0.012)

Female judges and younger judges display less lexical slant

Democrat	0.109				0.308
	(0.261)				(0.303)
Female		-0.502*			-0.621***
		(0.288)			(0.181)
Minority			-0.098		-0.128
			(0.329)		(0.184)
Born in 1920s				-0.069	0.122
				(0.191)	(0.208)
Born in 1930s				-0.765***	-0.682***
				(0.203)	(0.226)
Born after 1940				-0.537**	-0.518**
				(0.229)	(0.243)
Observations	139	139	139	139	139
Outcome Mean	0.000	0.000	0.000	0.000	0.000
Adjusted R2	-0.006	0.020	-0.007	0.087	0.447
Circuit FE					X
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Lexical slant and judicial decisions

We study whether judges with different levels of lexical slant vote differently in women rights' cases

$$feminist\ vote_{ijct} = \beta lexical\ slant_j + X_j'\gamma + \delta_{ct} + W_i'\eta + \epsilon_{ijct}$$

- i case, j judge, c circuit, t year
- $feminist\ vote_{ijct}$: vote in favor of female plaintiff or plaintiff representing women's interest
- $lexical\ slant_j$: gender lexical slant of judge j
- X_j: gender, party, race, cohort, religion, law school attended, prior experience, state of birth
- W_i: dummies for specific topic (sexual harassment, abortion..)
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Judges with more lexical slant are less likely to vote in favor of women's interests

Dataset	Epstein et al. (2013) Data			Glynn and Sen (2015) Data		
Gender Slant	-0.041***	-0.041***	-0.066***	-0.053***	-0.054***	-0.058**
	(0.013)	(0.013)	(0.018)	(0.019)	(0.019)	(0.023)
Democrat	0.150***	0.142***	0.185***	0.257***	0.259***	0.263***
	(0.031)	(0.031)	(0.035)	(0.044)	(0.046)	(0.056)
Female	0.122***	0.143***	0.089***	0.079**	0.105***	0.096**
	(0.026)	(0.036)	(0.022)	(0.035)	(0.037)	(0.041)
Democrat * Female		0.038			0.010	
		(0.057)			(0.070)	
Observations	2335	2335	2335	1719	1719	1719
Clusters	112	112	112	109	109	109
Outcome Mean	0.4167	0.417	0.417	0.383	0.383	0.383
Circuit-Year FE	X	X	X	X	X	X
Topic FE	X	X	X	X	X	X
Demographic Controls	X	X	X	X	X	X
+ Interactions		X			X	
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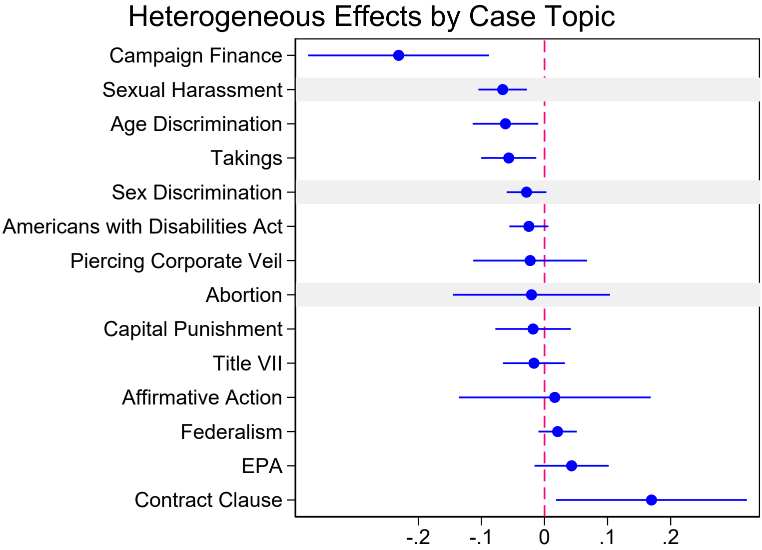
Judges with more lexical slant also vote conservative across some other issues



.. but not across all issues

Dataset	Songer-Auburn Data
Gender Slant	-0.002
	(0.002)
Democrat	0.012*
	(0.006)
Female	0.012
	(0.015)
Observations	39172
Clusters	544
Outcome Mean	0.405
Circuit-Year FE	X
Topic FE	X
Demographic Controls	X

Songer-Auburn is 5% random sample from 1925-2002; whereas Epstein is 1982-2008, Glynn-Sen is 1996-2002 using precedent or keyword searches "gender", "pregnancy", or "sex"

Previous results also hold controlling for Liberal % (Songer-Auburn)

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Implicit associations and disparate treatment

- We have shown evidence that lexical slant affects judicial decisions
- But, if we are indeed measuring attitudes toward women, we should expect implicit attitudes to affect treatment of women more generally
- We study three forms of disparate treatment:
  1. Are more slanted judges less likely to **assign opinions** to female judges?
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- Important: these are career-relevant dimensions
- Refereeing and tenure (Card et al. 2018; Hemel 2018, Sarsons 2019, Bohren et al. 2018)

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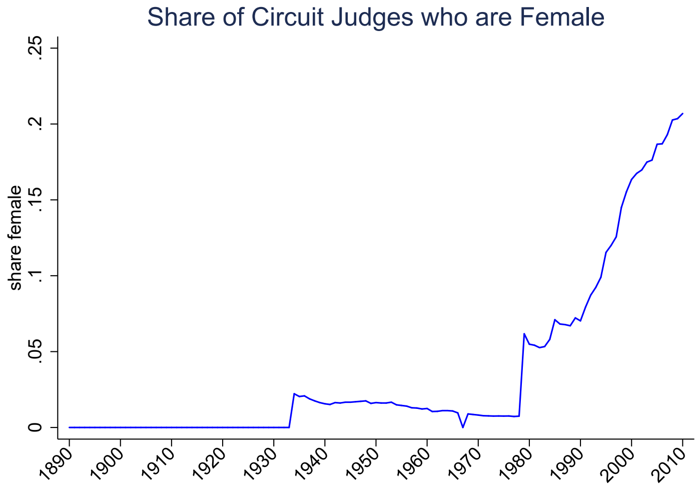
Implicit associations and disparate treatment

