Stereotypes in High-Stakes Decisions
Evidence from U.S. Circuit Courts

Daniel L. Chen
w/ Elliott Ash (EthZ) and Arianna Ortaghi (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.
- A truck driver should plan the travel route carefully.
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Does implicit bias exist?

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)

Does training affect implicit attitudes?
- exposure to female leaders (Beaman et al. 2009)
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- Generally measured using Implicit Association Tests (IATs)
- Subjects asked to assign words to categories (Greenwald et al. 1998)

Comparing reaction times across trials with different pairings
- subjects are faster and make fewer errors on stereotype-consistent trials
- difference yields “IAT score”

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Challenge: how can we measure implicit attitudes for the judiciary?

- We know that ideological/biographical characteristics matter
  - And that judges' decisions are often highly predictable
  - Suggesting that judges' preferences directly affect their decisions..
  - ..and that judges might use snap judgments/heuristics
    - Early predictability of asylum decisions - Chen, Dunn, Sagun, Sirin 2017
  - But we cannot elicit IAT scores from sitting judges (yet :-)

Proposed solution: proxy for IAT using large amounts of written text

- Corpus of U.S. Circuit Court opinions 1870s-2013
- Use machine learning to measure semantic biases in text corpora
- Represent judicial language in vector space
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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)
- \( A, B \) are career (company, work, business, service, pay) vs. family (family, wife, husband, mother, father)
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Dataset

- All 380K cases, 1,150K judge votes, 94 topics, from 1870s-
- 700M tokens, 2B 8-grams, 5M citation edges across cases
- 250 biographical features (D/R, law school, age)
- 5% sample, 400 hand-coded features (1-digit topic)
- 6K cases hand-coded for meaning in 25 legal areas
  - Sunstein et al. 2007; Glynn and Sen 2015 (includes information on daughters)
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Life-tenure, appointed by US President (in circuit and district)

Binding precedent within circuit

In C: Panels of 3, no juries, drawn from a pool of 8-40 judges

327K cases/yr in the 94 D ⇒ 67K cases/yr in 12 C ⇒ 100 cases/yr in Supreme Ct
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Introduce theories:

- **Contract duty posits a general obligation to keep promises** vs.
  a party should be allowed to breach a contract and pay damages, if it’s more economically efficient than performing (i.e., efficient breach theory) (Posner 7th Cir. 1985)

- **Tort law: duty of care** is breached when PL > B (i.e., least cost avoider theory)

Shift in standards or thresholds:

- Shift from reasonable person standard to reasonable woman standard for what constitutes sexual harassment.

- Waive need to prove emotional harm in court by plaintiff (to a jury).

Rule on states’ laws:

- 5th Circuit **allowed** Texas law requiring abortion clinics to meet building standards of ambulatory surgery centers. (would reduce to < 10 clinics)

Do implicit attitudes affect women’s rights rulings like these?
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Do implicit attitudes affect women’s rights rulings like these?
Measure causes and consequences of implicit attitudes

1. Identify *judge-specific measure* using random case assignment
   - Female and younger judges display less lexical slant

2. Identify *policy impact of lexically slanted judges* using random assignment
   - Fewer pro-women votes in women’s rights cases

3. Identify *impact on female colleagues* using random panel composition
   - Female judges reversed more and cited less by lexically slanted judges
   - Female judges assigned fewer opinions by lexically slanted senior judges

4. Identify *impact of diversity* using quasi-random exposure to females
   - Daughters reduce lexical slant

5. Assess whether lexical slant is *implicit or explicit*
   - Correlates with other forms of implicit cognition
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   - Female judges reversed more and cited less by lexically slanted judges
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How to represent text as data?

