AI and Rule of Law

Machine Learning, Causal Inference, and Judicial Analytics

Daniel L. Chen

The Great Transformation of Law *J of Artificial Intelligence & Law 2018*

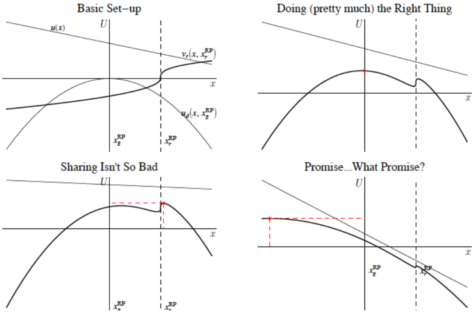
- Predictive judicial analytics may
  - Increase efficiency and fairness of law
- Many talk of robot judges
  - prediction accuracy is not always a good thing
  - decisions can reflect bias

Justice: **equal treatment before the law** $(y = f(X) + \varepsilon, a \rightarrow X)$
equality based on recognition of difference
$(y \perp W, var(\varepsilon) \perp W, a \nrightarrow W)$

control principle and **merit** principle: individuals responsible only for events that are under their control
W: race, gender, masculinity, name, football, weather, judge's lunchtime, preceding case, ...

Machine Learning and Rule of Law *Computational Analysis of Law* 2018

- Behavioral anomalies offer intuitive understanding of feature relevance
- "settings where people are closer to *indifference* among options are more likely to lead to detectable effects [of behavioral biases] outside of it." (Simonsohn, JPSP 2011)



A model of recognition-respect and

revealed preference indifference

Research in Experimental Economics 2017

Three uses of judicial analytics

- Predictive analytics of judges
  - Score nominees prior to appointment
- Predictive analytics for causal inference
  - Law platform for automated prospective impact analysis
- Predictive analytics to increase recognition, dignity
  - Randomized control trials

Judicial Corpora

U.S. Circuit Courts

- All 380K cases, 1,150K judge votes, from 1891-
- 2B 8-grams, 5M citation edges across cases
- 677 judges since 1800 (250 features)
- 5% sample, 400 hand-coded features

U.S. District Courts

- 5M criminal sentencing decisions, from 1992-
- FOIA linked to judge identity
- 1300 judicial biographies, 2.5M opinions from 1923-, defendant characteristics

U.S. Supreme Court

- Formants in oral arguments from 1955-
- Identical introductory sentences

U.S. Asylum Courts

- Administrative universe since creation of EOIR, from 1981-
- 1M asylum decisions, 15M hearing sessions, appeal
- 336 hearing locations, 441 judges, time of day

New Orleans District Attorney office

- Administrative data linked prior to screening for a decade
- Names, race category, 594 pg codebook

India

- 4.5M opinions from 24 High Courts from 1937-
- 8.7M cases and 67M hearings from 3000 subordinate courts

Behavioral Influences on Judicial Decisions

Circuit	District	SCOTUS	Asylum	New Orleans DA
Priming	Economics	Masculinity	Gambler's Fallacy	Implicit Egoism
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Judicial Analytics of Brett Kavanaugh

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Judicial Analytics and Causal Inference

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Judicial Analytics, Recognition, and Dignity

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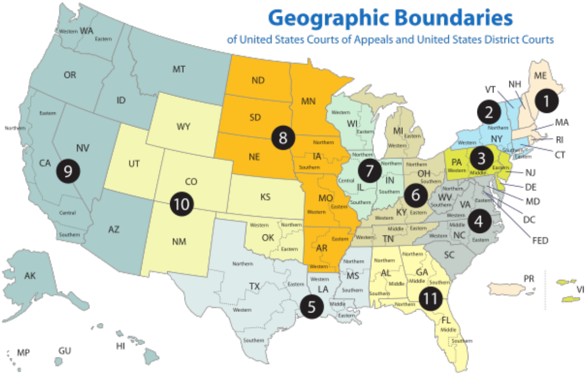
US Federal Courts as Natural Laboratory



- **Random** assignment of judges (in circuit and district)
- **Life-tenure**, **appointed** by US President (in circuit and district)
- Binding **precedent** within circuit, 92% unanimous
- In C: **Panels** of 3, no juries, drawn from a **pool** of 8-40 judges
- 327K cases/yr in the 94 D $\Rightarrow$ 67K cases/yr in 12 C $\Rightarrow$ 100 cases/yr in Supreme Ct

High-stakes common-law space

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:

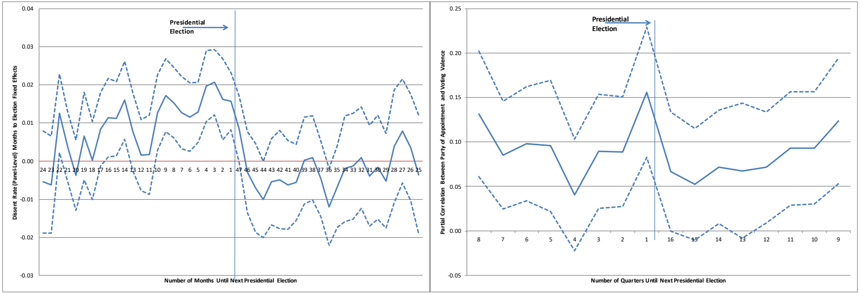
- Shift from **reasonable person** standard to **reasonable woman** standard for what constitutes sexual harassment.
- **Waive need to prove emotional harm** in court by plaintiff (to a jury).

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)

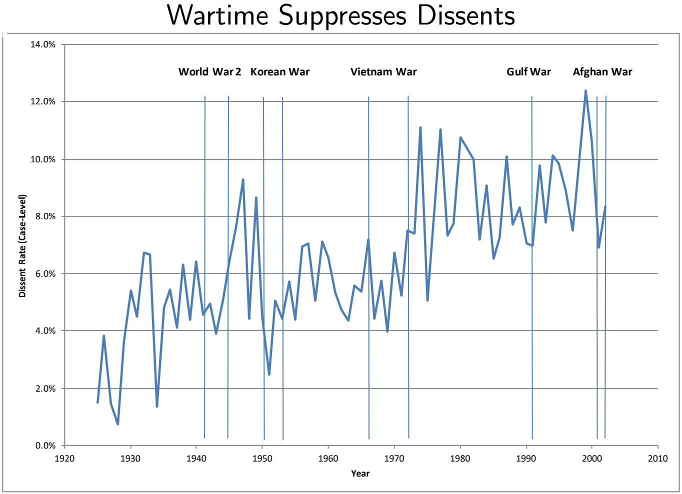
Electoral Cycles Among U.S. Circuit Judges *Berdejo and Chen, JLE 2017*

Figure: in Dissents and Partisan Voting



- **Dissents** (2-1 votes) increase in the months leading up to an election
  - Four times the effect of a politically mixed panel (DDR or RDD)
- **Partisanship** (correlation of party and liberal v. conservative) increase from 7 to 14%
- Impacts precedent, reversals of the lower court, crowds Supreme Court docket
- Dissent before election is 50% less likely to yield a Supreme Court reversal.

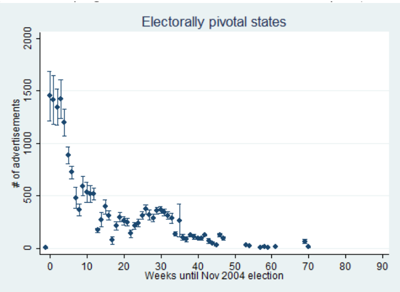
Priming Identity

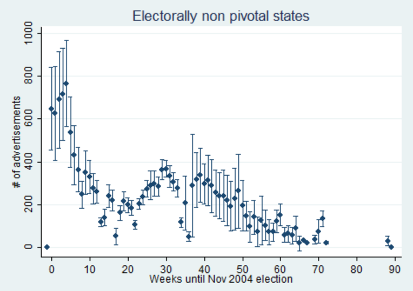


- Especially for mixed panels (DDR or RDD)
- And inexperienced judges

Why Presidential Elections Affect U.S. Judges JLS R&R

Figure: Campaign Ads in Pivotal and Non-Pivotal States

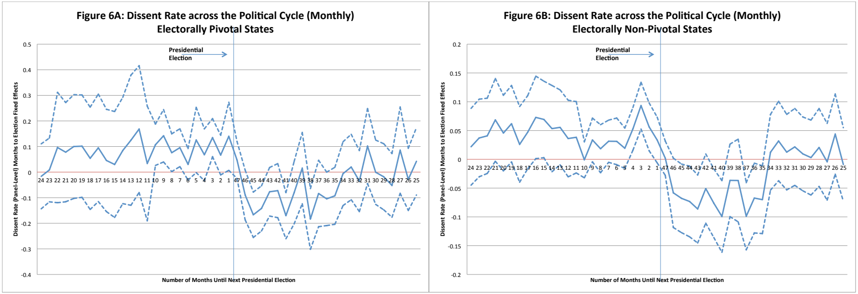




- Large states count heavily in winner-takes-all general election
- Small states count more in proportional system during primary season
  - Median voter in party primaries more extreme

Why Presidential Elections Affect U.S. Judges

Figure: Dissent Cycle in Pivotal and Non-Pivotal States



- Dissent elevation is higher in the electorally pivotal states
- But declines in electorally non-pivotal states after the primary season

Close Elections in Electorally Pivotal States

Panel B	Dissent Rate in Three Quarters Before Election - Dissent Rate in Three Quarters After Election	
	(1)	(2)
Electoral Vote Count	0.00160	0.000786
	[0.00114]	[0.00126]
Popular Vote Tightness	-0.0801	-0.0845
	[0.0772]	[0.0947]
Electoral Vote Count	0.0118	0.0121
* Popular Vote Tightness	[0.00622]*	[0.00702]*
Controls	N	Y
Observations	593	593
R-squared	0.007	0.026

- Dissent is correlated only with electoral conditions of dissenter's state
  - E.g., for a large state with 30 electoral votes, popular vote tightness from 5% to 0% (tie) would increase dissents by 1.7%
- U.S. Senate elections also elevate dissents, only via dissenter's state

Primary Season varies by state

	Dissent Vote						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
ΔCampaign Ads (t0)	0.00725	0.00998	0.0100	0.00810	0.00871	0.0223	0.0251
	[0.00316]**	[0.00475]**	[0.00487]**	[0.00479]*	[0.00551]	[0.0103]**	[0.0156]
ΔCampaign Ads (t1)		0.00824	0.00877	0.00430	0.00469		
		[0.00817]	[0.00870]	[0.00910]	[0.0116]		
ΔCampaign Ads (t2)			-0.00500	-0.00285	-0.00455		
			[0.0125]	[0.0127]	[0.0127]		
ΔCampaign Ads (f1)						0.00775	0.00893
						[0.00538]	[0.0112]
ΔCampaign Ads (f2)							0.00329
							[0.00535]
Controls	N	N	N	Y	Y*	N	N
N	7410	6674	5864	5864	5864	6674	6036
R-sq	0.000	0.001	0.001	0.012	0.086	0.001	0.001

- Dissents track spatial and temporal variation in electoral intensity, proxied by monthly campaign ads in the dissenting judge's state of residence
- Dissents increase most on the topic of campaign ads

Placebo Dates point towards transient priming mechanism

	Dissent (2-1 Decision) - 100% Sample (1971-2006)									
	Publication Date	Docket Date	Date Filed in District Court	Notice of Appeal Filed	Date Brief Notice Issued	Date of Last Brief Filing	Submitted on Merits	Date of Oral Argument	Final Judgment Date	Publication Date
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)*
Quartertoelect = 1	0.00847	-0.00239	0.00467	0.00436	-0.00503	0.00695	0.0102	0.00323	0.00721	0.00908
	[0.00337]**	[0.00357]	[0.00335]	[0.00342]	[0.00688]	[0.00429]	[0.00911]	[0.0101]	[0.00330]**	[0.00328]***
Quartertoelect = 2	0.00474	-0.00469	0.00387	-0.00208	-0.00664	0.00557	0.00662	0.00474	0.00390	0.00504
	[0.00318]	[0.00446]	[0.00345]	[0.00442]	[0.00716]	[0.00571]	[0.00888]	[0.0138]	[0.00341]	[0.00351]
Quartertoelect = 3	0.00445	-0.00131	0.00292	0.00166	-0.00295	0.00736	0.00485	-0.00134	0.00418	0.00282
	[0.00331]	[0.00557]	[0.00359]	[0.00556]	[0.00914]	[0.00773]	[0.00780]	[0.0129]	[0.00356]	[0.00386]
Quartertoelect = 4	0.00158	-0.00238	0.000658	0.00182	0.00412	0.0108	0.0104	0.0105	0.00116	0.000715
	[0.00368]	[0.00583]	[0.00363]	[0.00612]	[0.0104]	[0.00727]	[0.00799]	[0.0126]	[0.00411]	[0.00428]
Quartertoelect = 5	0.00454	-0.000143	0.00170	-0.000972	0.000219	0.0124	0.0146	0.0106	0.00314	0.00340
	[0.00450]	[0.00585]	[0.00368]	[0.00579]	[0.00979]	[0.00763]	[0.00918]	[0.0130]	[0.00482]	[0.00483]
Quartertoelect = 6	0.00185	-0.0000619	0.00402	0.00383	0.00431	0.00877	0.00580	0.00368	0.000993	-0.000504
	[0.00455]	[0.00600]	[0.00376]	[0.00610]	[0.0111]	[0.00769]	[0.00986]	[0.0153]	[0.00494]	[0.00502]
Quartertoelect = 7	-0.00330	0.000717	0.000956	0.00129	0.00366	0.00979	0.0155	0.0104	-0.000730	-0.00470
	[0.00448]	[0.00617]	[0.00349]	[0.00602]	[0.0107]	[0.00817]	[0.0101]	[0.0147]	[0.00554]	[0.00523]
Quartertoelect = 8	0.00528	-0.000674	-0.00253	0.00239	0.00613	0.0152	0.00950	0.0134	0.00181	0.00409
	[0.00415]	[0.00625]	[0.00346]	[0.00615]	[0.0119]	[0.00896]*	[0.00979]	[0.0144]	[0.00465]	[0.00481]
Quartertoelect = 9	0.00891	0.00591	-0.00000849	0.00630	0.0150	0.0167	0.0125	0.0113	0.00730	0.00970
	[0.00490]*	[0.00642]	[0.00363]	[0.00630]	[0.0128]	[0.00840]**	[0.00936]	[0.0139]	[0.00540]	[0.00574]*
Quartertoelect = 10	0.00326	0.00416	0.00439	0.00931	0.00871	0.0125	0.0169	0.00350	0.00284	0.00313
	[0.00490]	[0.00632]	[0.00400]	[0.00633]	[0.0122]	[0.00811]	[0.00986]*	[0.0145]	[0.00567]	[0.00564]
Quartertoelect = 11	0.00364	0.00571	-0.00111	0.00935	0.00754	0.0115	0.00604	0.00836	0.00587	0.00332
	[0.00497]	[0.00610]	[0.00353]	[0.00588]	[0.0129]	[0.00820]	[0.0101]	[0.0147]	[0.00509]	[0.00529]
Quartertoelect = 12	-0.00117	0.00160	0.000268	0.00460	-0.000817	0.0140	0.00692	0.00992	-0.00753	-0.00750
	[0.00351]	[0.00631]	[0.00346]	[0.00585]	[0.0114]	[0.00881]	[0.00826]	[0.0145]	[0.00411]*	[0.00406]*
Quartertoelect = 13	0.00141	0.00417	-0.00498	0.00425	-0.000679	0.00650	0.00857	0.00764	-0.00392	-0.00222
	[0.00374]	[0.00599]	[0.00305]	[0.00543]	[0.00948]	[0.00752]	[0.00633]	[0.0111]	[0.00442]	[0.00466]
Quartertoelect = 14	-0.00234	0.00455	0.00616	0.00996	-0.00595	0.00914	-0.000736	-0.00389	-0.0112	-0.0124
	[0.00391]	[0.00513]	[0.00320]*	[0.00515]*	[0.0105]	[0.00625]	[0.00732]	[0.00904]	[0.00462]**	[0.00511]**
Quartertoelect = 15	-0.00386	-0.00271	0.00139	0.00289	-0.00577	0.00681	0.00153	-0.00901	-0.00748	-0.0101
	[0.00377]	[0.00333]	[0.00347]	[0.00422]	[0.00558]	[0.00487]	[0.00548]	[0.00608]	[0.00446]*	[0.00452]**
Controls	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Observations	263388	164545	150293	151246	58773	155695	27231	134116	164545	164545
R-squared	0.013	0.019	0.019	0.019	0.026	0.019	0.018	0.019	0.019	0.019

- Mental decision to dissent may be shortly before publication of an opinion
- Electoral cycle also in concurrences (disagree about REASONING, after first draft)

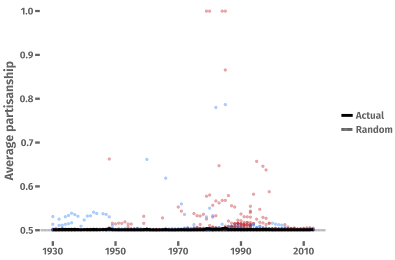
Motivated Reasoning in the Field *Ash, Chen, Lu*

"An Exit Interview With Richard Posner", New York Times (9/11/2017)

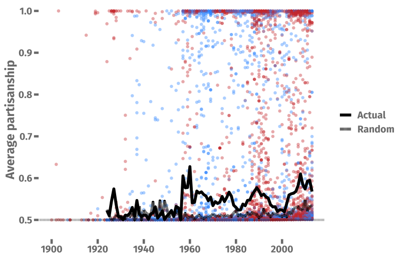
1. "'I pay very little attention to legal rules, statutes, constitutional provisions ... The first thing you do is ask yourself — forget about the law — what is a sensible resolution of this dispute?'"
2. "See if a recent Supreme Court precedent or some other legal obstacle stood in the way of ruling in favor of that sensible resolution."
3. "'When you have a Supreme Court case or something similar, they're often extremely easy to get around.'"