- We have shown evidence that lexical slant affects judicial decisions
- But, if we are indeed measuring attitudes toward women, we should expect implicit attitudes to affect treatment of women more generally
- We study three forms of disparate treatment:
  1. Are more slanted judges less likely to **assign opinions** to female judges?
  2. Are more slanted judges less likely to **cite** female judges?
  3. Are more slanted judges more likely to **reverse** district court cases when the deciding district judge is female?
- Important: these are career-relevant dimensions
- Refereeing and tenure (Card et al. 2018; Hemel 2018, Sarsons 2019, Bohren et al. 2018)



10% are women, 20% of panels have at least one female judge

Authorship assignment

- Opinions are assigned to judges by the most senior judge on panel
- Identification exploits random assignment of panels to cases
  - Lexical slant of most senior judge as good as randomly assigned
- Restrict sample to having at least one female judge on panel

Authorship assignment

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Authorship assignment

- Opinions are assigned to judges by the most senior judge on panel
- Identification exploits random assignment of panels to cases
  - Lexical slant of most senior judge as good as randomly assigned
- Restrict sample to having at least one female judge on panel

Panels with more slanted senior judges are less likely to assign opinions to women

Gender Slant	-0.020**	-0.020**	-0.015*	-0.023***	-0.023***	-0.026**
	(0.008)	(0.008)	(0.008)	(0.008)	(0.007)	(0.010)
Democrat	-0.065**	-0.033	-0.080**	-0.067**	-0.059**	-0.049
	(0.029)	(0.034)	(0.033)	(0.030)	(0.026)	(0.036)
Female	0.137***	0.146***	0.160***	0.137***	0.135***	
	(0.015)	(0.018)	(0.016)	(0.016)	(0.016)	
Democrat * Female		-0.120***				
		(0.039)				
Observations	32052	32052	32052	31858	36939	19940
Clusters	125	125	125	123	125	125
Outcome Mean	0.383	0.383	0.383	0.383	0.383	0.4325
Circuit-Year FE	X	X	X	X	X	X
Demographic Controls	X	X	X	X	X	X
+ Interactions		X				
Career FE			X			
Liberal % (Songer-Auburn)				X		
Includes 2-1					X	
Excludes Female Senior Judge						X

Panels with more slanted senior judges are less likely to assign opinions to women

Gender Slant	-0.020**	-0.020**	-0.015*	-0.023***	-0.023***	-0.026**
	(0.008)	(0.008)	(0.008)	(0.008)	(0.007)	(0.010)
Democrat	-0.065**	-0.033	-0.080**	-0.067**	-0.059**	-0.049
	(0.029)	(0.034)	(0.033)	(0.030)	(0.026)	(0.036)
Female	0.137***	0.146***	0.160***	0.137***	0.135***	
	(0.015)	(0.018)	(0.016)	(0.016)	(0.016)	
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Outcome Mean	0.383	0.383	0.383	0.383	0.383	0.4325
Circuit-Year FE	X	X	X	X	X	X
Demographic Controls	X	X	X	X	X	X
+ Interactions		X				
Career FE			X			
Liberal % (Songer-Auburn)				X		
Includes 2-1					X	
Excludes Female Senior Judge						X

Panels with more slanted senior judges are less likely to assign opinions to women

Gender Slant	-0.020**	-0.020**	-0.015*	-0.023***	-0.023***	-0.026**
	(0.008)	(0.008)	(0.008)	(0.008)	(0.007)	(0.010)
Democrat	-0.065**	-0.033	-0.080**	-0.067**	-0.059**	-0.049
	(0.029)	(0.034)	(0.033)	(0.030)	(0.026)	(0.036)
Female	0.137***	0.146***	0.160***	0.137***	0.135***	
	(0.015)	(0.018)	(0.016)	(0.016)	(0.016)	
Democrat * Female		-0.120***				
		(0.039)				
Observations	32052	32052	32052	31858	36939	19940
Clusters	125	125	125	123	125	125
Outcome Mean	0.383	0.383	0.383	0.383	0.383	0.4325
Circuit-Year FE	X	X	X	X	X	X
Demographic Controls	X	X	X	X	X	X
+ Interactions		X				
Career FE			X			
Liberal % (Songer-Auburn)				X		
Includes 2-1					X	
Excludes Female Senior Judge						X

.. but no more likely to yield unsigned or unanimous opinions

Dependent Variable	Has Author		Per Curiam		Decided Unanimously	
Gender Slant	0.001	0.003	-0.000	-0.001	0.002	0.000
	(0.005)	(0.004)	(0.003)	(0.003)	(0.006)	(0.005)
Democrat	-0.000	-0.020	-0.020*	0.009	-0.018	-0.021
	(0.015)	(0.016)	(0.010)	(0.013)	(0.021)	(0.019)
Female	0.000	0.009	0.003	-0.003	0.012	0.009
	(0.011)	(0.008)	(0.004)	(0.004)	(0.009)	(0.008)
Observations	171441	43601	171441	43601	171441	43601
Clusters	139	125	139	125	139	125
Outcome Mean	0.803	0.847	0.092	0.045	0.887	0.874
Circuit-Year FE	X	X	X	X	X	X
Demographic Controls	X	X	X	X	X	X
One Female Judge on Panel		X		X		X

Judges with more lexical slant cite female judges less

Dependent Variable	Cites at Least One Female Judge			
Gender Slant	-0.009*	-0.008*	-0.010*	-0.010*
	(0.005)	(0.005)	(0.006)	(0.005)
Democrat	-0.021	-0.030*	-0.046***	-0.026*
	(0.015)	(0.015)	(0.015)	(0.015)
Female	0.123***	0.107***	0.134***	0.122***
	(0.015)	(0.017)	(0.013)	(0.015)
Democrat * Female		0.049*		
		(0.027)		
Observations	107923	107923	107923	106557
Clusters	139	139	139	136
Outcome Mean	0.383	0.383	0.383	0.381
Circuit-Year FE	X	X	X	X
Demographic Controls	X	X	X	X
Interacted Demographic Controls		X		
Career FE			X	X
Liberal % (Songer-Auburn)				X