- (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.
   ```python
   model.similarity('woman', 'man')
   0.73723527
   ```
2. Finding odd one out.
   ```python
   model.doesnt_match('breakfast cereal dinner lunch'; .split())
   'cereal'
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3. Amazing things like woman+king−man = queen
   ```python
   model.most_similar(positive=['woman', 'king'], negative=['man'], topn=1)
   queen: 0.508
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4. Probability of a text under the model
   ```python
   model.score(['The fox jumped over the lazy dog'.split()])
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- Each word is mapped to one vector, often hundreds of dimensions
  - Contrast to 2B N-grams for sparse word representations
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How it works: Predict surrounding words given current word

Words as Vectors

Use cosine similarity as a measure of relatedness:

$$\cos \theta = \frac{v_1 \cdot v_2}{\|v_1\| \|v_2\|}$$

- Use cosine similarity as a measure of relatedness:

- Uses neural networks
- Moment conditions
  - In 2SLS, orthogonality of instruments and prediction error
  - In structural econometrics, means of the data
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Distance encodes semantic similarity between words

- **GloVe (Global Vectors)**
  - Based on intuition that co-occurrence probabilities convey meaning
  - Begins by constructing a co-occurrence matrix using a fixed window
    - Obtains word vectors \( w_i \in (-1, 1)^{300} \) that minimize
      \[
      J(w) = \sum_{i,j} f(X_{ij}) \left( w_i^T w_j - \log(X_{ij}) \right)^2
      \]
    - \( X_{ij} \) is the co-occurrence count between words \( i \) and \( j \)
    - \( f(\cdot) \) is a weighting function that down-weights frequent words
    - Objective function \( J(\cdot) \) trains word vectors to minimize squared difference between dot product of vectors representing two words and their empirical co-occurrence
      - 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
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Word embeddings identify cultural dimensions

- Identify cultural dimension by taking difference between pairs of words

\[
\overrightarrow{\text{male}} - \overrightarrow{\text{female}} = \sum_n \frac{\text{male word}_n}{|N_{\text{male}}|} - \sum_n \frac{\text{female word}_n}{|N_{\text{female}}|}
\]

where \(|N_{\text{male}}|\) is number of words used to identify the male dimension, e.g. \(\overrightarrow{\text{boy}} - \overrightarrow{\text{girl}}, \overrightarrow{\text{he}} - \overrightarrow{\text{she}}\), etc.
Word embeddings identify cultural dimensions

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\[ \overrightarrow{\text{man}} - \overrightarrow{\text{woman}} \text{ identifies a step in masculine direction} \]

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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(\vec{x}, \vec{y}) = \cos(\theta) = \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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- Work-family dimension, defined by \(\vec{work} - \vec{family}\)
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Linguistic Inquiry and Word Count Dictionaries (LIWC) provide human-validated list of word and word stems corresponding to concepts
- male, female, work, and family

From each list, select the 10 most frequent words in full judicial corpus
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Utility for judge $i$ at year $t$:

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

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 $j = \text{median slant across bootstrap samples}$
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**Figure:** Judge Specific Word Embeddings Capture Gender Information

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.
- Based on these stats, preferred specification includes 139 judges with >1.5M tokens.
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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

 - Not accounting for vacation, sick leave, senior status, en banc, remand, and recusal can lead to the inference that judges are not randomly assigned.
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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

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Circuit FE: X
Demographic Controls: X
Female judges and younger judges display less lexical slant

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Circuit FE: X
Demographic Controls: X
Lexical slant and judicial decisions

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

\[
\text{feminist vote}_{ijct} = \beta \text{lexical slant}_j + X_j' \gamma + \delta_{ct} + W_i' \eta + \epsilon_{ijct}
\]

- \( i \) case, \( j \) judge, \( c \) circuit, \( t \) year
- \( \text{feminist vote}_{ijct} \): vote in favor of female plaintiff or plaintiff representing women’s interest
- \( \text{lexical slant}_j \): 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..)
- \( \delta_{ct} \): circuit-year fixed effects
- Standard errors clustered at the judge level
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- $\delta_{ct}$: circuit-year fixed effects
- Standard errors clustered at the judge level