Can we predict political party of appointment from prose, precedent, votes?

Prose and Precedent Polarization, 1930-2013



Phrases

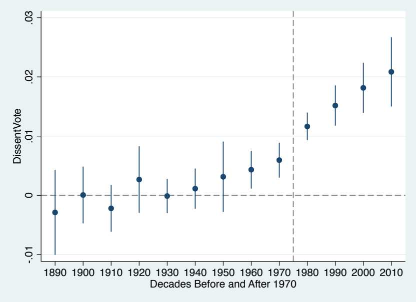


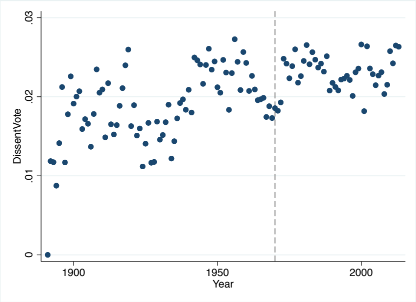
Citations

Judicial prose (0.5) << Congress prose (0.515) << Precedent (0.6) polarization

See also *Gentzkow, Shapiro, Taddy, ECMA 2019*

Growing Vote Polarization Since 1970s

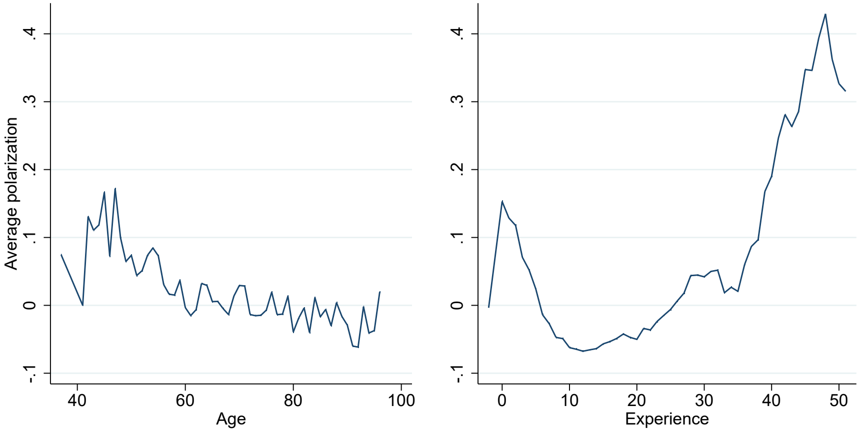




Minority dissent (DRR or RDD) growing more sharply than any dissent

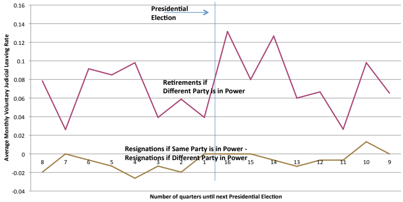
Precedent polarization also increases during elections (consistent with an identity mechanism)

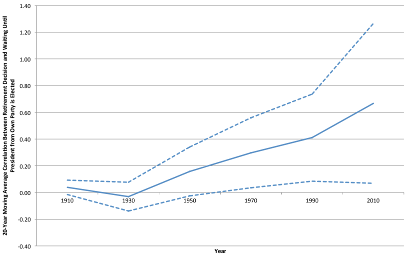
Motivated Reasoning Grows with Experience (Type II instead of Type I)



Declines with age; U-shape with Experience

Sclerotization of the Judiciary





Strategic Retirements around Presidential Elections

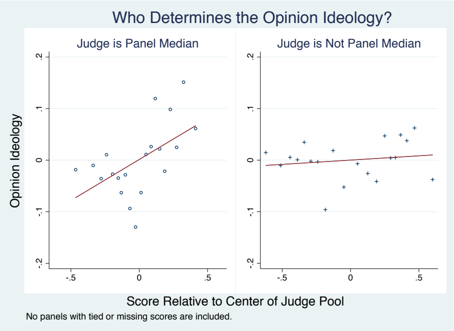
are also Growing

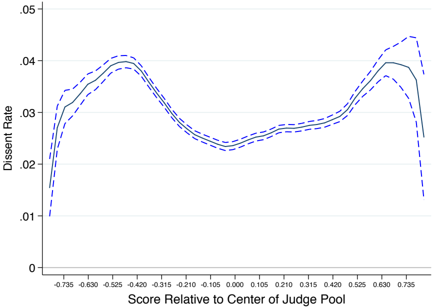
Politically Motivated Judicial Exits

- Less than 1% of U.S. Federal judges report political motivations for exits
- But 13% of retirements, 36% of resignations are political since 1800

Source of motivated reasoning is likely ideology that confronts social pressure to appear unbiased

Non-Confrontational Extremists *Chen, Michaeli, Spiro, in review*



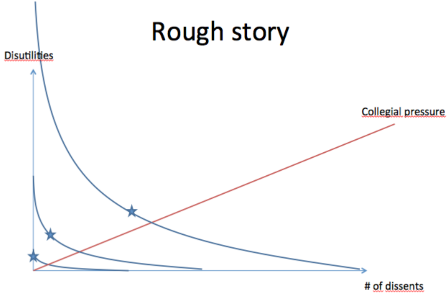


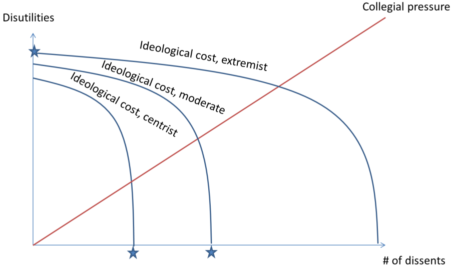
- Median judge determines opinion ideology
- But extremists "cave-in" on dissents

Deontological Motivations

- Economics tends to gravitate towards the assumption that costs – be they economic, effort or cognitive – are convex
  - Analytically tractable
  - Intuitively plausible
- Intuition fragile following a number of recent experiments
  - when it comes to moral and ethical issues, individuals perceive a concave cost of deviating from what they believe is right
  - i.e., individuals are perfectionist as they do not distinguish much between small and large deviations from their bliss points
  - has also been argued to be realistic in ideological settings (Osbourne 1995)
- Individuals with concave costs will tend to cave-in on principles if they cannot follow them fully
  - highest % of lies is from reporting maximal outcome (Gneezy et al. AER 2018)
  - "What-the-hell" effect (Ariely 2012; Baumeister et al. 1996)

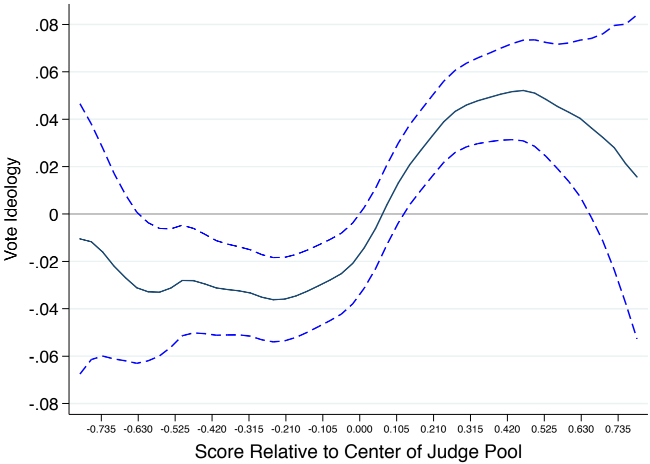
Judicial Perfectionism





- Convex costs render a bowl shape in dissents
- Concave costs render cave-in on dissents and votes

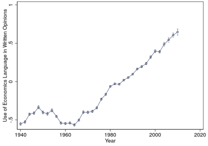
Extremists Cave-In in Vote Ideology



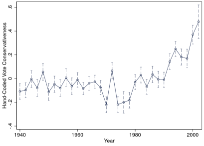
Vote Ideology and Ideology Score of Judge Relative to Center of Judge Pool

Impact of Law and Economics on American Justice *Ash, Chen, Naidu*

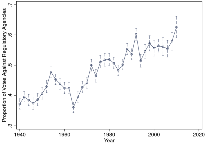
Increasing conservatism in the federal judiciary



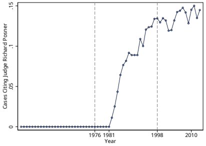
Language similarity to law-and-economics articles



Conservative Votes



Voting against government regulation



Citation to Richard Posner

Impact of Law and Economics on American Justice

The New York Times

19 U.S. Judges Study Economics To Help Them in Work on Bench

Special to The New York Times

KEY LARGO, Fla., Dec. 18—For three weeks, 19 Federal judges from around the country took a grueling, six-day-a-week course in economics that ended here yesterday.

With classes starting at 9 A.M. and sometimes ending at 10 P.M. or later, the judges received the equivalent of a full semester at the college level.

Their teachers were, among others, two Nobel laureates in economics, Paul Samuelson and Milton Friedman. The courses, sponsored by the Law and Economics Center of the University of Miami School of Law, made up what is believed to have been the first such institute for Federal judges.

"It was a very enriching experience," said Chief Judge John W. Reynolds of the Federal District Court in the Eastern District of Wisconsin. "We were here not to become economists, but to understand the language of economics. Courts are only as good as judges and the lawyers who appear before us. By and large, our training in economics is not really satisfactory, and yet we are being increasingly called upon to decide economic issues."

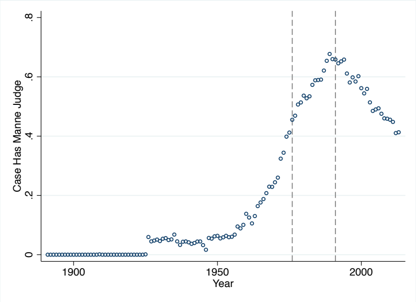
The program dealt basically with economic theory, and an effort was made not to relate the theoretical studies [to] cases now pending in Federal cour[ts].

"One has to be very cautious in deal[ing] with Federal judges," said Henry Man[ne], director of the center. "Our goal has be[en] to give them the most recent think[ing] in economic theory and enable them [to] better understand the testimony of exp[ert] witnesses and lawyers."

Chief Judge David N. Edelstein of [the] Federal District Court in the South[ern] District of New York, who is the jud[ge] in the International Business Machin[es] Corporation antitrust case—regarded [by] many lawyers as the most important an[ti]trust litigation of the century—inform[ed] attorneys in the case of his intention [to] attend the institute to clear any fut[ure] questions about a possible conflict of [in]terest.

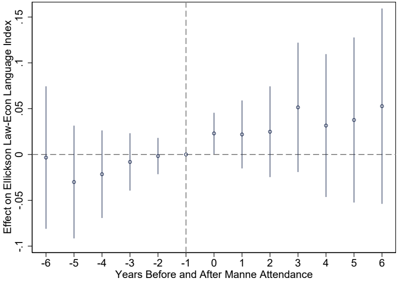
"All the lawyers were very cordial a[nd] replied that they saw no grounds for a [a] conflict of interest in my coming her[e]," Judge Edelstein said.

From the beginning, the judges, so[me] of them 60 years old or over, beha[ved] like students, deferring to their teach[ers] and reminiscing about undergradu[ate] days decades ago.

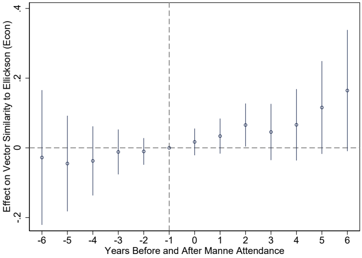


By 1990, 40% of federal judges had attended an economics training program.

Impact of Economics Training on Economics Language



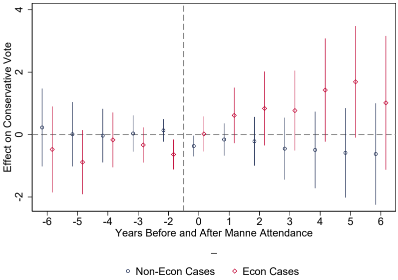
Ellickson Index



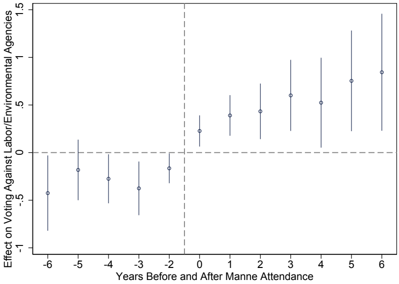
Ellickson Vector

externalit*, transaction_costs, efficien*, deterr*, cost_benefit, capital, game_theo, chicago_school, marketplace, law1economic, law2economic

Impact of Economics Training on Conservative Votes

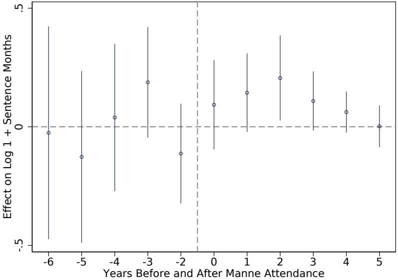


Econ vs Non-Economics Cases

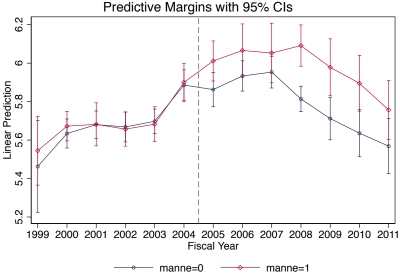


on Labor/Environmental Cases

Impact of Economics Training in District Courts

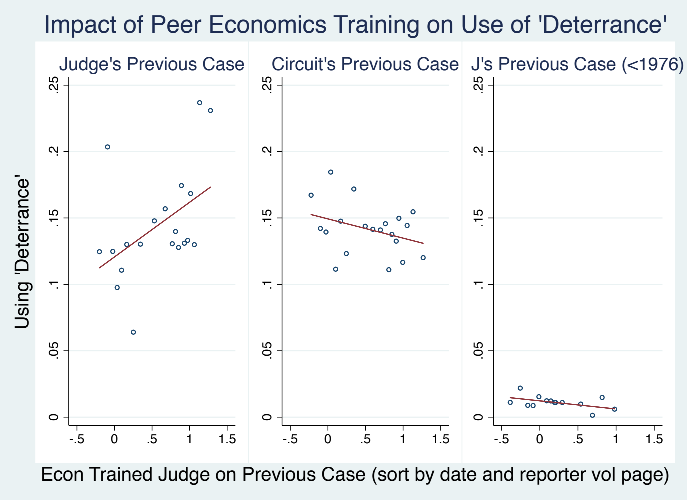


on Sentencing



with Discretion

Identifying Memetic Economic Phrases



Peer Impacts on Never-Attenders

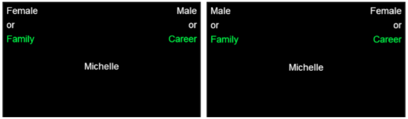
	Ellickson Average	
	(1)	(2)
Econ Case	0.0300***	0.0294***
	(0.00524)	(0.00249)
Post-Manne	**0.0141****	
	(0.00630)	
Econ Case *	0.00170	
Post-Manne	(0.00919)	
Econ Training on	-0.00559	**0.00513***
Previous Case	(0.0106)	**(0.00292)**
N	143144	486673
adj. R-sq	0.042	0.042
Circuit-Year FE	X	X
Judge FE	X	X
Sample	**Ever-Manne**	**Never-Manne**

Highlights persuasion of sparse thinking ***(Gabaix QJE 2014)***

Implicit Attitudes in the Judiciary *Ornaghi, Ash, Chen*

- Implicit associations: "attitudes that affect our understanding, actions, and decisions in an unconscious manner" Kirnan institute OSU

- Generally measured using Implicit Association Tests (IATs)
- Subjects asked to assign words to categories



- Compares reaction times across trials when pairing is consistent with stereotypes and when it is not
  - subjects are faster and make fewer errors on stereotype-consistent trials than stereotype-inconsistent trials; difference yields "IAT score"

Challenges of Studying Implicit Attitudes

- Challenge: how can we measure implicit attitudes for the judiciary?
  - We cannot elicit IAT scores from sitting judges
- Proposed solution: proxy for IAT using large amounts of written text
- e.g., 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.
- Are words representing different groups associated to certain attributes?