Judges with more lexical slant cite female judges less

Dependent Variable	Cites at Least One Female Judge			
Gender Slant	-0.009*	-0.008*	-0.010*	-0.010*
	(0.005)	(0.005)	(0.006)	(0.005)
Democrat	-0.021	-0.030*	-0.046***	-0.026*
	(0.015)	(0.015)	(0.015)	(0.015)
Female	0.123***	0.107***	0.134***	0.122***
	(0.015)	(0.017)	(0.013)	(0.015)
Democrat * Female		0.049*		
		(0.027)		
Observations	107923	107923	107923	106557
Clusters	139	139	139	136
Outcome Mean	0.383	0.383	0.383	0.381
Circuit-Year FE	X	X	X	X
Demographic Controls	X	X	X	X
Interacted Demographic Controls		X		
Career FE			X	X
Liberal % (Songer-Auburn)				X

Judges with more lexical slant cite female judges less

Dependent Variable	Cites at Least One Female Judge			
Gender Slant	-0.009*	-0.008*	-0.010*	-0.010*
	(0.005)	(0.005)	(0.006)	(0.005)
Democrat	-0.021	-0.030*	-0.046***	-0.026*
	(0.015)	(0.015)	(0.015)	(0.015)
Female	0.123***	0.107***	0.134***	0.122***
	(0.015)	(0.017)	(0.013)	(0.015)
Democrat * Female		0.049*		
		(0.027)		
Observations	107923	107923	107923	106557
Clusters	139	139	139	136
Outcome Mean	0.383	0.383	0.383	0.381
Circuit-Year FE	X	X	X	X
Demographic Controls	X	X	X	X
Interacted Demographic Controls		X		
Career FE			X	X
Liberal % (Songer-Auburn)				X

.. and cite each other

Dependent Variable	Cites Democrat	Cites Minority	Average Age	Average Bias
Gender Slant	-0.011**	-0.005	-0.069	0.112***
	(0.005)	(0.005)	(0.083)	(0.012)
Democrat	0.014	-0.032*	0.010	0.003
	(0.018)	(0.019)	(0.153)	(0.034)
Female	0.027**	0.049***	-0.017	-0.025
	(0.011)	(0.010)	(0.156)	(0.020)
Observations	107923	107923	107923	98435
Clusters	139	139	139	139
Outcome Mean	0.607	0.336	61.407	0.052
Circuit-Year FE	X	X	X	X
Demographic Controls	X	X	X	X

Reversals

$$\begin{aligned} \textit{votes to reverse}_{ijdct} = {} & \alpha \textit{female district judge}_i \\ & + \beta \textit{female district judge}_i * \textit{lexical slant}_j \\ & + \textit{female district judge}_i * X_j' \gamma \\ & + \delta_j + \delta_{dt} + \epsilon_{ijct} \end{aligned}$$

- District-year fixed effects
- Circuit judge fixed effects

Judges with more lexical slant reverse female district judges more

Gender Slant * Female District Judge	0.010***	0.010***	0.012***	0.012***
	(0.004)	(0.004)	(0.004)	(0.004)
Democrat * Female District Judge	-0.009	-0.024**	-0.006	-0.007
	(0.014)	(0.009)	(0.014)	(0.013)
Female * Female District Judge	-0.009	-0.022***	-0.007	-0.011
	(0.009)	(0.008)	(0.009)	(0.010)
Democrat * Female * Female District Judge		0.152***		
		(0.015)		
Observations	145862	145862	144965	145563
Clusters	133	133	130	133
Outcome Mean for Male Judges	0.180	0.180	0.180	0.180
Outcome Mean for Female Judges	0.157	0.157	0.157	0.157
Circuit-Year FE	X	X	X	X
Judge FE	X	X	X	X
District Judge FE	X	X	X	X
Demographic Controls	X	X	X	X
+ Interactions		X		
Liberal Score Interaction			X	
District-Year FE				X

Judges with more lexical slant reverse female district judges more

Gender Slant * Female District Judge	0.010***	0.010***	0.012***	0.012***
	(0.004)	(0.004)	(0.004)	(0.004)
Democrat * Female District Judge	-0.009	-0.024**	-0.006	-0.007
	(0.014)	(0.009)	(0.014)	(0.013)
Female * Female District Judge	-0.009	-0.022***	-0.007	-0.011
	(0.009)	(0.008)	(0.009)	(0.010)
Democrat * Female * Female District Judge		0.152***		
		(0.015)		
Observations	145862	145862	144965	145563
Clusters	133	133	130	133
Outcome Mean for Male Judges	0.180	0.180	0.180	0.180
Outcome Mean for Female Judges	0.157	0.157	0.157	0.157
Circuit-Year FE	X	X	X	X
Judge FE	X	X	X	X
District Judge FE	X	X	X	X
Demographic Controls	X	X	X	X
+ Interactions		X		
Liberal Score Interaction			X	
District-Year FE				X

But female judges are 3.6% less likely to be reversed

Gender Slant * Female District Judge	0.010***	0.010***	0.012***	0.012***
	(0.004)	(0.004)	(0.004)	(0.004)
Democrat * Female District Judge	-0.009	-0.024**	-0.006	-0.007
	(0.014)	(0.009)	(0.014)	(0.013)
Female * Female District Judge	-0.009	-0.022***	-0.007	-0.011
	(0.009)	(0.008)	(0.009)	(0.010)
Democrat * Female * Female District Judge		0.152***		
		(0.015)		
Observations	145862	145862	144965	145563
Clusters	133	133	130	133
Outcome Mean for Male Judges	0.180	0.180	0.180	0.180
Outcome Mean for Female Judges	0.157	0.157	0.157	0.157
Circuit-Year FE	X	X	X	X
Judge FE	X	X	X	X
District Judge FE	X	X	X	X
Demographic Controls	X	X	X	X
+ Interactions		X		
Liberal Score Interaction			X	
District-Year FE				X