 Judges with more lexical slant are less likely to vote in favor of women’s interests

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Notes: *** p < 0.001, ** p < 0.01, * p < 0.05.
Judges with more lexical slant are less likely to vote in favor of women’s interests

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| Observations     | 2335                       | 1719                      |
| Clusters         | 112                        | 109                       |
| Outcome Mean     | 0.4167                     | 0.383                     |

| Circuit-Year FE | X                          | X                          |
| Topic FE        | X                          | X                          |
| Demographic Controls | X            | X                          |
| + Interactions  | X                          | X                          |
| Career FE (judge bio) | X                     | X                          |
Judges with more lexical slant also vote conservative across some other issues.

Heterogeneous Effects by Case Topic

- Campaign Finance
- Sexual Harassment
- Age Discrimination
- Takings
- Sex Discrimination
- Americans with Disabilities Act
- Piercing Corporate Veil
- Abortion
- Capital Punishment
- Title VII
- Affirmative Action
- Federalism
- EPA
- Contract Clause
.. but not across all issues

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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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Previous results also hold controlling for Liberal % (Songer-Auburn)
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.
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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
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Panels with more slanted senior judges are less likely to assign opinions to women

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| 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

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|                   |              |              |              |              |              |              |
| 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      |

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

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| 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

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| Observations       | 171441    | 43601      | 171441              |
|                    |           |            | 43601               |
| Clusters           | 139       | 125        | 139                 |
|                    |           |            | 125                 |
| Outcome Mean       | 0.803     | 0.847      | 0.092               |
|                    |           |            | 0.045               |
| Circuit-Year FE    | X         | X          | X                   |
| Demographic Controls | X     | X          | X                   |
| One Female Judge on Panel | X     | X          | X                   |
Judges with more lexical slant cite female judges less

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Judges with more lexical slant cite female judges less

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- 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

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.. and cite each other

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Reversals

\[
votes \ to \ reverse_{ijdct} = \alpha \text{female district judge}_i \\
+ \beta \text{female district judge}_i \times \text{lexical slant}_j \\
+ \text{female district judge}_i \times X'_j \gamma \\
+ \delta_j + \delta_{dt} + \epsilon_{ijct}
\]

- District-year fixed effects
- Circuit judge fixed effects
Judges with more lexical slant reverse female district judges more

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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

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Judges with more lexical slant reverse female district judges more

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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

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<td>-0.022***</td>
<td>-0.007</td>
<td>-0.011</td>
</tr>
<tr>
<td></td>
<td>(0.009)</td>
<td>(0.008)</td>
<td>(0.009)</td>
<td>(0.010)</td>
</tr>
<tr>
<td>Democrat * Female * Female District Judge</td>
<td>0.152***</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.015)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Observations</td>
<td>145862</td>
<td>145862</td>
<td>144965</td>
<td>145563</td>
</tr>
<tr>
<td>Clusters</td>
<td>133</td>
<td>133</td>
<td>130</td>
<td>133</td>
</tr>
<tr>
<td>Outcome Mean for Male Judges</td>
<td>0.180</td>
<td>0.180</td>
<td>0.180</td>
<td>0.180</td>
</tr>
<tr>
<td>Outcome Mean for Female Judges</td>
<td>0.157</td>
<td>0.157</td>
<td>0.157</td>
<td>0.157</td>
</tr>
<tr>
<td>Circuit-Year FE</td>
<td>X</td>
<td>X</td>
<td>X</td>
<td>X</td>
</tr>
<tr>
<td>Judge FE</td>
<td>X</td>
<td>X</td>
<td>X</td>
<td>X</td>
</tr>
<tr>
<td>District Judge FE</td>
<td>X</td>
<td>X</td>
<td>X</td>
<td>X</td>
</tr>
<tr>
<td>Demographic Controls</td>
<td>X</td>
<td>X</td>
<td>X</td>
<td>X</td>
</tr>
<tr>
<td>+ Interactions</td>
<td></td>
<td></td>
<td></td>
<td>X</td>
</tr>
<tr>
<td>Liberal Score Interaction</td>