See also *Caliskan, et al., Science 2017* - distance between IAT vectors correlate with behavioral delays

Words closest to female and male dimension

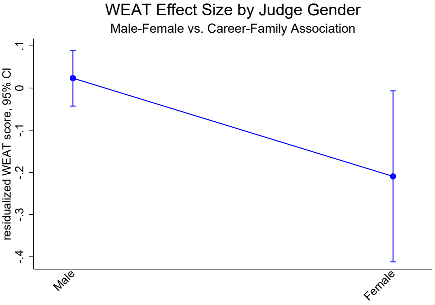
- Migraine, ex-husband, infertility, dancer, hysterical, pregnant, battered, stewardess
- Reserve, industrial, honorable, board, commanding, armed, conscientious, duty

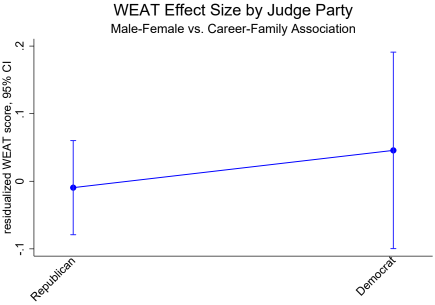
Word-Embedding Association Test: $WEAT = \sum_{x \in X} s(x, A, B) - \sum_{y \in Y} s(y, A, B)$ (Caliskan et al. 2017)

- X, Y are male vs. female words
  - man, men, he, him, his, boy, boys vs. woman, women, she, her, hers, girl, girls
- A, B are attribute words (career vs. family, positive vs. negative)
  - career, careers, work, working, business, office vs. family, families, home, caring, family, house
- Words from LIWC
  - e.g., top 10 most frequent words in judicial corpus for each concept

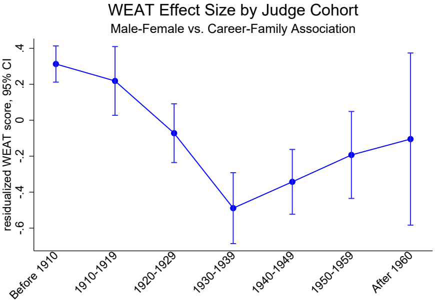
word sets actually used

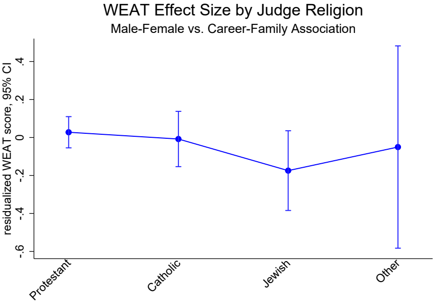
Female judges display lower lexical slant, but no difference across parties





Older judges display more lexical slant; judges of different religions do not differ





WEAT is more than demographic characteristics (adj R-sq of 0.287)

Lexical slant predicts voting against women's interests..

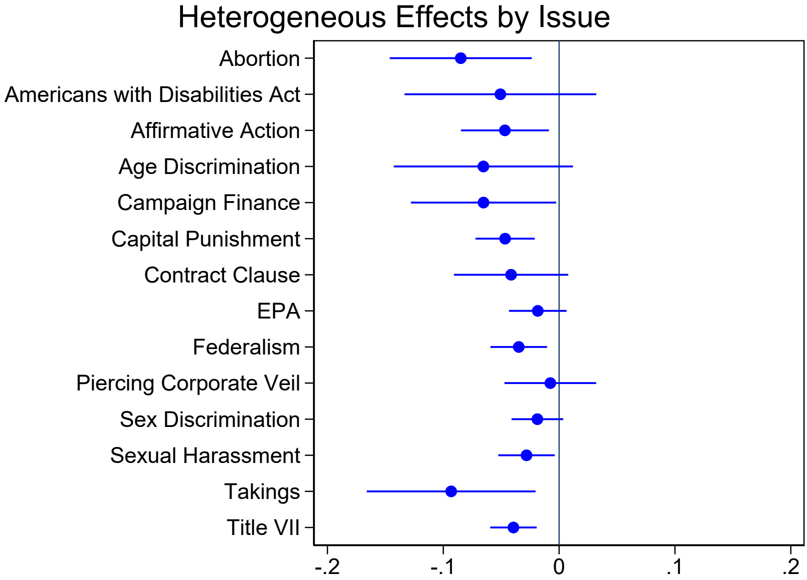
and this is confirmed across different datasets.

Dependent variable	Voted in favor of plantiff representing women's interest					
Dataset	Glynn and Sen (2015)			Epstein et al. (2013) Data		
	(1)	(2)	(3)	(4)	(5)	(6)
Male/Female vs. Career/Family	-0.025**	-0.039***	-0.033**	-0.023**	-0.035***	-0.025**
	(0.012)	(0.013)	(0.014)	(0.011)	(0.013)	(0.012)
Democrat		0.151***			0.136***	
		(0.038)			(0.031)	
Female		0.061*			0.014	
		(0.034)			(0.026)	
Observations	2891	2891	2891	3804	3804	3804
Clusters	255	255	255	293	293	293
Outcome Mean	0.396	0.396	0.396	0.435	0.435	0.435
Adjusted R2	0.100	0.122		0.116	0.127	
Circuit-Year FE	X	X	X	X	X	X
Topic FE	X	X	X	X	X	X
Biographic Controls		X	X		X	X
Lasso			X			X

2 std dev of WEAT $\sim$ 5-8% out of 40%

$\frac{1}{2}$ Democrat effect; $\geq$ female effect

Judges with more lexical slant also vote less liberally across a number of issues



Panels with more slanted senior judges are less likely to assign opinions to women, but only when they decide

Dependent variable	Author is Female					
Sample	All Circuits but 9th			9th Circuit		
	(1)	(2)	(3)	(4)	(5)	(6)
Male/Female vs. Career/Family	-0.0063***	-0.0034***	-0.0017*	-0.0029	0.0004	-0.0023
	(0.0022)	(0.0012)	(0.0009)	(0.0060)	(0.0032)	(0.0024)
Democrat		0.0013			0.0067	
		(0.0025)			(0.0095)	
Female		0.1690***	0.1674***		0.1425***	0.1472***
		(0.0113)	(0.0126)		(0.0123)	(0.0141)
Observations	324609	324609	324609	52642	52642	52642
Clusters	520	520	520	97	97	97
Outcome Mean	0.035	0.035	0.035	0.055	0.055	0.055
Adjusted R2	0.195	0.222		0.193	0.221	
Circuit-Year FE	X	X	X	X	X	X
Number of Female Judges FE	X	X	X	X	X	X
Biographic Controls		X	X		X	X
Lasso			X			X

2 std dev of WEAT $\sim$ 0.7-1.3% out of 3.5%; $>$ Democrat effect, but $<$ female effect

Judges with more lexical slant cite female judges less

Dependent variable	Share of citations from female judges		
	(1)	(2)	(3)
Male/Female vs. Career/Family	-0.0028***	-0.0013**	-0.0014**
	(0.0010)	(0.0005)	(0.0006)
Democrat		0.0011	
		(0.0013)	
Female		0.0402***	0.0404***
		(0.0037)	(0.0041)
Observations	242231	242231	242231
Clusters	667	667	667
Outcome Mean	0.064	0.064	0.064
Adjusted R2	0.265	0.265	
Circuit-Year FE	X	X	X
Judge FE	X	X	X
Biographic Controls		X	X
Lasso			X

2 std dev of WEAT $\sim$ 0.2-0.5% out of 6.4%; $>$ Democrat effect, but $<$ female effect

Judges with more lexical slant reverse female district judges more

Dependent variable	Votes to Reverse District Decision		
	(1)	(2)	(3)
Female District Judge	-0.005	0.524***	0.454**
	(0.004)	(0.187)	(0.185)
Male/Female vs. Career/Family * Female District Judge	0.004*	0.008**	0.007**
	(0.003)	(0.004)	(0.004)
Democrat * Female District Judge		0.008	0.0003
		(0.011)	(0.0007)
Female * Female District Judge		-0.005	-0.008
		(0.008)	(0.007)
Observations	253861	253861	253861
Clusters	785	785	785
Outcome Mean, Male District Judge	0.200	0.200	0.200
Outcome Mean, Female District Judge	0.164	0.164	0.164
Adjusted R2	0.037	0.037	
Circuit-Year FE	X	X	X
District-Year FE	X	X	X
Judges FE	X	X	X
Interacted Biographic Controls		X	X
Lasso			X

2 std dev of WEAT $\sim$ 0.1-0.2% out of 3.6%; $>$ Democrat and female effect

Implicit or Explicit?

Dependent variable	WEAT (family/career)
% Electoral Dissent	0.00262**
	(0.00109)
% Dissent	-0.00210*
	(0.00111)
% Posner Similarity	-0.000522
	(0.000690)
% Economics Vector	-0.00116
	(0.00136)
% Minority Dissent	-0.000225
	(0.000950)
% Generate Dissent	0.00118
	(0.000863)
N	580
adj. R-sq	0.334
Judge Bio, Circuit FE	X

More lexically slanted judges appear more "primeable"

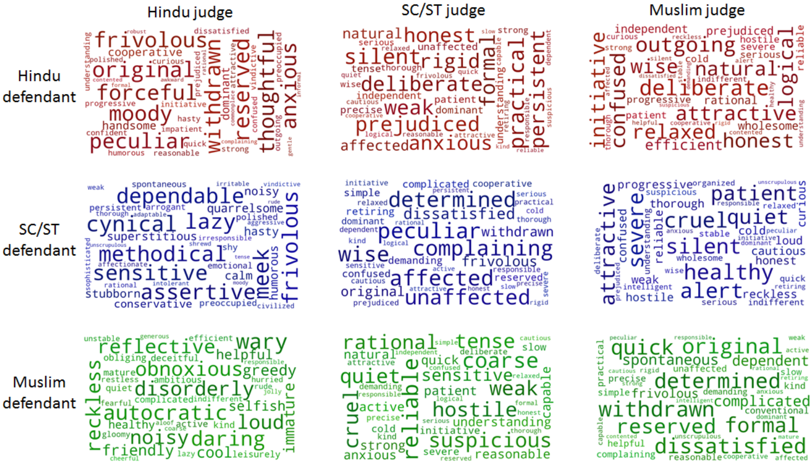
Daughters Reduce Some Lexical Slant Against Women

Dependent variable	WEAT (family/career)		
	(1)	(2)	(3)
Has Daughters	-0.177***	-0.247***	-0.141**
	(0.065)	(0.084)	(0.068)
Democrat	-0.046	-0.123***	
	(0.055)	(0.070)	
Female	0.000	0.020	
	(0.071)	(0.089)	
N	223	223	223
Circuit FE	X	X	X
Some Biographical Controls	X		
All Biographical Controls		X	
LASSO			X
# of Children FE	X	X	X

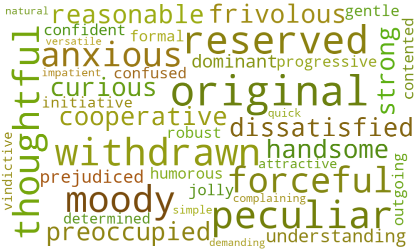
Conditional on number of children, having a daughter as good as random.

career, careers, work, working, business, office vs. family, families, home, caring, family, house

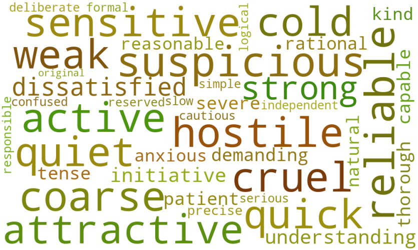
Hindu, Muslim, and caste in India *Ash, Asher, Chen, Novosad, Ornaghi, Siddaqi*



Sentiment analysis



Hindu judges describe Hindu litigants more positively



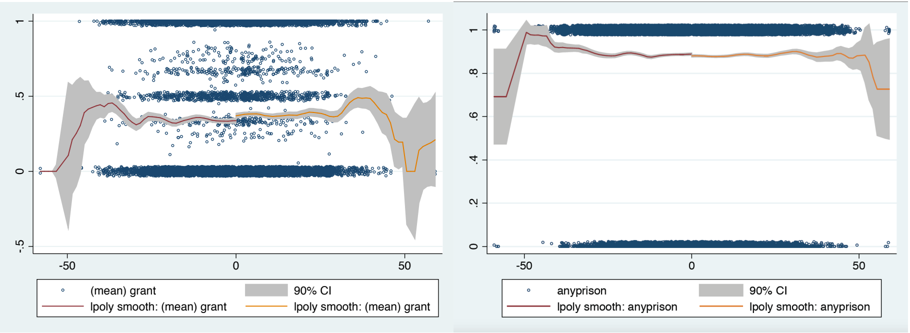
SC/ST judges describe Muslims more negatively

Besides sentiment, there is mood

Emotions and Moral Reasoning

"Judge Reid is best avoided on a Monday following a weekend in which the USC football team loses."

Morris Wolf, California Courts and Judges (1996)



Harsher after NFL football losses (and on bad weather days)

Chen and Loecher, *Science Advances* response requested

Effect of NFL on Sentencing

Dependent variable	Any Prison	Probation Length
	(1)	(2)
Upset Loss (Loss X Predicted Win)	0.016***	-0.109***
	(0.005)	(0.039)
Close Loss (Loss X Predicted Close)	-0.002	0.008
	(0.004)	(0.028)
Upset Win (Win X Predicted Loss)	-0.004	0.050
	(0.008)	(0.047)
Predicted Win	-0.012***	0.071**
	(0.005)	(0.033)
Predicted Close	-0.007	0.059
	(0.005)	(0.037)

JudgeXCity FE, City-Specific Trends, Week FE, Case Controls

Unrepresented Parties in Asylum Bear Brunt of Mood Effects

Dependent variable	Granted Asylum		
Sample	All	With Lawyer	Without Lawyer
	(1)	(2)	(3)
Upset Loss (Loss X Predicted Win)	-0.066***	-0.007	-0.067**
	(0.022)	(0.011)	(0.030)
Upset Loss (Loss X Predicted Win)	0.061**		
X Lawyer	(0.023)		
Close Loss (Loss X Predicted Close)	-0.046**	0.008	-0.045**
	(0.022)	(0.011)	(0.021)
Close Loss (Loss X Predicted Close)	0.054**		
X Lawyer	(0.024)		
Upset Win (Win X Predicted Loss)	-0.023	-0.001	-0.036
	(0.035)	(0.015)	(0.032)
Upset Win (Win X Predicted Loss)	0.020		
X Lawyer	(0.036)		

JudgeXCity FE, City-Specific Trends, Week FE, Case Controls

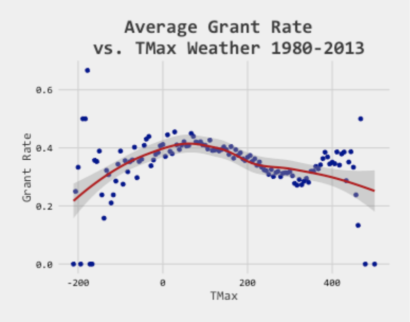
Judges Affected if Born in the Same State of NFL team

Dependent variable	Any Prison	Probation Length	Any Prison	Probation Length
	(1)	(2)	(3)	(4)
Upset Loss	0.020**	-0.145***	0.011	-0.042
	(0.008)	(0.051)	(0.008)	(0.060)
Close Loss	0.000	-0.004	-0.007	0.028
	(0.005)	(0.034)	(0.006)	(0.038)
Upset Win	-0.004	0.038	-0.003	0.074
	(0.010)	(0.063)	(0.011)	(0.065)
Predicted Win	-0.013	0.069	-0.010	0.058
	(0.008)	(0.053)	(0.008)	(0.059)
Predicted Close	-0.009	0.062	-0.002	0.045
	(0.007)	(0.047)	(0.008)	(0.051)
Sample	Born In State		Born Out-of-State	

JudgeXCity FE, City-Specific Trends, Week FE, Case Controls

Impact of Weather on Judicial Decisions

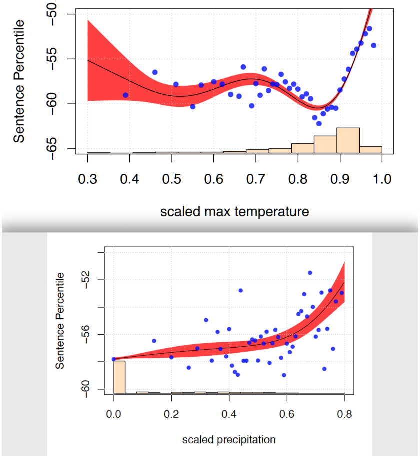
Can Machine Learning Help Predict Asylum Decisions?