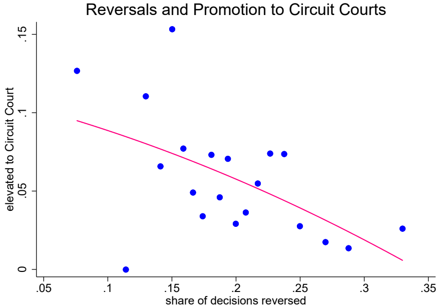
But female judges are 3.6% less likely to be reversed

Gender Slant * Female District Judge	0.010***	0.010***	0.012***	0.012***
	(0.004)	(0.004)	(0.004)	(0.004)
Democrat * Female District Judge	-0.009	-0.024**	-0.006	-0.007
	(0.014)	(0.009)	(0.014)	(0.013)
Female * Female District Judge	-0.009	-0.022***	-0.007	-0.011
	(0.009)	(0.008)	(0.009)	(0.010)
Democrat * Female * Female District Judge		0.152***		
		(0.015)		
Observations	145862	145862	144965	145563
Clusters	133	133	130	133
Outcome Mean for Male Judges	0.180	0.180	0.180	0.180
Outcome Mean for Female Judges	0.157	0.157	0.157	0.157
Circuit-Year FE	X	X	X	X
Judge FE	X	X	X	X
District Judge FE	X	X	X	X
Demographic Controls	X	X	X	X
+ Interactions		X		
Liberal Score Interaction			X	
District-Year FE				X

Gender Slanted Judges also reverse Democrats and minorities

Gender Slant * Democrat District Judge	0.006*	
	(0.004)	
Democrat * Democrat District Judge	-0.022	
	(0.014)	
Female * Democrat District Judge	-0.007	
	(0.008)	
Gender Slant * Minority District Judge		0.011**
		(0.005)
Democrat * Minority District Judge		-0.009
		(0.010)
Female * Minority District Judge		0.018*
		(0.010)
Observations	145862	145862
Clusters	133	133
Outcome Mean	0.177	0.177
Circuit-Year FE, Judge FE	X	X
District Judge FE, Demographic Controls	X	X

Figure: Reversals and Promotions from District to Circuit Courts



Notes: The graph shows the relationship between the probability of being elevated from a District to a Circuit Court and the share of decisions that were reversed on appeal, conditional on demographic controls and circuit fixed effects. The sample is restricted to district judges for which we observe at least 50 cases.

Reversals and Promotion from District to Circuit Courts

Dependent Variable	Promoted to Circuit Court	
Share of Decisions Reversed on Appeal	-0.351***	
	(0.136)	
Share of Votes to Reverse on Appeal		-0.372***
		(0.116)
Female	0.036	0.037
	(0.028)	(0.029)
Democrat	-0.022	-0.018
	(0.0191)	(0.018)
Observations	862	862
Outcome Mean	0.058	0.058
Circuit FE	X	X
Demographic Controls	X	X

Signpost

- We have shown evidence that randomly assigning a judge with lexical slant affects case outcomes and treatment of colleagues
- .. and there are many other kinds of implicit bias

Is it robust?

Is it implicit or explicit?

What affects attitudes?

Signpost

- We have shown evidence that randomly assigning a judge with lexical slant affects case outcomes and treatment of colleagues
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- .. and there are many other kinds of implicit bias

Is it robust?

Is it implicit or explicit?

What affects attitudes?

Robustness

- Robustness by context window
- Robustness by word dropped
- Robustness by size of word set
- Robustness to increasing set of judges considered
- Robustness to dropping cases

  Tiny fraction of gender cases ($\frac{1,719}{114,702}$) involved in calculating gender slant

- Omitted variables
  - Is it gender slant or something else?
  - Is it the affected judge's gender or something else?
- Assessment of randomization

Robustness

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- Robustness by word dropped
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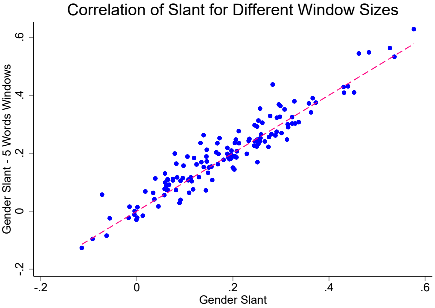
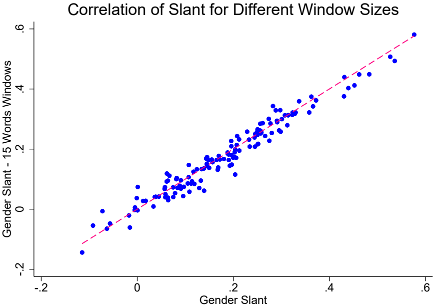
  Tiny fraction of gender cases ($\frac{1{,}719}{114{,}702}$) involved in calculating gender slant

- Omitted variables
  - Is it gender slant or something else?
  - Is it the affected judge's gender or something else?
- Assessment of randomization