<td></td>
<td></td>
<td></td>
<td>X</td>
</tr>
<tr>
<td>District-Year FE</td>
<td></td>
<td></td>
<td></td>
<td>X</td>
</tr>
</tbody>
</table>
But female judges are 3.6% less likely to be reversed

<table>
<thead>
<tr>
<th>Interaction</th>
<th>Outcome Mean for Male Judges</th>
<th>Outcome Mean for Female Judges</th>
</tr>
</thead>
<tbody>
<tr>
<td>Gender Slant * Female District Judge</td>
<td>0.180</td>
<td>0.157</td>
</tr>
<tr>
<td>Democrat * Female District Judge</td>
<td>0.180</td>
<td>0.157</td>
</tr>
<tr>
<td>Female * Female District Judge</td>
<td>0.180</td>
<td>0.157</td>
</tr>
<tr>
<td>Democrat * Female * Female District Judge</td>
<td>0.180</td>
<td>0.157</td>
</tr>
</tbody>
</table>

| Observations                                      | 145862                       | 145862                         | 144965                         | 145563                         |
| Clusters                                         | 133                          | 133                            | 130                            | 133                            |

<table>
<thead>
<tr>
<th>Circuit-Year FE</th>
<th>Judge FE</th>
<th>District Judge FE</th>
<th>Demographic Controls</th>
<th>+ Interactions</th>
<th>Liberal Score Interaction</th>
<th>District-Year FE</th>
</tr>
</thead>
<tbody>
<tr>
<td>X</td>
<td>X</td>
<td>X</td>
<td>X</td>
<td>X</td>
<td>X</td>
<td>X</td>
</tr>
</tbody>
</table>
Gender Slanted Judges also reverse Democrats and minorities

<table>
<thead>
<tr>
<th>Term</th>
<th>Coefficient</th>
<th>Standard Error</th>
</tr>
</thead>
<tbody>
<tr>
<td>Gender Slant * Democrat District Judge</td>
<td>0.006*</td>
<td>(0.004)</td>
</tr>
<tr>
<td>Democrat * Democrat District Judge</td>
<td>-0.022</td>
<td>(0.014)</td>
</tr>
<tr>
<td>Female * Democrat District Judge</td>
<td>-0.007</td>
<td>(0.008)</td>
</tr>
<tr>
<td>Gender Slant * Minority District Judge</td>
<td>0.011**</td>
<td>(0.005)</td>
</tr>
<tr>
<td>Democrat * Minority District Judge</td>
<td>-0.009</td>
<td>(0.010)</td>
</tr>
<tr>
<td>Female * Minority District Judge</td>
<td>0.018*</td>
<td>(0.010)</td>
</tr>
</tbody>
</table>

| 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

<table>
<thead>
<tr>
<th>Dependent Variable</th>
<th>Promoted to Circuit Court</th>
</tr>
</thead>
<tbody>
<tr>
<td>Share of Decisions Reversed on Appeal</td>
<td>-0.351*** (0.136)</td>
</tr>
<tr>
<td>Share of Votes to Reverse on Appeal</td>
<td>-0.372*** (0.116)</td>
</tr>
<tr>
<td>Female</td>
<td>0.036 (0.028) 0.037 (0.029)</td>
</tr>
<tr>
<td>Democrat</td>
<td>-0.022 (0.0191) -0.018 (0.018)</td>
</tr>
<tr>
<td>Observations</td>
<td>862 862</td>
</tr>
<tr>
<td>Outcome Mean</td>
<td>0.058 0.058</td>
</tr>
<tr>
<td>Circuit FE</td>
<td>X X</td>
</tr>
<tr>
<td>Demographic Controls</td>
<td>X X</td>
</tr>
</tbody>
</table>
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?
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?
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.. and there are many other kinds of implicit bias.

Is it robust?

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What affects attitudes?
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?
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

- 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 \( \left( \frac{1,719}{114,702} \right) \) involved in calculating gender slant

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- Robustness by size of word set
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- Robustness to dropping cases
  
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Robustness

- Robustness by context window
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- Robustness by size of word set
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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-Related Decisions

Effect on Share of Citations of Female Judges

Effect on Reversals if District Judge is Female

Effect on Opinion Assignment
Effect on Decisions on Gender Related Cases
Robustness by Word Dropped

Effect on Share of Citations of Female Judges
Robustness by Word Dropped

Effect on Reversals if District Judge is Female
Robustness by Word Dropped

Effect on Opinion Assignment
Robustness by Word Dropped
Effect on Decisions on Gender Related Cases
Robustness by Size of Word Set

Effect on Share of Citations of Female Judges
Robustness by Size of Word Set

Effect on Reversals if District Judge is Female
Robustness by Size of Word Set

Effect on Opinion Assignment
Robustness by Size of Word Set
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

<table>
<thead>
<tr>
<th>Dependent Variable: Author is</th>
<th>Democrat</th>
<th>Democrat &amp; Female</th>
<th>Minority</th>
<th>Age</th>
</tr>
</thead>
<tbody>
<tr>
<td>Gender Slant</td>
<td>-0.027**</td>
<td>0.001</td>
<td>0.006</td>
<td>0.069</td>
</tr>
<tr>
<td></td>
<td>(0.010)</td>
<td>(0.010)</td>
<td>(0.008)</td>
<td>(0.168)</td>
</tr>
<tr>
<td>Democrat</td>
<td>0.156***</td>
<td>-0.010</td>
<td>0.019</td>
<td>1.176**</td>
</tr>
<tr>
<td></td>
<td>(0.021)</td>
<td>(0.037)</td>
<td>(0.024)</td>
<td>(0.566)</td>
</tr>
<tr>
<td>Female</td>
<td>-0.045**</td>
<td>-0.019</td>
<td>0.025</td>
<td>-0.009</td>
</tr>
<tr>
<td></td>
<td>(0.019)</td>
<td>(0.022)</td>
<td>(0.015)</td>
<td>(0.499)</td>
</tr>
<tr>
<td>Observations</td>
<td>46735</td>