Chen and Eagel, JCAIL, 2017

Weather RF weight similar as lawyer or nationality

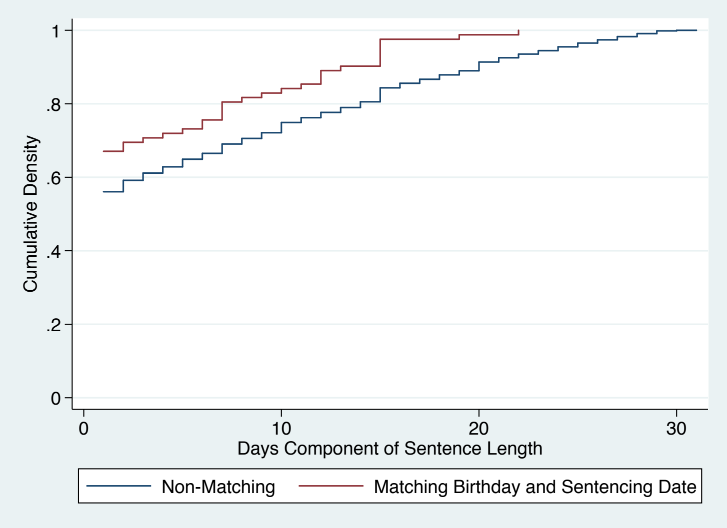
Impact of Weather on Judicial Decisions



See also *Hayes and Saberian AEJ 2018, Eren and Mocan AEJ 2017*

Besides mood, there are norms

Judicial Leniency on Defendant Birthdays *Chen and Philippe, in review*



US federal judges round down the # of sentencing days

Individuals being subject to everyday rituals (Interpellation-Althusser 1970)

Judicial Leniency on Defendant Birthdays

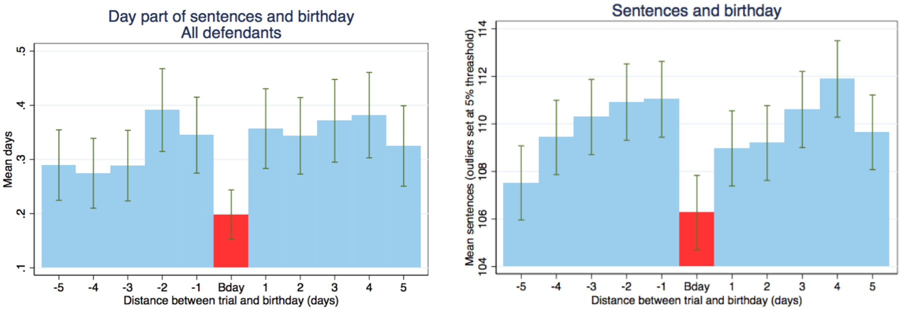
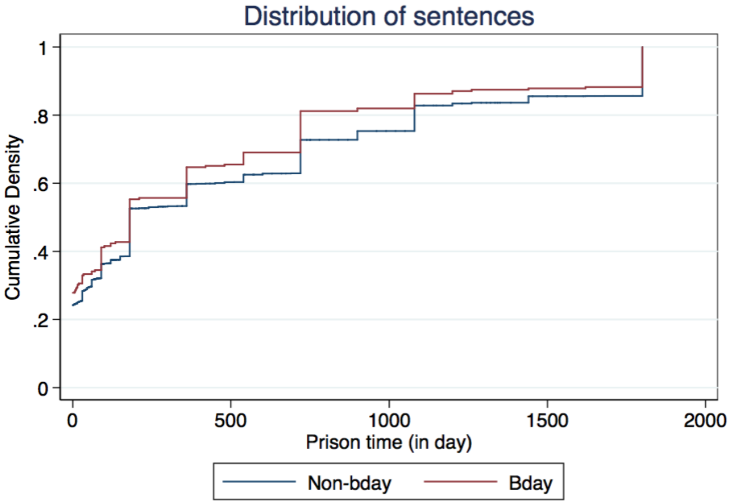


Figure: US and French judicial leniency on defendant birthdays

No effects on placebo days

- French judges reduce by 1% probability to get any prison time (4.6M decisions)

Larger Effects in Weaker Institutional Settings



New Orleans District Attorney's office - Sentences 15% shorter on defendant's birthday

Behavioral bias can be Type II (present with more deliberation time)

	Accelerated		Caseload	
	Yes	No	> Median	≤ Median
	Sentence > 0 (FR)		# days (US)	
Birthday	0.00020	-0.012**	-0.017	-0.12*
	(0.0091)	(0.0053)	(0.13)	(0.064)
Placebo time controls	Y	Y	Y	Y
N	397,988	4,210,221	119,230	154,600

Deterrence Thinking Erodes Sympathy/Empathy

USA		Day Component	
Birthday	-0.018	-0.078	-0.17
	(0.057)	(0.076)	(0.053)
Birthday * Same race	-0.061		
	(0.038)		
Same race	-0.017		
	(0.011)		
Birthday *		-0.026	
Tenure>median		(0.062)	
Birthday *			0.15**
Deterrence>median			(0.065)
Dfdn & J Race FE	Yes	Yes	Yes
Sample	Blk or Wht defendants	Tenure Known	Civil Writings Known
N	103,177	170,772	167,404

Economical thinking trades off with emotions and ..

Impact of Economics Judges on Racial Gaps *Ash, Chen, Naidu*

	Life	Months	Life	Months
	(1)	(2)	(3)	(4)
Minority	*0.00395****	*20.84****	*0.00388****	*20.34****
	(0.000770)	*(1.979)*	*(0.00102)*	*(2.170)*
*** Economics**	**0.00401****	**5.413*****	**0.00379****	**3.180***
	(0.00157)	**(2.044)**	**(0.00170)**	**(1.910)**
*** Republican**			0.000641	**4.096****
			(0.00103)	**(1.723)**
*** Minority J**			-0.00119	**-7.451****
			(0.00135)	**(3.167)**
N	156650	155977	154920	154253
adj. R-sq	0.015	0.102	0.015	0.102
Judge FE	Y	Y	Y	Y
Sample	All	All	All	All

Economics Trained Judges harsher to minorities (1992-2003 30% merge to USSC)

Ingroup bias coefficient reduces gradient by one-third

Impact of Economics Judges on Gender Gaps

	Life	Months	Life	Months
	(1)	(2)	(3)	(4)
Female	*-0.00397****	*-31.01****	*-0.00395****	*-29.84****
	(0.000562)	*(1.676)*	*(0.000718)*	*(2.127)*
*** Economics**	**-0.00247****	**-5.083*****	**-0.00227***	**-4.120****
	(0.00113)	**(1.717)**	**(0.00116)**	**(1.617)**
*** Republican**			-0.000372	**-2.549***
			(0.000678)	**(1.456)**
*** Female J**			0.000697	0.145
			(0.000750)	(1.218)
N	160402	159713	158634	157951
adj. R-sq	0.014	0.109	0.015	0.109
Judge FE	Y	Y	Y	Y
Sample	All	All	All	All

Economics Trained Judges more lenient to females (1992-2003 30% merge to USSC)

- Use of stereotypes under information constraints *(Bordalo et al. QJE 2016)*

Coarse Communication

- Communication constraint works as a magnifier of correlation (Kweik 2013)

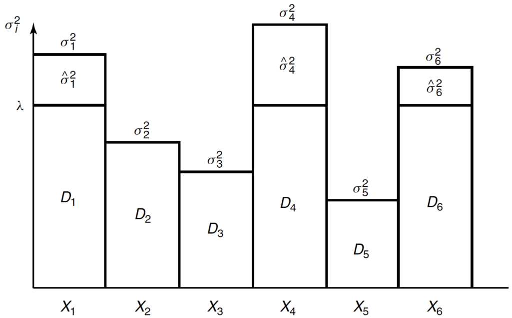


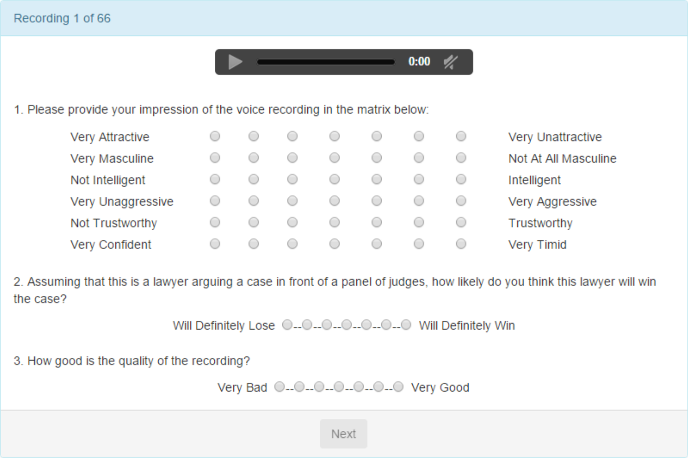
FIGURE 10.7. Reverse water-filling for independent Gaussian random variables.

Elements of Information Theory (Cover and Thomas 1991)

- No bits used to describe information with variance less than a constant
- Results in exaggerating pre-existing correlations

REPRESENTATIVE HEURISTICS WILL "OVERWEIGHT"

Perceived Masculinity Predicts US Supreme Court Outcomes


Recording 1 of 66

0:00

1. Please provide your impression of the voice recording in the matrix below:

Very Attractive	○	○	○	○	○	○	○	Very Unattractive
Very Masculine	○	○	○	○	○	○	○	Not At All Masculine
Not Intelligent	○	○	○	○	○	○	○	Intelligent
Very Unaggressive	○	○	○	○	○	○	○	Very Aggressive
Not Trustworthy	○	○	○	○	○	○	○	Trustworthy
Very Confident	○	○	○	○	○	○	○	Very Timid

2. Assuming that this is a lawyer arguing a case in front of a panel of judges, how likely do you think this lawyer will win the case?

Will Definitely Lose ○--○--○--○--○--○--○ Will Definitely Win

3. How good is the quality of the recording?

Very Bad ○--○--○--○--○--○--○ Very Good

Next

Identical first sentence: "Mr. Chief Justice, (and) may it please the Court?"

1,901 U.S. Supreme Court oral arguments between 1999 and 2013

Chen, Halberstam, Yu, Plos-ONE 2016

Perceived Masculinity Predicts US Supreme Court Outcomes

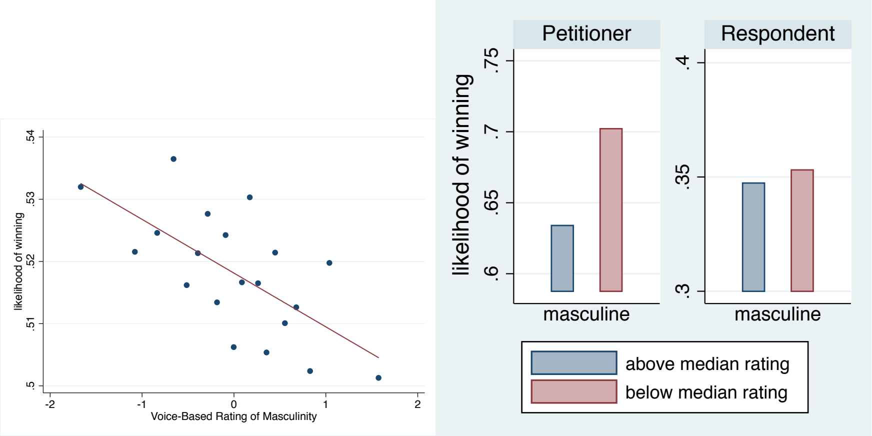
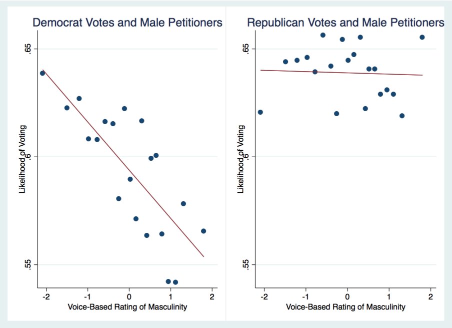


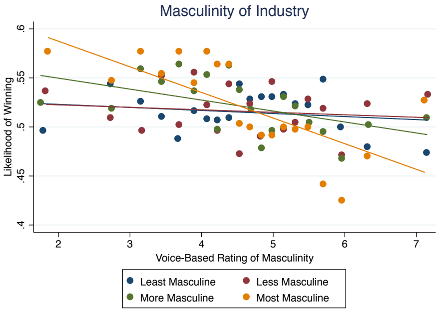
Figure: Males are more likely to win when they are perceived as less masculine

- Petitioner (first speaker) is main driver
- Below median masculinity rating $\sim$ 7 percentage points more likely to win
- Robust to lawyer controls

Sample clips at 10%-ile and 90%-ile in masculinity ratings

Covering *Chen, Halberstam, Yu, ReStud* invited to resubmit





- Votes of Democrats negatively correlated with perceived masculinity
- Stronger negative correlation in more masculine industries (as coded by SCDB)
- Consistent with taste differences or misbeliefs in those industries

De-Biasing Experiment Reduces Misbeliefs

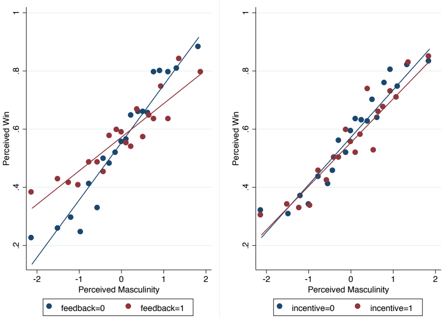


Figure: Feedback ($p < 0.01$), Incentives

Incentives Reveals Taste-Based Discrimination

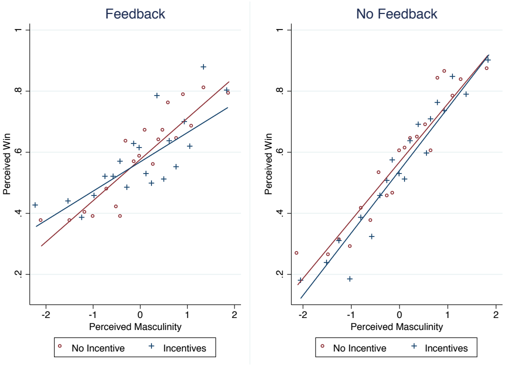


Figure: Incentives ($p < 0.05$) with Feedback

- Incentives to choose correctly erode the effect of taste on choices ($\pi_F - \pi_M > \frac{d}{\alpha}$)
- Any changes in behavior are due to preferences ($d > 0$)

See also *Rao, AER 2018* - testing "contact hypothesis"

Gender

- Female lawyers are also coached to be more masculine (Starecheski 2014)
  - Are our findings restricted to male advocates alone or do they extend?