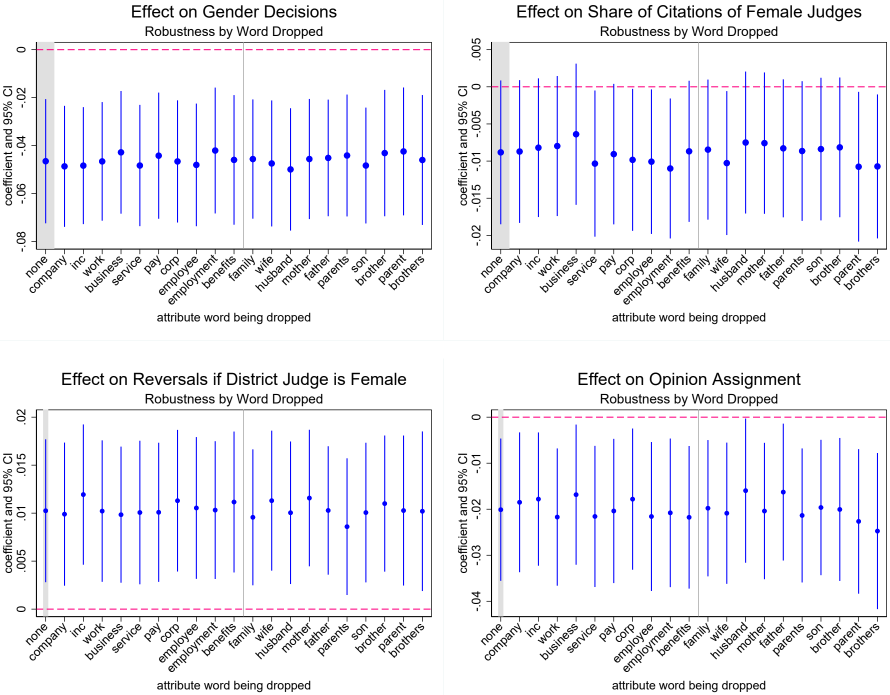
Robustness by Context Window

Figure: Correlation of Gender Slant for Embeddings Based on Different Windows

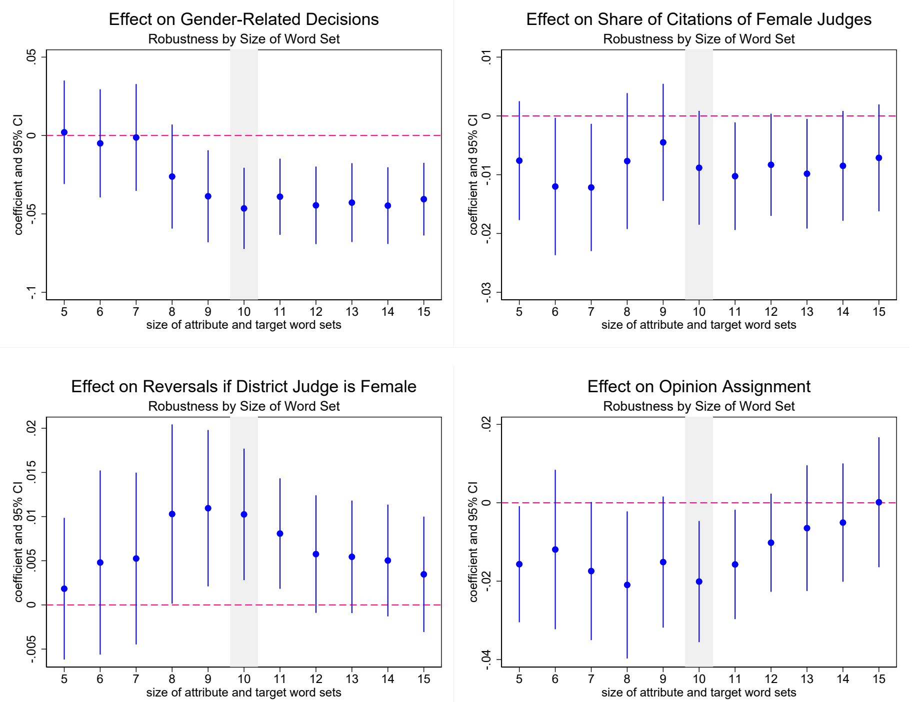




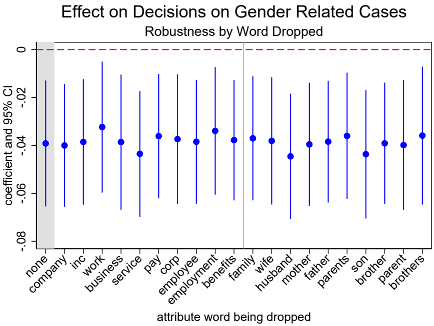
Notes: The graphs show a scatter plot of the gender slant measure obtained by training embeddings using different window sizes (5 vs. 10; 10 vs. 15) to construct co-occurrence matrix.

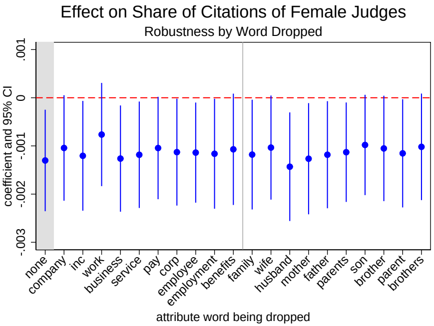


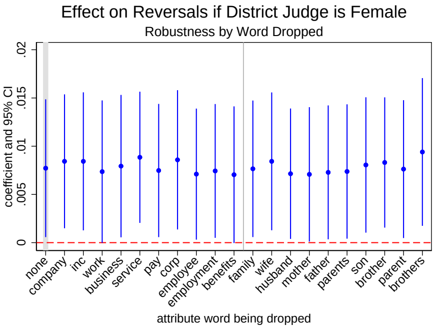
Effect on Gender Decisions
Robustness by Word Dropped
coefficient and 95% CI
0
-.02
-.04
-.06
-.08
none company inc work business service pay corp employee employment benefits family wife husband mother father parents son brother parent brothers
attribute word being dropped
Effect on Share of Citations of Female Judges
Robustness by Word Dropped
coefficient and 95% CI
.005
0
-.005
-.01
-.015
-.02
none company inc work business service pay corp employee employment benefits family wife husband mother father parents son brother parent brothers
attribute word being dropped
Effect on Reversals if District Judge is Female
Robustness by Word Dropped
coefficient and 95% CI
.02
.015
.01
.005
0
none company inc work business service pay corp employee employment benefits family wife husband mother father parents son brother parent brothers
attribute word being dropped
Effect on Opinion Assignment
Robustness by Word Dropped
coefficient and 95% CI
0
-.01
-.02
-.03
-.04
none company inc work business service pay corp employee employment benefits family wife husband mother father parents son brother parent brothers
attribute word being dropped