<td>3907</td>
<td>23436</td>
<td>120365</td>
</tr>
<tr>
<td>Clusters</td>
<td>137</td>
<td>99</td>
<td>126</td>
<td>139</td>
</tr>
<tr>
<td>Outcome Mean</td>
<td>0.366</td>
<td>0.305</td>
<td>0.340</td>
<td>63.030</td>
</tr>
</tbody>
</table>

- Circuit-Year FE: X X X X X
- Demographic Controls: X 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 Variation by Circuit: Democrat

Expected # of Democrat appointees per seat

Actual # of Democrat appointees per seat

Year
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
  - $(1001^{th} \text{ random string should have a statistic anywhere between 1-1000})$
  - Kolmogorov-Smirnov Test for whether the empirical distribution of p-values approaches the CDF of a uniform distribution
Appellate Randomization Check $E[\rho_{ct} \varepsilon_{ict}] = 0$

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

<table>
<thead>
<tr>
<th></th>
<th>(1)</th>
<th>(2)</th>
<th>(3)</th>
<th>(4)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Econ Training</td>
<td>0.00788</td>
<td>-0.000716</td>
<td>-0.00512</td>
<td>0.00540</td>
</tr>
<tr>
<td></td>
<td>(0.00807)</td>
<td>(0.00454)</td>
<td>(0.00893)</td>
<td>(0.00416)</td>
</tr>
<tr>
<td>N</td>
<td>123519</td>
<td>115561</td>
<td>500266</td>
<td>389105</td>
</tr>
<tr>
<td>adj. R-sq</td>
<td>0.115</td>
<td>0.024</td>
<td>0.112</td>
<td>0.023</td>
</tr>
</tbody>
</table>

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

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

Notes: Significant at +10%, *5%, **1%. Heteroskedastic-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).
### Table: Randomization Check: Orthogonality with Case Characteristics as Determined by Lower Court

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

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

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
   - Compare demographic correlates of implicit and explicit bias
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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)

Precedent polarization also increases during elections (Ash et al. 2019)
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)

Precedent polarization also increases during elections (Ash et al. 2019)
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)

Precedent polarization also increases during elections (Ash et al. 2019)
Electoral Cycles Correlate With WEAT

<table>
<thead>
<tr>
<th>Dependent variable</th>
<th>Dissent</th>
</tr>
</thead>
<tbody>
<tr>
<td>9 Mo. Before Election</td>
<td>0.00439*</td>
</tr>
<tr>
<td></td>
<td>(0.00224)</td>
</tr>
<tr>
<td>9 Mo. Before Election X WEAT (family/career)</td>
<td>-0.00225**</td>
</tr>
<tr>
<td></td>
<td>(0.00113)</td>
</tr>
</tbody>
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N: 997494

Judge FE: X

9 Mo. Before Election x Judge Bio: X
## Correlates of Implicit and Explicit Bias

<table>
<thead>
<tr>
<th>Dependent Variable</th>
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<tr>
<td>Liberal</td>
<td>-0.070***</td>
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<td>(0.024)</td>
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</tr>
<tr>
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<td>0.118***</td>
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</tr>
<tr>
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<td>(0.021)</td>
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<tr>
<td>Age</td>
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<td>-0.005***</td>
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<tr>
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<tr>
<td>Observations</td>
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<td>9954</td>
</tr>
<tr>
<td>Outcome Mean</td>
<td>0.000</td>
<td>0.000</td>
</tr>
<tr>
<td>Adjusted R2</td>
<td>0.001</td>
<td>0.003</td>
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10,000 self-identified lawyers in Project Implicit database

More work or experiments needed
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| 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
Daughters Reduce Gender Slant

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<tr>
<td>Daughter</td>
<td>-0.477*</td>
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<tr>
<td></td>
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<td>(0.278)</td>
</tr>
<tr>
<td>Democrat</td>
<td>-0.016</td>
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<tr>
<td></td>
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<tr>
<td></td>
<td>(0.232)</td>
<td>(0.239)</td>
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<tr>
<td>Democrat * Female</td>
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<td></td>
</tr>
<tr>
<td></td>
<td>(0.631)</td>
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</tr>
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Circuit FE: X
Number of Children FE: X
Demographic Controls: X
Interacted Demographic Controls: X

Conditional on number of children, having a daughter as good as random.
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<th>Outcome 2</th>
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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

- Having a daughter
  5. 0.5 standard deviation lower gender slant
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