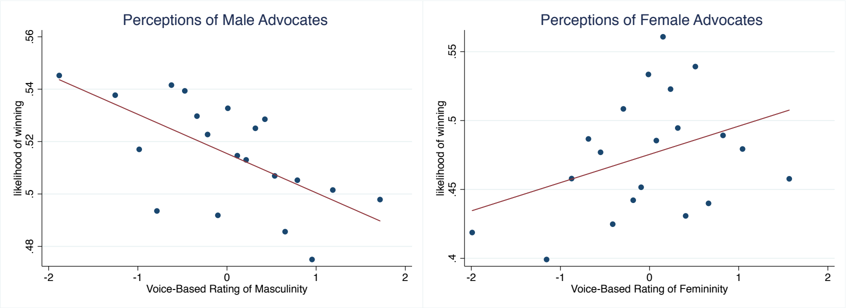


Figure: Voice-Based Perceptions and Court Outcomes by Advocate Gender

- Extends: Less masculine males and more feminine females ↑win
  - If masculine = - feminine, pooled results would be stronger

Reverse voice analysis

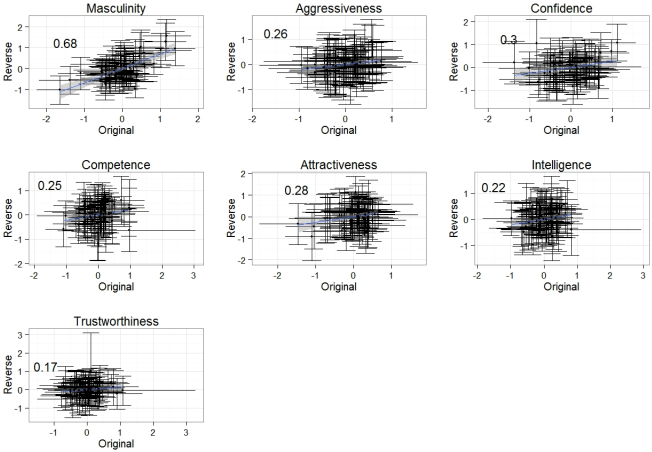


Figure: Correlation in Voice Perceptions across Reversal

Robust to Lawyer Heterogeneity (and lawyer FE)

	Dependent Variable: Case Outcome (win = 1, lose = 0)				
Masculine	-0.0149***	-0.0145***	-0.0151***	-0.0139***	-0.0864**
	(0.00565)	(0.00559)	(0.00558)	(0.00537)	(0.0340)
Confident	0.00508	0.00535	0.00595	0.00482	0.0851
	(0.00387)	(0.00386)	(0.00385)	(0.00382)	(0.0539)
Attractive	0.0000377	-0.000927	-0.000399	0.000460	-0.00237
	(0.00445)	(0.00445)	(0.00441)	(0.00431)	(0.0501)
Intelligent	0.00244	0.00264	0.00309	0.00166	-0.0167
	(0.00385)	(0.00384)	(0.00381)	(0.00375)	(0.0639)
Trust	0.00356	0.00336	0.00330	0.00305	0.0644
	(0.00344)	(0.00343)	(0.00345)	(0.00338)	(0.0618)
Aggressive	-0.00134	-0.00139	-0.00145	-0.00170	-0.0235
	(0.00345)	(0.00343)	(0.00343)	(0.00339)	(0.0472)
Likely winner	-0.000977	-0.00118	-0.000821	-0.00152	-0.0401
	(0.00411)	(0.00411)	(0.00412)	(0.00405)	(0.0755)
Masculinity of Name	N	Y	Y	N	N
SCOTUS Experience	N	N	Y	N	N
Additional Lawyer Covariates	N	N	N	Y	Y
Collapsed	N	N	N	N	Y
Observations	18542	18542	18542	18542	856
R-squared	0.002	0.006	0.008	0.018	0.026
Sample: Male Petitioners					

Figure: Case Outcomes and Perceived Masculinity

Linguistic Profiling: Possible reasons for judicial behavior

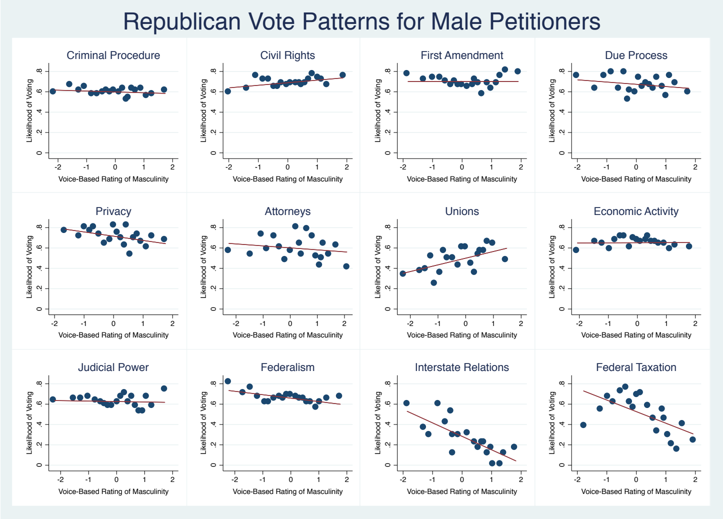


Figure: Republicans vote like Democrats in less-ideological cases

- Attorneys, Interstate Relations, Federal Taxation ($p < 0.1$)

Rater Heterogeneity

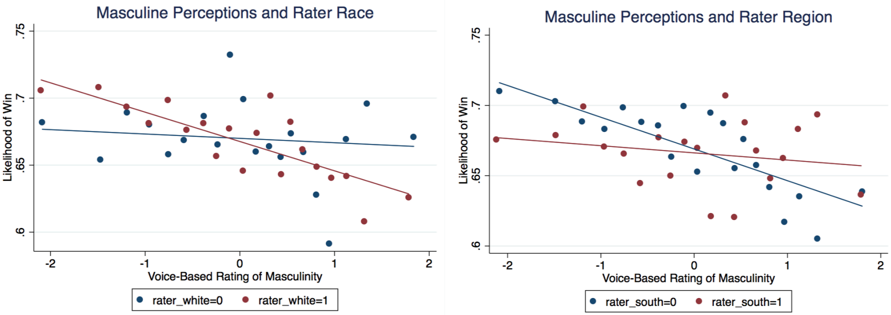


Figure: White ($p < 0.05$) and Non-Southerner ($p < 0.05$) raters' perceptions of masculinity predicted court outcomes

- If White non-Southerners $\sim$ law firm HR, consistent with firm heterogeneity

Predicting Behavior of the Supreme Court

	Judge Votes for Lawyer					
Predicted Vote	0.257***		0.258***	0.250***		0.248***
from Random Forest	(0.0486)		(0.0487)	(0.0485)		(0.0489)
Masculine		-0.0223**	-0.0207**		-0.0852**	-0.0780**
		(0.0101)	(0.0101)		(0.0359)	(0.0361)
Cluster	Lawyer and Judge					
Collapsed	No	No	No	Yes	Yes	Yes
Observations	26447	26391	26391	1229	1229	1229
R-squared	0.061	0.002	0.063	0.058	0.008	0.064
Sample: Male Petitioners, Democrat Judges						

Figure: Best Prediction and Perceived Masculinity

- Perceived masculinity basically orthogonal to random forest prediction
- Rater-level: Additional 3% of variance explained
- Lawyer-level: Additional 10% of variance explained
- Random forest also selects perceptions, improves accuracy by 2%
    - Katz, Bonmarito, Blackman (Plos-ONE 2017) don't predict close cases well

Acoustic Data (formant, dispersion, spectral tilt, duration, rate, rhythm, pitch)

	Dependent Variable: Case Outcome (win = 1, lose = 0)		
Masculine	-0.0875**	-0.0972**	-0.0858**
	(0.0369)	(0.0364)	(0.0348)
Confident		0.0258	0.0360
		(0.0247)	(0.0220)
Attractive		-0.0171	-0.0197
		(0.0181)	(0.0144)
Educated		0.0158*	0.0146
		(0.00878)	(0.00932)
Intelligent		0.00549	0.00635
		(0.00893)	(0.00783)
Trust		-0.00512	-0.00528
		(0.00979)	(0.00786)
Likely winner		-0.00355	-0.00132
		(0.00793)	(0.00729)
Acoustic Controls	No	No	Yes
Observations	10920	10080	10080

Figure: Case Outcomes and Perceived Masculinity

- Perceptions matter beyond acoustics
- Results extend with pre-1999 data
  - Pitch (Dietrich, Enos, Sen, Political Analysis 2018)
  - ML prediction of masculinity using 15 years of training data (Chen and Kumar 2016)

Mimicry *Chen and Yu*

- Text-audio alignment for vowel extraction
  - Eg. AA, AE, UH, etc.
  - Formants = frequency components: shape/position of tongue
  - The first two formants typically disambiguate vowels
- ABA triplets
  - The first segment with speaker A: A_1
  - The second segment with speaker B's response: B
  - The thrid segment with speaker A's response to speaker B: A_2
- Convergence definition:

$$\mathbf{E}[f_j - \bar{f}_j(A_1) | \bar{f}_j(A1), \bar{f}_j(B)]$$
$$= \mathbf{conv} \cdot [\bar{f}_j(B) - \bar{f}_j(A_1)] + \gamma \cdot \bar{f}_j(A_1)$$

Lawyers converge to judges more than judges do (role of heirarchy)

Table: ABA Basic Convergence Parameters

	F1 Estimate	(S.E.)	F2 Estimate	(S.E.)
I. Overall (Non Directional)				
Overall	0.175	(0.003)	0.156	(0.003)
II. Lawyer $\longrightarrow$ Judge				
Overall	0.213	(0.005)	0.187	(0.005)
Winning Lawyer	0.222	(0.006)	0.186	(0.006)
Losing Lawyer	0.205	(0.009)	0.188	(0.006)
III. Judge $\longrightarrow$ Lawyer				
Overall	0.190	(0.004)	0.151	(0.003)
Winning Lawyer	0.200	(0.006)	0.157	(0.004)
Losing Lawyer	0.181	(0.006)	0.146	(0.004)

Winning lawyers may converge to judges more than losing lawyers do (F1)

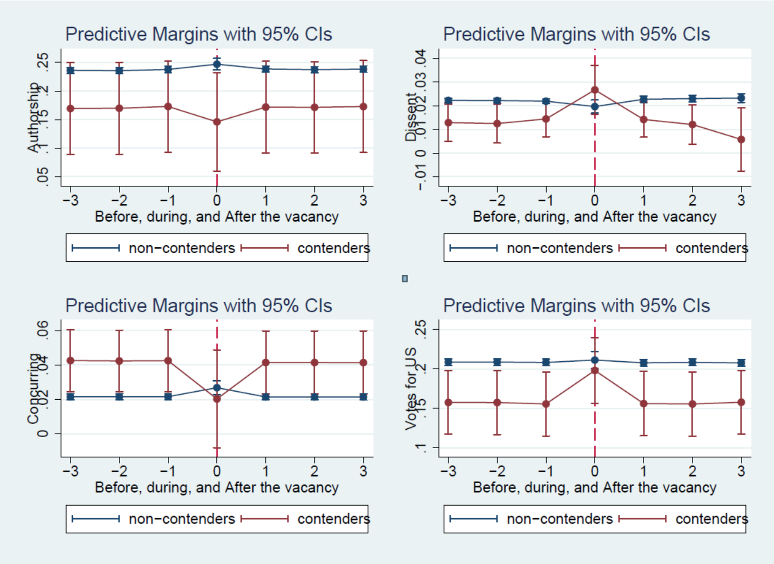
Judges converge more when concurring

Table: AxByA Basic Convergence Parameters

	F1 Estimate	(S.E.)	F2 Estimate	(S.E.)
	I. Overall			
Overall	0.363	(0.007)	0.339	(0.006)
	II. By Decision			
Concurring	0.374	(0.007)	0.359	(0.007)
Not Concurring	0.227	(0.032)	0.159	(0.020)

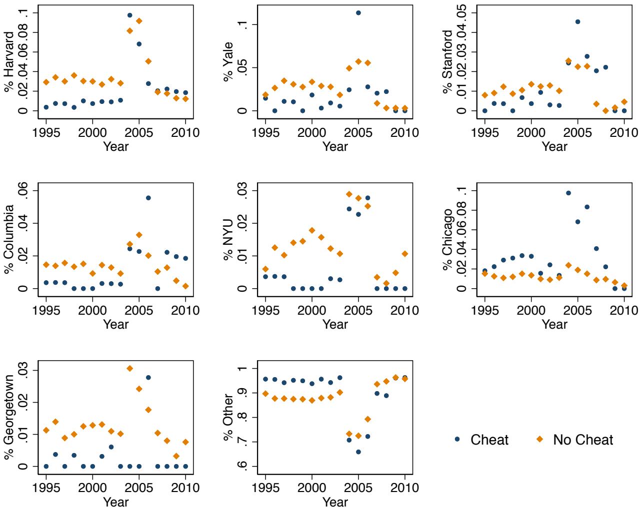
Mimicry is a very basic human tendency

Contenders converge during SCOTUS Vacancies *Ash, Chen, Lu*



in dissents, concurrences, voting for the US

.. and judges cheat when vying for judicial clerks *Chen, He, Yamashita*



Besides mimicry and career incentives, another human tendency is..

Decision Making Under Gambler's Fallacy *Chen, Moskowitz, Shue, QJE* 2016

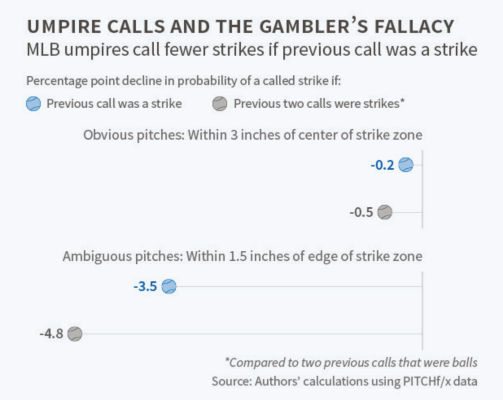
How people often imagine a sequence of coin flips:

0101001011001010100110100

A real sequence of coin flips:

0101011111011000001001101

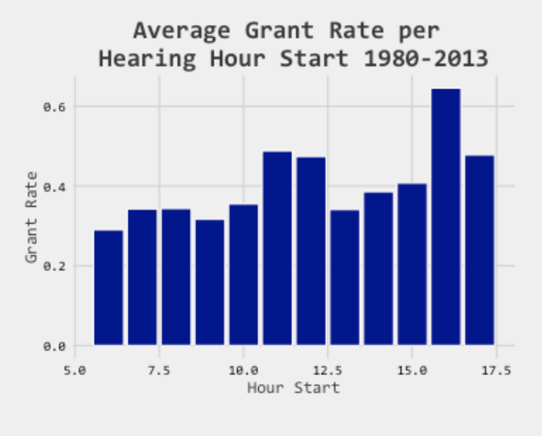
Evidence from Asylum, Loan Officers, and Baseball Umpires



Larger effects when current pitch is more ambiguous

- Asylum judges are up to 5 percentage points less likely to grant asylum if the previous case(s) were granted
- Indian loan officers do the same, under weak incentives for accuracy
- Experience reduces negative autocorrelation

Time of Day

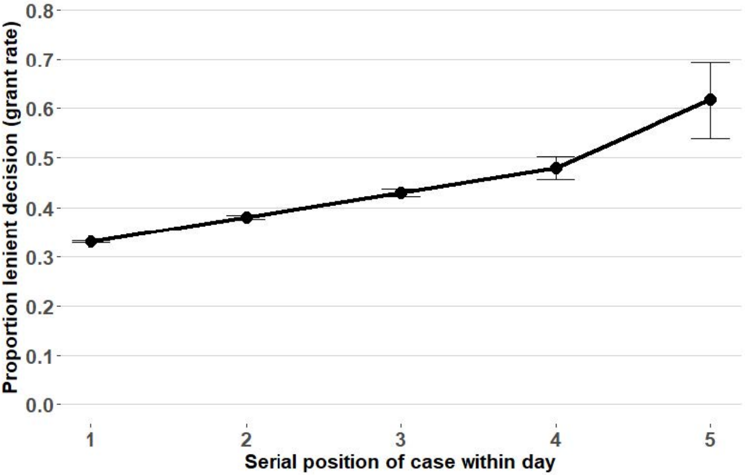


More lenient before lunch and towards the end of day (1M decisions)

Cases prescheduled and randomly assigned

See also *Danziger, Levav, Avnaim-Pesso, PNAS 2011* (1K decisions)

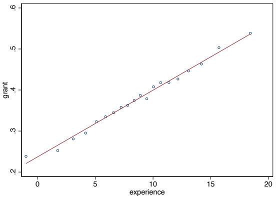
Sequence Effects *Plonsky, Chen, Netzer, Steiner, Feldman*



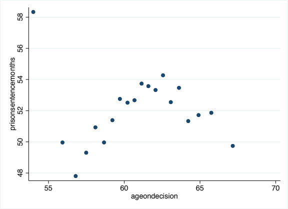
Best to be last

Confirmed also in vignette experiments

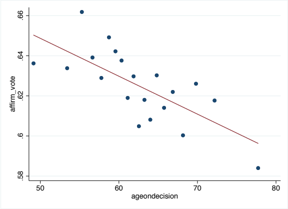
Leniency Grows with Age



in granting asylum



in sentence lengths



in criminal appeals

Early Predictability of Asylum Decisions *Chen, Dunn, Sagun, Sirin, JCAIL, 2017*

- Gambler's fallacy, mood, time of day, order, age ...
  - highlight fragility of asylum courts
    - "In a crowded immigration court, 7 minutes to decide a family's future" (Wash Post 2/2/14)
- High stakes: Denial of asylum usually results in deportation
  - "Applicant for asylum reasonably fears imprisonment, torture, or death if forced to return to her home country" (Stanford Law Review 2007)

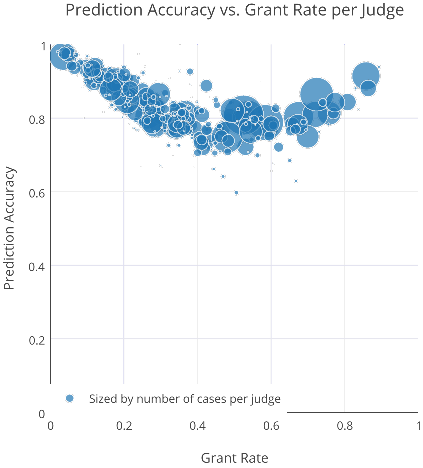
WHAT IS AN AGGREGATE MEASURE OF "REVEALED PREFERENCE INDIFFERENCE"?