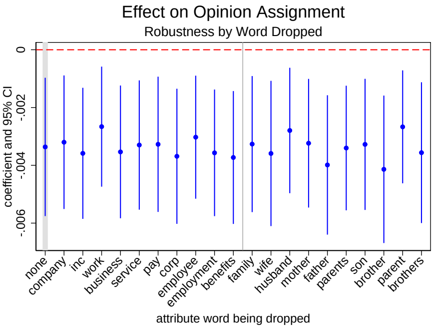


Effect on Gender-Related Decisions
Robustness by Size of Word Set
coefficient and 95% CI
.05
0
-.05
-.1
5 6 7 8 9 10 11 12 13 14 15
size of attribute and target word sets
Effect on Share of Citations of Female Judges
Robustness by Size of Word Set
coefficient and 95% CI
.01
0
-.01
-.02
-.03
5 6 7 8 9 10 11 12 13 14 15
size of attribute and target word sets
Effect on Reversals if District Judge is Female
Robustness by Size of Word Set
coefficient and 95% CI
.02
.015
.01
.005
0
-.005
5 6 7 8 9 10 11 12 13 14 15
size of attribute and target word sets
Effect on Opinion Assignment
Robustness by Size of Word Set
coefficient and 95% CI
.02
0
-.02
-.04
5 6 7 8 9 10 11 12 13 14 15
size of attribute and target word sets


Effect on Decisions on Gender Related Cases
Robustness by Word Dropped
coefficient and 95% CI
0
-.02
-.04
-.06
-.08
none
company
inc
work
business
service
pay
corp
employee
employment
benefits
family
wife
husband
mother
father
parents
son
brother
parent
brothers
attribute word being dropped


Effect on Share of Citations of Female Judges
Robustness by Word Dropped
coefficient and 95% CI
.001
0
-.001
-.002
-.003
none
company
inc
work
business
service
pay
corp
employee
employment
benefits
family
wife
husband
mother
father
parents
son
brother
parent
brothers
attribute word being dropped


Effect on Reversals if District Judge is Female
Robustness by Word Dropped
coefficient and 95% CI
.02
.015
.01
.005
0
none
company
inc
work
business
service
pay
corp
employee
employment
benefits
family
wife
husband
mother
father
parents
son
brother
parent
brothers
attribute word being dropped


Effect on Opinion Assignment
Robustness by Word Dropped
coefficient and 95% CI
0
-.002
-.004
-.006
none
company
inc
work
business
service
pay
corp
employee
employment
benefits
family
wife
husband
mother
father
parents
son
brother
parent
brothers
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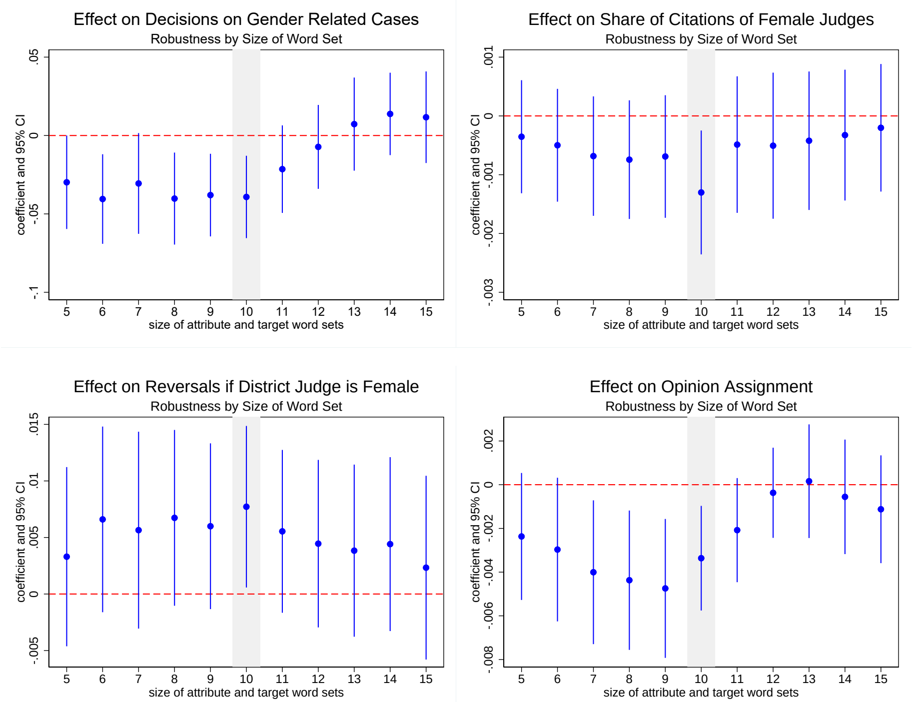

Effect on Decisions on Gender Related Cases
Robustness by Size of Word Set
coefficient and 95% CI
.05
0
-.05
-.1
5 6 7 8 9 10 11 12 13 14 15
size of attribute and target word sets
Effect on Share of Citations of Female Judges
Robustness by Size of Word Set
coefficient and 95% CI
.001
0
-.001
-.002
-.003
5 6 7 8 9 10 11 12 13 14 15
size of attribute and target word sets
Effect on Reversals if District Judge is Female
Robustness by Size of Word Set
coefficient and 95% CI
.015
.01
.005
0
-.005
5 6 7 8 9 10 11 12 13 14 15
size of attribute and target word sets
Effect on Opinion Assignment
Robustness by Size of Word Set
coefficient and 95% CI
.002
0
-.002
-.004
-.006
-.008
5 6 7 8 9 10 11 12 13 14 15
size of attribute and target word sets

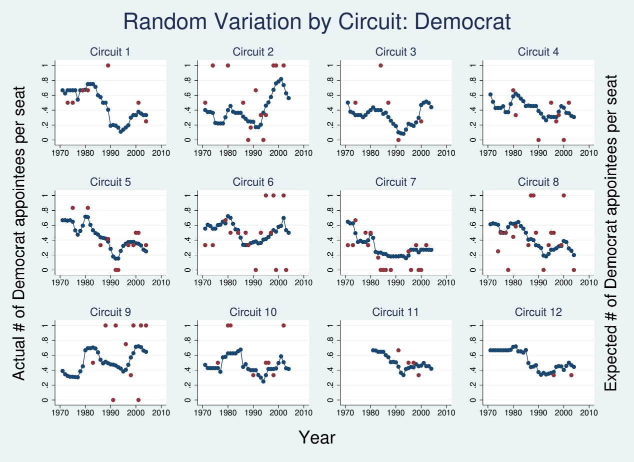
Robustness

- Estimate of how 'unobservables would need to be 'delta' as important as observables for the treatment effect to be 0. (Oster 2016)
  - Reversals: 53
  - Authorship: 1.2
  - Citations: 0.6
  - Decisions: 2.6
  - Daughters: 6

Effect of language slant of senior judge on author characteristics

Dependent Variable: Author is	Democrat	Democrat & Female	Minority	Age
Gender Slant	-0.027**	0.001	0.006	0.069
	(0.010)	(0.010)	(0.008)	(0.168)
Democrat	0.156***	-0.010	0.019	1.176**
	(0.021)	(0.037)	(0.024)	(0.566)
Female	-0.045**	-0.019	0.025	-0.009
	(0.019)	(0.022)	(0.015)	(0.499)
Observations	46735	3907	23436	120365
Clusters	137	99	126	139
Outcome Mean	0.366	0.305	0.340	63.030
Circuit-Year FE	X	X	X	X
Demographic Controls	X	X	X	X
Panel Includes Democrat Judge	X			
Panel Includes Democrat and Female Judge		X		
Panel Includes Minority Judge			X	

Graphical Intuition of Randomization



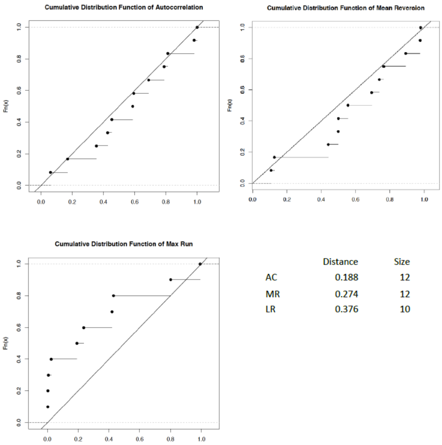
Random Strings

- 1. Propose a statistic summarizing the yearly sequence of numbers of democratic appointees per seat within a circuit.
  - Test for autocorrelation (judges seeking out cases), mean-reversion (judges 'due' for certain cases), and longest-run (specialization)
- 2. Compute the statistic for the actual sequence, s*.
- 3. Compute the statistic for each of 1,000 bootstrap samples like the actual sequence, i.e., s_1, s_2, s_3... s_n.
- 4. Compute the empirical p-value, p_i by determining where s* fits into s_1, s_2, s_3... s_n.
- 5. Repeat steps 1-4 and calculate p_i for each circuit.

Random Strings

- p-values should look uniformly distributed
  - (1001^{th} random string should have a statistic anywhere between 1-1000)
  - Kolmogorov-Smirnov Test for whether the empirical distribution of p-values approaches the CDF of a uniform distribution

Appellate Randomization Check $\mathbf{E}[p_{ct}\varepsilon_{ict}] = 0$



	Distance	Size
AC	0.188	12
MR	0.274	12
LR	0.376	10

- Test for autocorrelation (judges seeking out cases), mean-reversion (judges 'due' for certain cases), and longest-run (specialization)
- p-values should look uniform (1001th random string should have a statistic anywhere between 1-1000)
- KS-Test for whether the empirical distribution of p-values approaches the CDF of a uniform distribution

Judge Randomization Check

	Economics Case			
	(1)	(2)	(3)	(4)
Econ Training	0.00788	-0.000716	-0.00512	0.00540
	(0.00807)	(0.00454)	(0.00893)	(0.00416)
N	123519	115561	500266	389105
adj. R-sq	0.115	0.024	0.112	0.023
Circuit-Year FE	Y	Y	Y	Y
Sample	Author	Author	On Panel	On Panel
Sample	Year $<$ 1976	Year $>$ 1991	Year $<$ 1976	Year $>$ 1991

Omnibus check: No endogenous settlement or selection of cases.

Table: Randomization Check: Orthogonality with Case Characteristics as Determined by Lower Court

Case Characteristics as Determined by Lower Court	Male Democrat (1)	Female Republican (2)
Direction of Lower Court Decision	0.0115	-0.171
	(0.0856)	(0.187)
Plaintiff claims employer acted in retaliation	-0.102	0.184
	(0.0936)	(0.205)
All plaintiffs are female	0.0126	-0.0920
	(0.0747)	(0.164)
Title IX claim	0.0415	-0.0558
	(0.0252)	(0.0553)
Section 1983 claim	0.0533	-0.0474
	(0.0500)	(0.110)
Constructive discharge from employment	0.00764	0.0726
	(0.0559)	(0.122)
Procedural issues dominate	0.0167	0.163
	(0.0586)	(0.128)

Table: Randomization Check: Orthogonality with Case Characteristics as Determined by Lower Court

Case Characteristics as Determined by Lower Court	Male Democrat (1)	Female Republican (2)
Plaintiff suing under state law	0.0677	-0.283
	(0.0830)	(0.181)
Plaintiff claims illegally denied promotion	-0.0591	-0.0465
	(0.0755)	(0.165)
Plaintiff claims illegally not being hired	-0.0909+	0.105
	(0.0529)	(0.116)
Plaintiff claims illegally fired	0.0460	-0.159
	(0.0961)	(0.210)
Plaintiff claims unequal pay	-0.0235	-0.0868
	(0.0675)	(0.148)
Plaintiff sued under 14th Amendment	0.0606	-0.167+
	(0.0429)	(0.0938)
Plaintiff sued under 1st Amendment	0.0574	-0.0503
	(0.0353)	(0.0775)

Table: Randomization Check: Orthogonality with Case Characteristics as Determined by Lower Court

Case Characteristics as Determined by Lower Court	Male Democrat (1)	Female Republican (2)
Damages major point of contention	0.0765	0.166
	(0.0669)	(0.147)
Contains Section 1981 claim	0.0295	-0.0818
	(0.0585)	(0.128)
Contains age discrimination claim	0.0368	-0.241
	(0.0695)	(0.152)
Contains pregnancy discrimination claim	0.0232	0.0911
	(0.0484)	(0.106)
Contains emotional distress claim	-0.0781	0.0432
	(0.0530)	(0.116)

Notes: Significant at +10%, *5%, **1%. Heteroskedasticity-robust standard errors are in parentheses. Each coefficient represents a separate regression of a distinct case characteristic on the fraction of the panel comprising of male Democrats (respectively, female Republicans).