- Using only data available up to the **decision date**, 82% accuracy
  - base rate of 64.5% asylum requests denied
  - predominantly trend features and judicial characteristics - unfair?
  - one third-driven by case, news events, and court information
- Using only data available up to the **case opening**, 78% accuracy

Revealed Preference Indifference

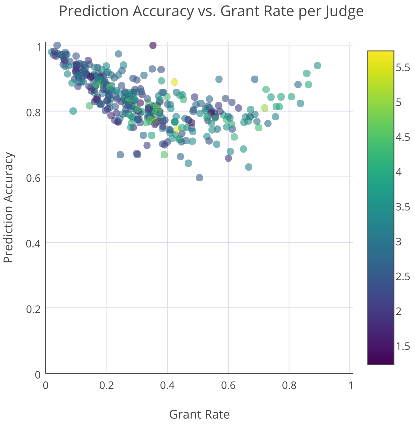
- If case outcomes could be **completely predicted**
  - **prior to judicial inquiry** into the case,
  - then judges **did not take into account** differences between cases
  - (did not recognize-respect defendant's individuality/dignity)
- There may be cases for which country and date of application *should* completely determine outcomes (e.g., during violent conflict)
  - But significant inter-judge disparities in predictability suggest that this understanding of the country circumstances does not apply to all
- Some judges are highly predictable, always granting or rejecting
  - **Snap judgments** and **predetermined** judgments (Ambady and Rosenthal 1993)
  - Stereotypes pronounced with time pressure & distraction (Bless et al 1996)

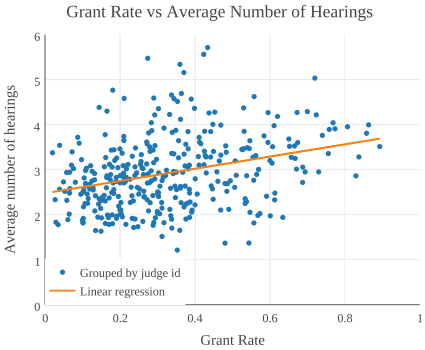
Early Predictability of Asylum Decisions



Judges with high and low grant rates are more predictable

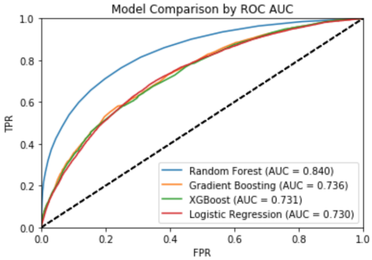
Early Predictability of Asylum Decisions





Less predictable judges are not simply flipping a coin: hearing sessions are greater for less predictable judges and for judges with higher grant rates

Machine Prediction of Appeal Success *Andrus, Ash, Chen, Godevais, Ng*



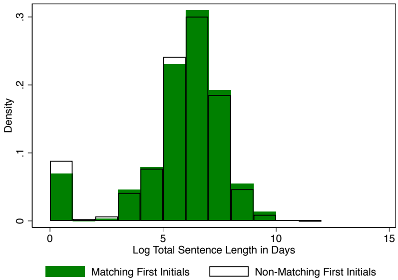
Feature Importance	
Time Horizon Features	0.377804
Judge Features	0.277066
Respondent	0.177945
Trend Features	0.074494
Proceeding Features	0.060490
Location Features	0.042636

A successfully appealed denial of asylum means the lower-court judge made a mistake.

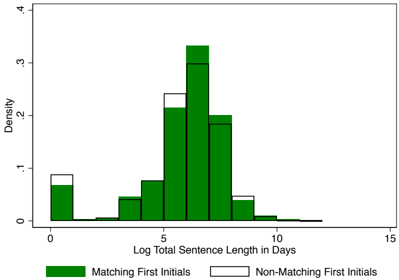
Among cases predicted to be successful in appeal, **26%** did not appeal.

Do some defendants bear brunt of revealed preference indifference?

Implicit Egoism in review



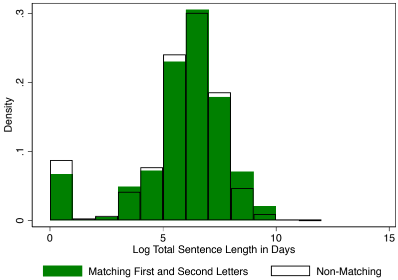
First Letter of First Name



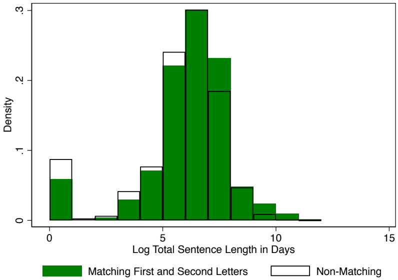
First Letter of Last Name

- Judges assign 8% longer sentences when their first initial matches the defendant's
  - Implicit Egoism: people's unconscious associations with first initials (Nuttin 1985)
  - conditional black-white sentence differences $\sim 10\%$ (Rehavi and Starr, JPE 2014)

Phoneme/Formant Effects

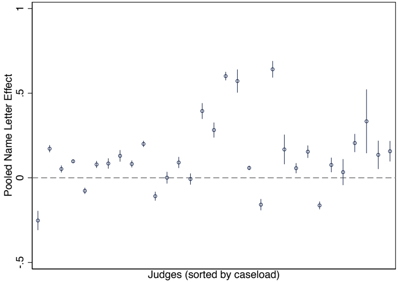


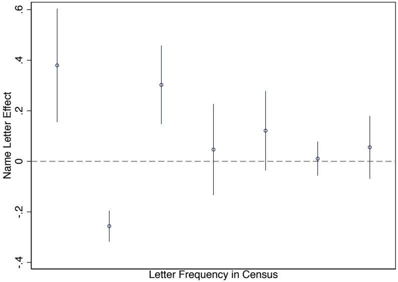
First and Second Letter of First Name



First and Second Letter of Last Name

Heterogeneity





All but 3 judges display significant name letter effects

Effects amplify with uncommon letters

Judge with the largest point estimate paid $14 per year in property taxes instead of $2,200.

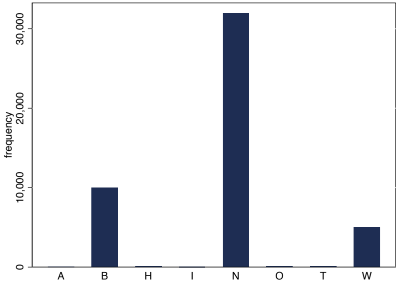
Full Name Match

	Log of Total Sentence in Days						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Full Name Match	0.191*	0.185	0.206**	0.194*	0.183*	0.180*	0.181*
	(0.112)	(0.112)	(0.0940)	(0.0970)	(0.0958)	(0.0940)	(0.0939)
N	47371	47363	47235	47190	47190	47190	47190
adj. R-sq	0.307	0.319	0.461	0.473	0.473	0.475	0.475
Judge FE	X	X	X	X	X	X	X
Month × Year FE		X	X	X	X	X	X
Case Type FE			X	X	X	X	X
Case Type × Month × Year FE				X	X	X	X
Letter FE					X	X	X
Week of Year FE						X	X
Day of Week FE							X

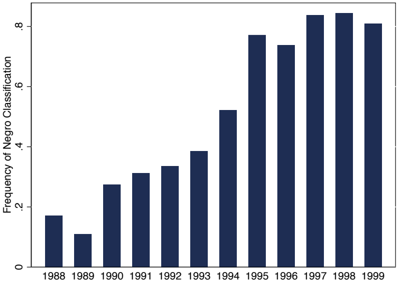
Effect of first initial matches hold even excluding defendants with a full name match

See also *Jena, Sunstein, Tanner, NYT 2018* (4M police stops)

Recognition and Dignity



Distribution of Race Classification by police



Distribution of N Classification Over Time

- Labels play an important role in defining groups—to gain respect
  - The term "Negro" is considered offensive because of association with long history of slavery, segregation, and discrimination that denigrated African Americans
  - Split-ballot experiment finds term "homosexual" (as opposed to "gay") increases negative attitudes about LGBT rights (Smith, et al. *American Politics Research 2018*)

Revealed Preference Indifference

	Log of Total Sentence in Days	
	(1)	(2)
First Letter Match × Negro	0.174**	0.168**
	(0.0687)	(0.0686)
N	41793	40011
adj. R-sq	0.475	0.442
First Letter Match × Judge FE	X	X
First Letter Match × Month × Year FE	X	X
First Letter Match × Case Type FE	X	X
First Letter Match × Skin, Hair, Eye Color FE		X

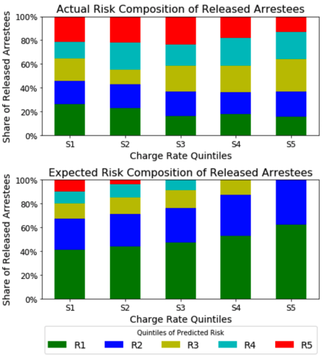
- Effects appear only for African Americans labeled "Negro" and is absent for "Black"
  - robust to controls for skin, hair, eye color
- "settings where people are closer to *indifference* among options are more likely to lead to detectable effects [of behavioral biases] outside of it." (Simonsohn, JPSP 2011)

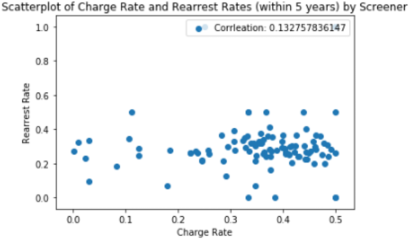
Now let's use machine learning and future outcomes to measure "revealed preference indifference"

Algorithms as Prosecutors *Amaranto, Ash, Chen, Ren, Roper, NIPS 2017*

Information acquisition can be endogenous to preferences ("Redlining"; Brewer 1998)

- How the screeners rank the risk of the arrestees is unobserved. But, **we can assess their implicit risk ranking by comparing the distribution of predicted risk of the arrestees charged by the (randomly assigned) "strict" and the "lenient" screeners.**



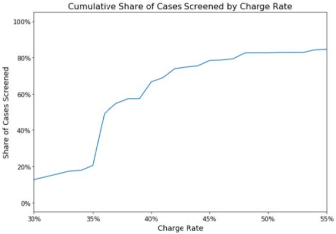


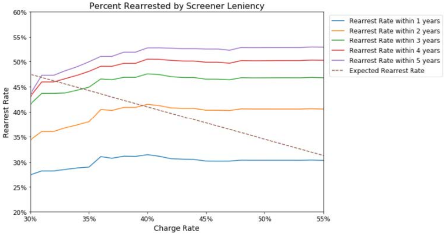
Risk distribution of defendants released by screeners of increasing strictness (from L to R).

- If screeners were to release defendants at random, we would see an even distribution of predicted risk for each set of screeners (which is what we see in upper left and lower right).

Using ML to Understand how Screeners Screen

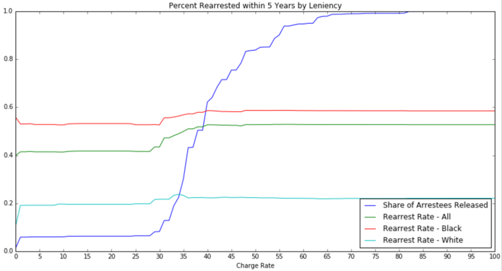
We can also assess the performance against actual rearrest rates.

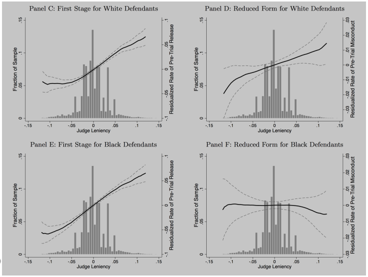




- We should observe a diagonal downwards slope from the upper left to the lower right if the screeners were releasing based on risk.
  - Instead, it is slightly *upward* sloping.

Using ML to Understand how Screeners Screen



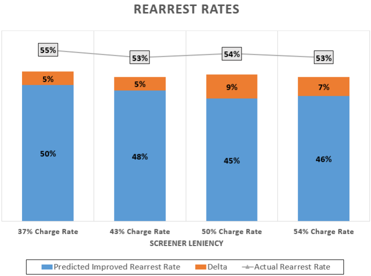


Actually, flat for Whites, *upward* slope for Blacks

- Judges released along "right" diagonal for Whites but not Blacks

See also *Arnold, Dobbie, Yang, QJE 2017*

Potential Reduction in Rearrest from Using ML



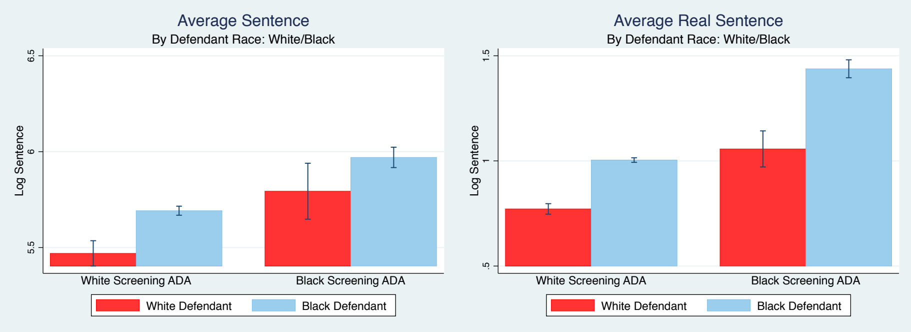
We analyze the "marginal" defendant.

- Given a screener(s), we define the marginal defendant as the defendant with the highest predicted risk that was seen and released by that screener(s).
  1. We calculate the additional number of arrestees that would need to be charged for the "lenient" group of screeners to reach the same charge rate as the next "strictest"
  2. We choose these "marginal" defendants based on estimated risk
- Racial disparities did not increase with the model
  - Consistent with "wrong" slope for Black defendants

See also *Kleinberg, Lakkaraju, Leskovec, Ludwig, Mullainathan, QJE 2017*

Why "wrong diagonal" for Black defendants?

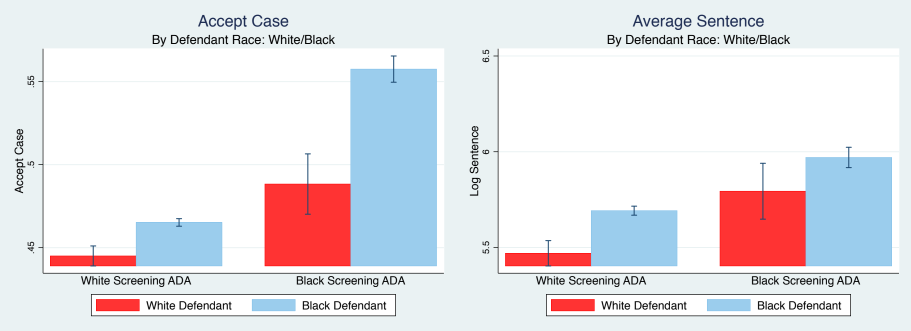
1. Screening Increases Racial Sentencing Gap



- Conditional black-white sentence differences (on left)
- Disparity magnifies (on right), since black arrests are less likely to be dropped
  - Effects are quite large in log scale
  - Is statistical discrimination the reason for disparate screening?

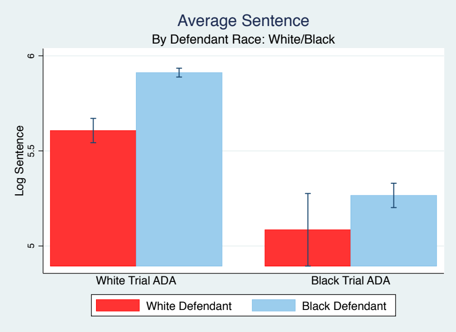
Anwar and Fang, AER 2006

2. White Screener Cases are Fewer and Leniently Sentenced



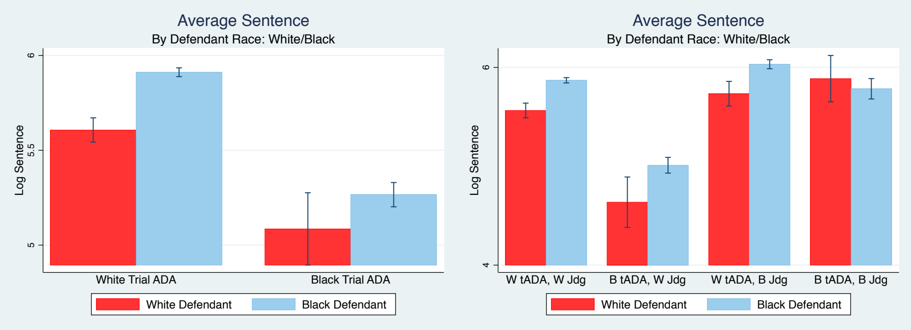
- White screeners are more lenient (on left)
  - If targeting the most severe ones, should have *longer* sentences
- White and black screeners let in different cases (on right)
  - Suggests not about statistical discrimination

3. White Trial Prosecutors Obtain Longer Sentences



- Most District Attorneys are elected; want to appear tough-on-crime (Pfaff 2016)
- Why are white trial prosecutors more effective in this goal?

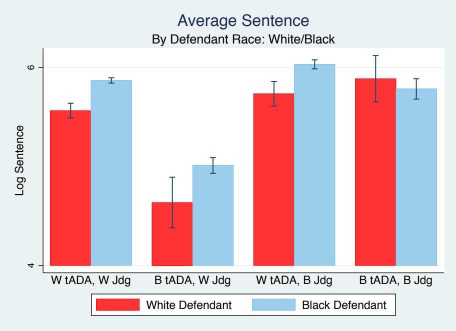
4. Black Trial Prosecutors + White Judges Render Shorter Sentences



- The difference seems attributeable to the interaction of hierarchy and race
  - Black trial prosecutors + Black judges render similar average sentences as White trial prosecutors do
  - Effects are quite large in log scale (on right)

Reproduction of Heirarchy in Sentencing Gaps; See also *Acemoglu and Wolitzky, in review*

5. Black Trial Prosecutors + Black Judges Eliminate or Reverse Racial Sentencing Gap

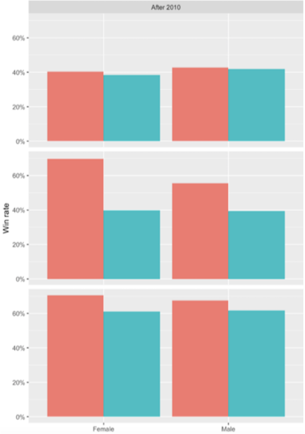


- Hard to explain as statistical discrimination rather than ingroup bias
  - But ingroup bias by whom is not knowable without *benchmark*

Reforms Can Reduce Ingroup Bias Ash, Chen, Chheda, Dominguez, Maqueda, Siddiqi

Win-Rate by Judge and Litigants' Gender

Judge Gender



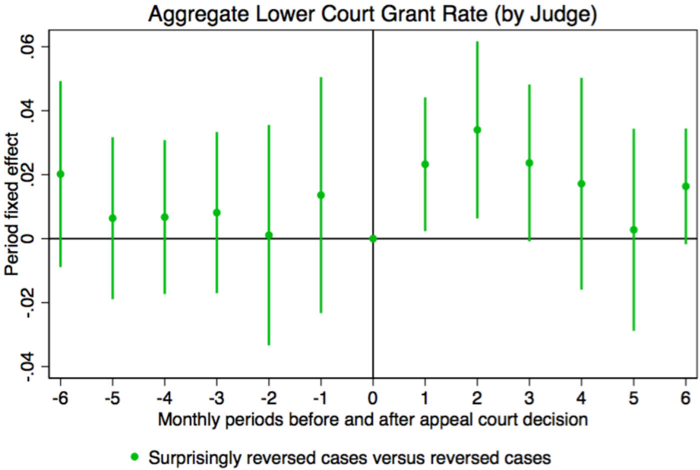
Judge Gender

in Kenya (130K cases)

Now let's use ML to measure Judicial Inattention

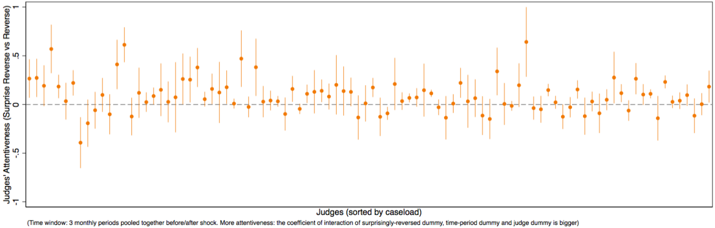
Effect of "Surprise" Appeal Rulings Ash and Chen

Within-judge change in grant rates before/after "surprising" reversals (model predicts affirm), relative to unsurprising reversals (model predicts reverse):



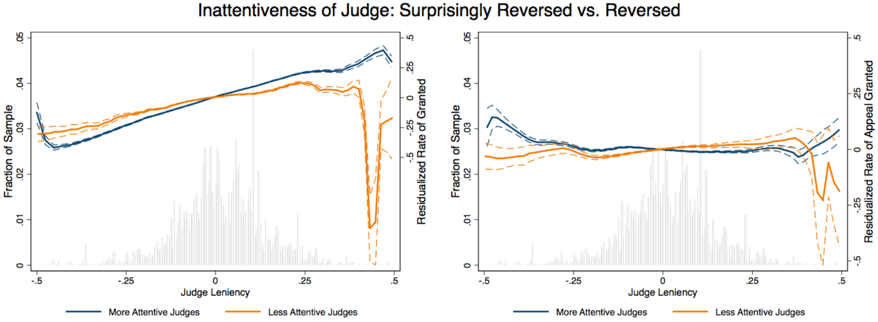
(With appeal decision year-month fixed effect, weighted on number of cases in each aggregation unit.)

Judges Vary in Attention



Do implicit rankings (of asylees) by judges differ by attentiveness?

But attentive judges rank asylees more like the appeal board



(Time window: 3 monthly periods pooled together before/after shock. More attentiveness: the coefficient of interaction of surprisingly reversed dummy and time-period dummy is bigger)

Let's apply these analytics to juridical and jurisprudential questions

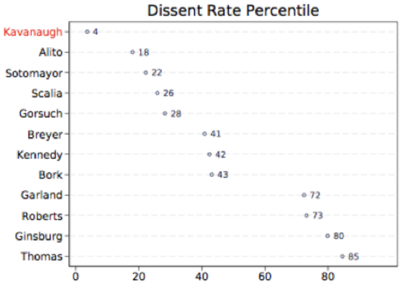
What Kind of Judge is Brett Kavanaugh? *Ash and Chen, Cardozo L Rev 2018*

Circuit	**District**	**SCOTUS**	**Asylum**	**New Orleans DA**
Priming	Economics	Masculinity	Gambler's Fallacy	Implicit Egoism
Motivated Cognition	Mood	Mimicry	Mood	Indifference
Deontological	Interpellation	Vocal Bias	Time of Day	Interpellation
Implicit Bias	Stereotypes	Visual Cues	Snap Judgments	Heirarchy
Economics	In-group Bias			In-group Bias

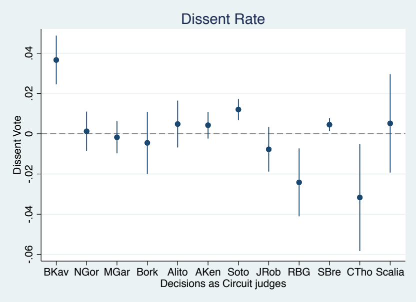
India	**France**
Implicit Bias	Interpellation
In-group Bias	

Kavanaugh is radically conservative, Ash and Chen, Washington Post, July 10, 2018

Kavanaugh is an Outlier in Dissents

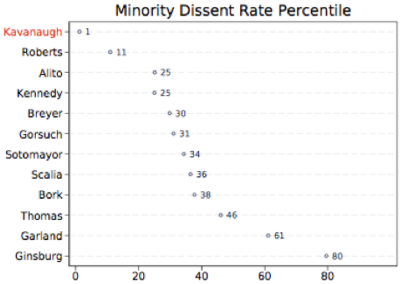


compared to past SCOTUS nominees/judges

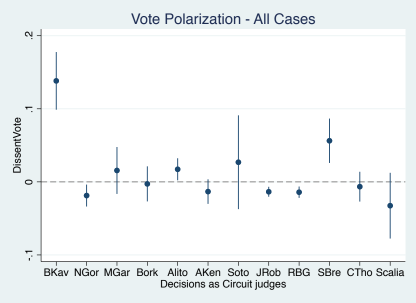


adjusting for case FE

Kavanaugh is an Outlier in Partisan Dissents

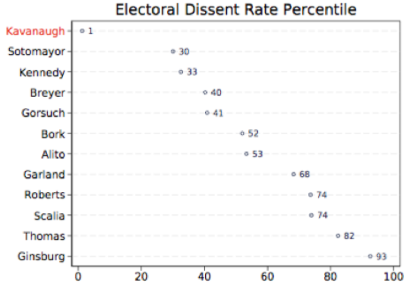


compared to past SCOTUS nominees/judges

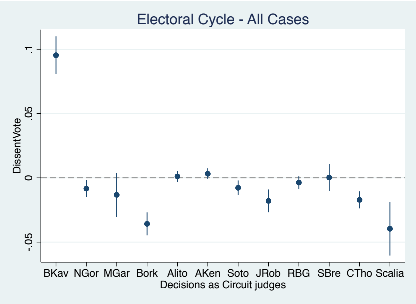


adjusting for case and judge FE

Kavanaugh is an Outlier in Electoral Dissents Primeable/emotional

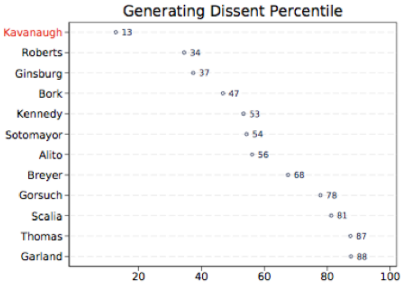


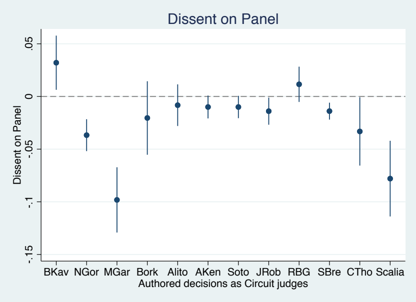
compared to past SCOTUS nominees/judges



adjusting for circuit-year and judge FE

Kavanaugh is an Outlier in Generating Dissents

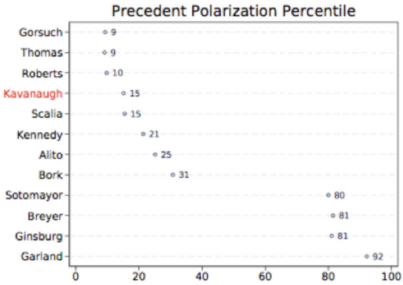




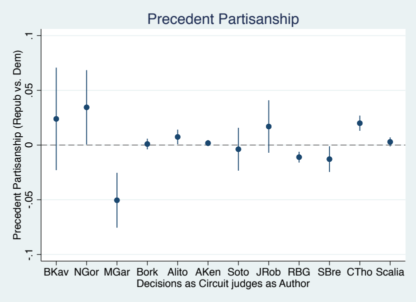
compared to past SCOTUS nominees/judges

adjusting for Circuit-year-month FE

Kavanaugh is Partisan on Cited Precedent

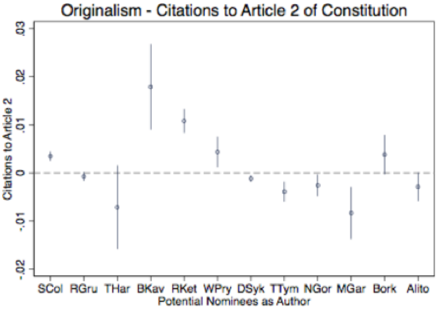


compared to past SCOTUS nominees/judges



adjusting for Circuit-year-month FE

Kavanaugh is an Outlier in Citing Article II



compared to Trump's shortlist of nominees

- Conservative jurists cite Article II as favoring expanded executive power

Circuit Measures Predict SCOTUS Votes

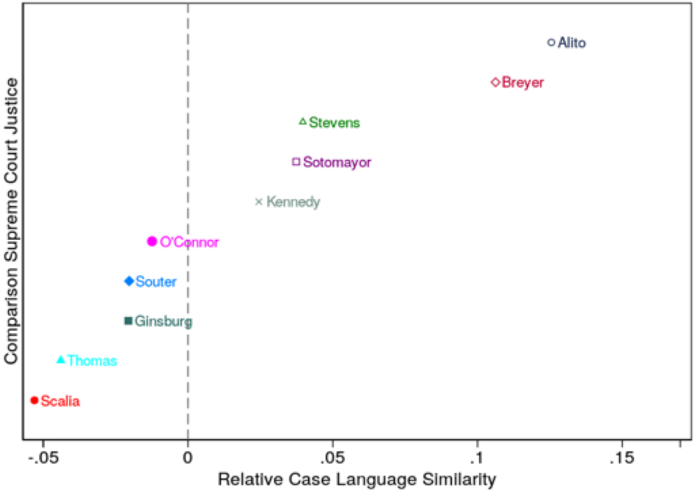
Using all 26 SCOTUS judges (1946-2016) who sat on 50+ circuit cases

- A judge who moves from the most Democrat to the most Republican in **precedent** and **phrase** usage is **32%** and **23%**, respectively, more likely to vote conservative.

- A judge who moves from the lowest to highest rank in Posner similarity and economics usage is 18% and 6%, respectively, more likely to vote conservative.

- A judge who moves from the lowest to highest rank in **vote polarization** and electoral dissent is **25%** and 8%, respectively, more likely to vote conservative.

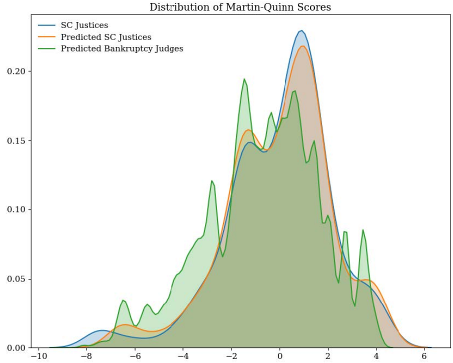
Kavanaugh is linguistically most similar to Alito not Kennedy



Document embeddings

Text predicts Martin-Quinn scores well (Cai, Ash, Chen)

Applying the model to bankruptcy judges



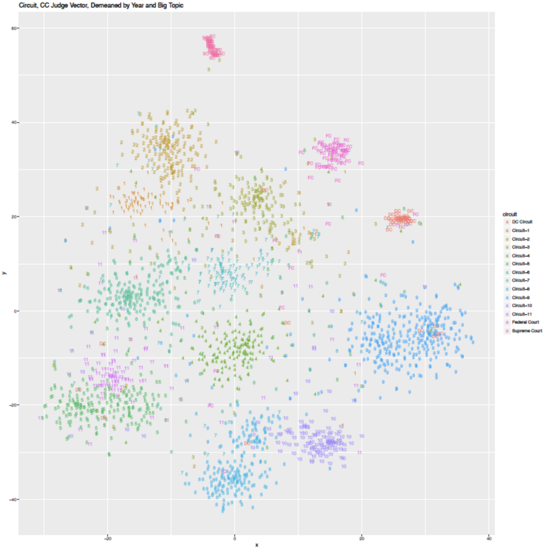
is predictive of their leniency

Document embeddings

Can we use document embeddings for doctrinal analysis?