Is it Implicit or Explicit?

- Is inattention the mechanism for heuristics?
- Or explicit, consciously drawing out gender stereotypes into the text?
- (1) Examine correlation with other forms of implicit cognition
  - Arguably clean extraneous factor, such as presidential elections
- (2) Examine Project Implicit data from 10,000 self-reported lawyers
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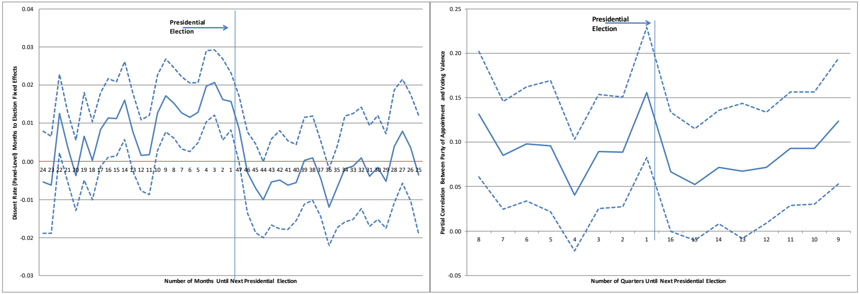
Electoral Cycles Among U.S. Circuit Judges (Berdejo and Chen 2017)

Figure: Dissents and Partisan Voting



Increases with campaign intensity across states and time (Chen 2019)

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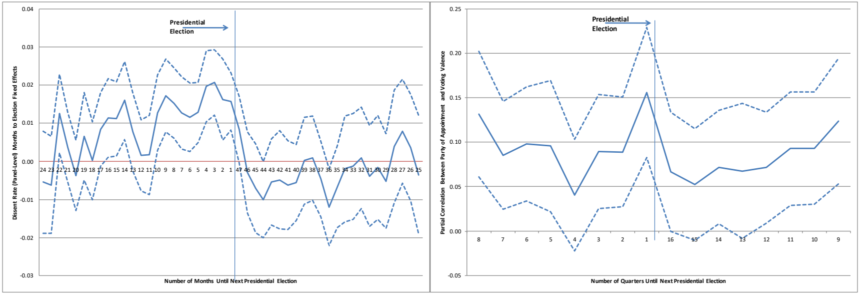

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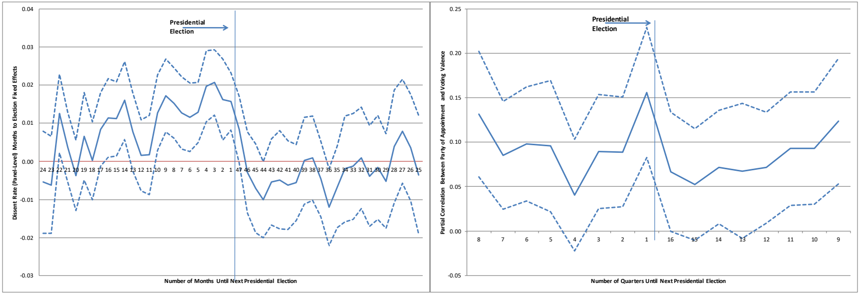

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Electoral Cycles Correlate With WEAT

Dependent variable	Dissent
	(1)
9 Mo. Before Election	0.00439*
	(0.00224)
9 Mo. Before Election	-0.00225**
X WEAT (family/career)	(0.00113)
N	997494
Judge FE	X
9 Mo. Before Election x Judge Bio	X

Correlates of Implicit and Explicit Bias

Dependent Variable	Implicit Bias (Career-Family IAT)			Explicit Bias (self-reported)		
Liberal	-0.070***			-0.170***		
	(0.024)			(0.026)		
Female		0.118***			0.022	
		(0.021)			(0.021)	
Age			0.004***			-0.005***
			(0.001)			(0.001)
Observations	9954	9954	9954	9954	9954	9954
Outcome Mean	0.000	0.000	0.000	0.000	0.000	0.000
Adjusted R2	0.001	0.003	0.002	0.005	0.000	0.004

10,000 self-identified lawyers in Project Implicit database

More work or experiments needed

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			(0.001)			(0.001)
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Outcome Mean	0.000	0.000	0.000	0.000	0.000	0.000
Adjusted R2	0.001	0.003	0.002	0.005	0.000	0.004

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Daughters Reduce Gender Slant

Daughter	-0.477*	-0.468*
	(0.274)	(0.278)
Democrat	-0.016	-0.069
	(0.535)	(0.613)
Female	-0.659***	-0.683***
	(0.232)	(0.239)
Democrat * Female		0.321
		(0.631)
Observations	98	98
Outcome Mean	-0.085	-0.085
Adjusted R2	0.528	0.520
Circuit FE	X	X
Number of Children FE	X	X
Demographic Controls	X	X
Interacted Demographic Controls		X

Conditional on number of children, having a daughter as good as random.

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Interacted Demographic Controls		X

Conditional on number of children, having a daughter as good as random.

We find evidence that lexical slant matters in the judiciary

- Two standard deviations of gender slant

  1. 20% lower likelihood of pro-women's rights vote
     - $\sim\frac{2}{3}$ of party effect; $\sim$ female effect
  2. 10% lower likelihood of female assigned authorship
     - $\sim$ party effect; $\sim\frac{1}{3}$ of female effect
  3. 6% lower likelihood of citing a female
     - $\sim$ party effect; $\sim\frac{1}{6}$ of female effect
  4. 10% more likely to reverse a female
     - $>>$ party and female effects; $\exists$ reverse gender gap
     - Female district judges 12% less likely to be elevated than a male

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     - Are female judges assigned different types of opinions?
     - Does bias impact the career of female judges?
  2. More work needed to define exactly what we are measuring
     - Are these implicit attitudes?
     - How does our measure correlate with actual IAT scores?
  3. Extensions to other domains
     - Preliminary analysis on congressional speech shows similar results
     - What about disparities in criminal sentencing? (w/ judge FE)

  - What about peer effects, precedent effects
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  3. Extensions to other domains
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