Visual Structure of Case Vectors by Circuit

Figure 1: Centered by Topic-Year, Averaged by Judge, Labeled by Court

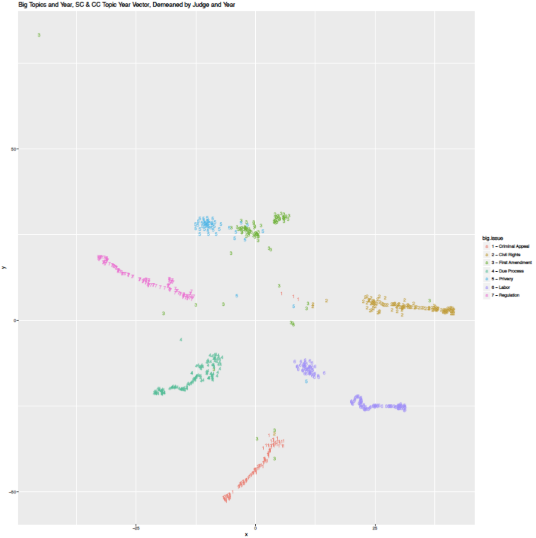


Visual Structure of Case Vectors by Decade

Figure 2: Centered by Court-Topic, Averaged by Court-Year, Labeled by Decade

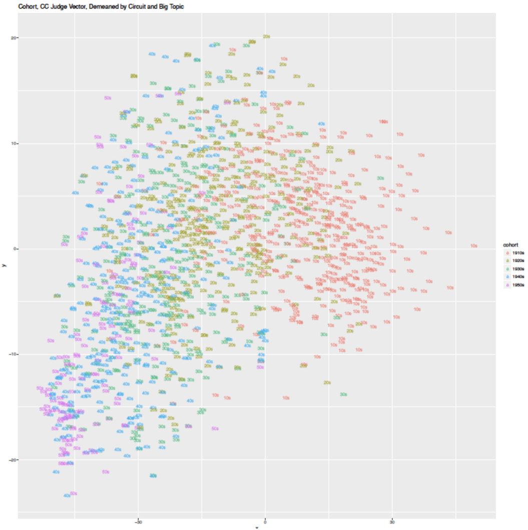
Visual Structure of Case Vectors by Topic

Figure 3: Centered by Judge-Year, Averaged by Topic-Year, Labeled by Topic



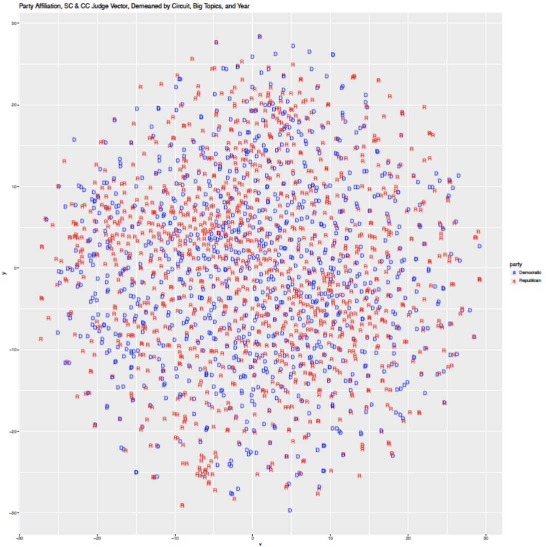
Visual Structure of Case Vectors by Birth Cohort

Figure 5: Centered by Court-Topic-Year, Averaged by Judge, Labeled by Judge Birth Cohort



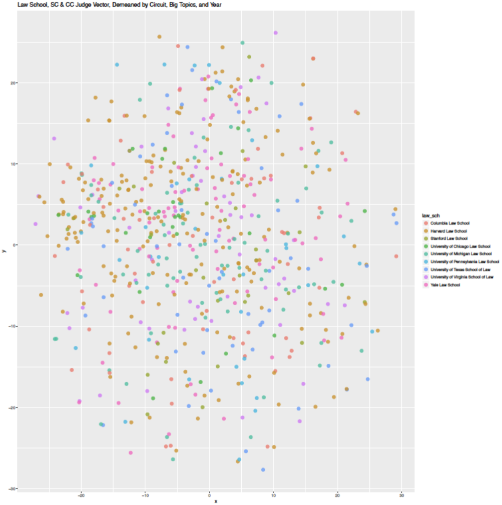
Visual Structure of Case Vectors by Party

Figure 4: Centered by Court-Topic-Year, Averaged by Judge, Labeled by Political Party



Visual Structure of Case Vectors by Law School

Figure 6: Centered by Court-Topic-Year, Averaged by Judge, Labeled by Law School Attended



Relatedness between judges

Circuit Judge Name	Similarity	Rank	Circuit Judge Name	Similarity	Rank
POSNER, RICHARD A.	1.000	1	TONE, PHILIP W.	0.459	16
EASTERBROOK, FRANK H.	0.663	2	SIBLEY, SAMUEL	0.459	17
SUTTON, JEFFREY S.	0.620	3	SCALIA, ANTONIN	0.456	18
NOONAN, JOHN T.	0.596	4	COLLOTON, STEVEN M.	0.445	19
NELSON, DAVID A.	0.592	5	DUNIWAY, BENJAMIN	0.438	20
CARNES, EDWARD E.	0.567	6	GIBBONS, JOHN J.	0.422	21
FRIENDLY, HENRY	0.566	7	BOGGS, DANNY J.	0.420	22
KOZINSKI, ALEX	0.563	8	BREYER, STEPHEN G.	0.414	23
GORSUCH, NEIL M.	0.559	9	GOODRICH, HERBERT	0.412	24
CHAMBERS, RICHARD H.	0.546	10	LOKEN, JAMES B.	0.410	25
FERNANDEZ, FERDINAND F.	0.503	11	WEIS, JOSEPH F.	0.408	26
EDMONDSON, JAMES L.	0.501	12	SCALIA, ANTONIN (SCOTUS)	0.406	27
KLEINFELD, ANDREW J.	0.491	13	BOUDIN, MICHAEL	0.403	28
WILLIAMS, STEPHEN F.	0.481	14	RANDOLPH, A. RAYMOND	0.397	29
KETHLEDGE, RAYMOND M.	0.459	15	MCCONNELL, MICHAEL W.	0.390	30

Law-and-Economics Vectors

Hermemetrics (hermeneutics + econometrics) Making Doctrinal Work Rigorous

Principals, superiors, employers, patrons and the like all, to be sure, expect loyalty. On what basis, according to Commons, will loyalty secured? A traditional rational choice approach would look to incentives (structural loyalty) or to preferences (characterological loyalty), but Commons considered that approach limiting, if not misleading. He instead identified what he thought to be a more promising direction in Wesley Hohfeld's analysis of legal entitlements.[75] Hohfeld's conceptualization of entitlements was, to Commons, nothing short of a general theory of conduct rules,[76] shedding light on "the way in which the common practices of *any* going concern control the individual members of that concern and hold them to the conduct necessary to preserve the existence of the concern."[77] Bentham's actively

Legal scholars are interested in **typology** of loyalty

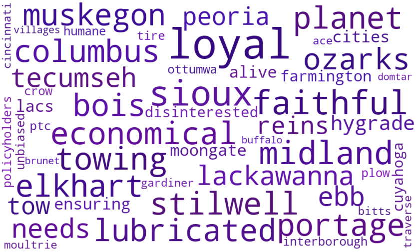
"common practices of any concern" = norms vs. intrinsic vs. self-interested ..

Textual Analysis

Obedience, the correlative to the master's authority, is the essence of what it means to be a loyal servant here. A master-servant relation, to be sure, is not a master-slave one, but that fact does not render the former simply contractual. Slavery and strict contractual compliance do not exhaust the scope of possibility for securing loyalty from servants. Coase appears to identify the loyalty of servants with a broad, though not unlimited, duty of obedience.[82] As such, their actions and choices may follow from behavioral loyalty, separate and apart from incentives provided by the

"obedience" = loyalty?

Loyalty and Obedience Vectors

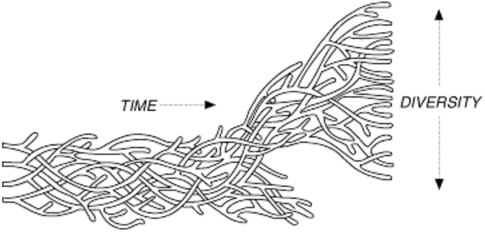


Loyalty

Obedience

- "Loyalty" and "obedience" don't seem very related
- Loyalty associated with certain native american tribes
- See if vectors cluster along typology or identify "original meaning"

The Geneology of Ideology *Chen, Parthasarathy, Verma, JCAIL 2017*



$$P_m = \frac{d_{m \to m}}{d_{\to m} + \delta} \Big/ \frac{d_{m \to \cancel{m}} + \delta}{d_{\to \cancel{m}} + \delta}$$

Scoring Memetic Phrases

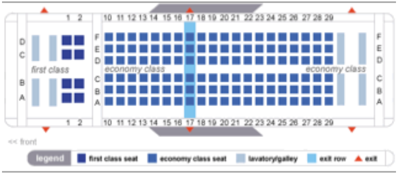
Memetic Phrases

Phrase	Normalized Meme Score
red heat	0.138
salvage services	0.0039
said cars	0.0029
Atlantic coast	0.00216
citizens of different states	0.00212
insurance effected	0.0020
separable controversy	0.0018
taken in tow	0.0017
schooner was	0.00126
fourteenth amendment	0.00125
contract of affreightment	0.00119
patented design	0.0011
constitution or laws	0.0009
mere transient or sojourner	0.0008

Maritime Law: salvage services, Atlantic coast, citizens of different states, insurance effected, taken in tow, schooner was, contract of affreightment, mere transient or sojourner; Fourteenth Amendment one of the most litigated parts of Constitution, basis for *Brown v. Board of Education* (1954) [racial segregation], *Roe v. Wade* (1973) [abortion], *Bush v. Gore* (2000) [2000 election], and *Obergefell v. Hodges* (2015) [same-sex marriage].

Causal memes?

Identification of Learning & Memetic Effects



Impact of law-and-economics exposure $a_{i-\ell}$ on

- case i, judge j, court c, year t

$$F_{ijct} = \sum_{\ell=0}^{L_s} \beta_s^\ell s_{i-\ell} a_{i-\ell} + \sum_{\ell=0}^{L_d} \beta_t^\ell t_{i-\ell} a_{i-\ell} + \mu_j + \xi_{ct} + \epsilon_{ijct}$$

- $s_{i-\ell}$: exogenous seat network, $t_{i-\ell}$: time network, $c_{i-\ell}$: citation network
- β_s^ℓ: Impact of Economics Training on **Previous Case of this Judge**
- β_t^ℓ: Impact of Economics Training on **Previous Case in this Circuit**

Separately identify within- (β_{sT}^ℓ) vs. across-topic (β_s^ℓ) impacts:

- β_{sT}^ℓ: Impact of Economics Training on **Previous Case of Judge on Topic**
- β_{tT}^ℓ: Impact of Economics Training on **Previous Case of Circuit on Topic**

Transmission from Regulatory to Criminal Cases

			Ellickson Average			
Econ Training	[N] = (-1)	(0)	(1)	(2)	(3)	(4)
			[N] Cases Ago is Regulation, Current Case is Criminal			
[N] cases later	0.0119	-	**0.0304*** **	-0.00639	**0.0180***	**0.0253***
	(0.0114)	-	**(0.0103)**	(0.0146)	**(0.00951)**	**(0.0117)**
N	17314	-	17238	17714	17658	17723
adj. R-sq	0.035	-	0.314	0.119	0.078	0.209
			[N] Case Ago is Criminal, Current Case is Regulation			
[N] cases later	-0.00277	-	-0.00371	0.0110	-0.0383	-0.0243
	(0.00981)	-	(0.0136)	(0.00990)	(0.0242)	(0.0246)
N	17176	-	17355	17552	17731	17636
adj. R-sq	0.042	-	0.080	0.034	0.047	0.072
Circuit-Year FE	Y	-	Y	Y	Y	Y
Circuit Order	Y	-	Y	Y	Y	Y
Sample	Year > 1991	-	Year > 1991	Year > 1991	Year > 1991	Year > 1991
Order within	Judge	-	Judge	Judge	Judge	Judge
Cluster	Judge	-	Judge	Judge	Judge	Judge

Transmission from Regulatory to Criminal Cases

	# Uses of "Deterrence"					
Econ Training	[N] = (-1)	(0)	(1)	(2)	(3)	(4)
	[N] Cases Ago is Regulation, Current Case is Criminal					
[N] cases later	-0.0145	-	**0.122****	**0.0340***	-0.0234	0.0245
	(0.0179)	-	**(0.0580)**	**(0.0189)**	(0.0259)	(0.0178)
N	17314	-	17238	17714	17658	17723
adj. R-sq	0.066	-	0.180	0.141	0.077	0.111
	[N] Case Ago is Criminal, Current Case is Regulation					
[N] cases later	0.0172	-	0.0114	0.00765	0.00637	-0.00926
	(0.0169)	-	(0.0216)	(0.0172)	(0.0126)	(0.0124)
N	17176	-	17355	17552	17731	17636
adj. R-sq	0.097	-	0.065	0.208	0.035	0.046
Circuit-Year FE	Y	-	Y	Y	Y	Y
Circuit Order	Y	-	Y	Y	Y	Y
Sample	Year > 1991	-	Year > 1991	Year > 1991	Year > 1991	Year > 1991
Order within	Judge	-	Judge	Judge	Judge	Judge
Cluster	Judge	-	Judge	Judge	Judge	Judge

Impact of Economics Judges, by Crime Type

	Log of Total Sentence				
	(1)	(2)	(3)	(4)	(5)
Econ Training	-0.0695	-0.00621	-0.0369	-0.0213	-0.0226
	(0.0839)	(0.0347)	(0.0559)	(0.0619)	(0.0599)
Econ Training *	**0.245****	**0.0467**	**0.200****	**0.184****	**0.219****
Booker (≥2005)	**(0.100)**	**(0.0411)**	**(0.0856)**	**(0.0903)**	**(0.0900)**
N	600010	697844	798823	838643	786472
adj. R-sq	0.043	0.044	0.051	0.037	0.043
Courthouse and Calendar FE	Y	Y	Y	Y	Y
Drop Crime	Drug	**Immigration**	Fraud	Weapon	Other

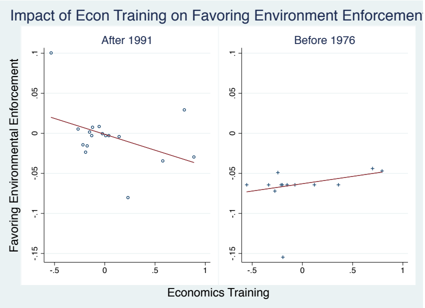
Largest effects of economic training found in immigration crimes

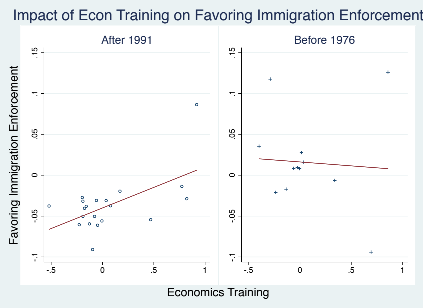
Immigration Charges

Lead Charge	Count	Rank	1 yr ago	5 yrs ago	10 yrs ago	20 yrs ago
08 USC 1325 - Entry of alien at improper time or place; etc.	35,367	1	1	1	2	3
08 USC 1326 - Reentry of deported alien	28,930	2	2	2	1	1
08 USC 1324 - Bringing in and harboring certain aliens	3,794	3	3	3	3	2
18 USC 1546 - Fraud and misuse of visas, permits, and other documents	502	4	4	4	4	4
18 USC 1544 - Misuse of passport	333	5	5	8	15	16
18 USC 1028 - Fraud and related activity - id documents	165	6	6	5	6	7
18 USC 1542 - False statement in application and use of passport	72	7	7	9	10	8
18 USC 922 - Firearms; Unlawful acts	50	8	11	12	13	22
21 USC 841 - Drug Abuse Prevention & Control-Prohibited acts A	45	9	10	14	14	11
18 USC 371 - Conspiracy to commit offense or to defraud US	40	10	16	10	11	5

Immigration severity consistent with no 'rehabilitation' margin (and limited liability)

Ideological Shifts





After attendance, Economics Trained Judges reject environmental enforcement (normalized)

but support immigration enforcement (normalized). Note: both **switch in direction.**

Peer Behavior Effects, Labor/Environmental

	Voting Against Environmental or Labor Agency [N] cases later					
Econ Training on	[N] = (-1)	(0)	(1)	(2)	(3)	(4)
[N] cases later	-0.00338	-	-0.00438	**0.0192****	0.00929	-0.00420
	(0.0111)	-	(0.0100)	**(0.00887)**	(0.00995)	(0.0101)
Circuit-Year FE	Y	-	Y	Y	Y	Y
[N] cases later	-0.00811		-0.00544	**0.0236****	0.0113	-0.0145
	(0.0160)		(0.0136)	**(0.0120)**	(0.0128)	(0.0139)
Circuit-Year FE	Y	-	Y	Y	Y	Y
Judge FE	Y	-	Y	Y	Y	Y
Circuit Order	Y	-	Y	Y	Y	Y
Order within	Judge	-	Judge	Judge	Judge	Judge
Cluster	Judge	-	Judge	Judge	Judge	Judge

What spurs innovation of normative ideas?

Integration and Assimilation? or Dis-integration, Radicalization, Other-ing, and Egotism?

Unique setting of DDD, DDR, DRR, RRR (uniformity, majority, minority)

- Repeated random assignment to teams

◂ The Effect of Being Minority (**D**RR or **R**DD): Instead of assimilation, we see **dis-assimilation**

◂ The Effect of Being Majority (**D**DR or **R**RD): Instead of integration, we see **radicalization**

◂ The Effect of Uniformity (**D**DD or **R**RR): Instead of conformity, we see **egotism**

Minority: **D**RR	Majority: **D**DR	Uniformity: **D**DD
Assimilation: --→**D**RR	Integration: --→**D**DR	Conformity: --→**D**DD
Dis-assimilation: **D**←--RR	Radicalization: **D**←--DR	Egotism: **D**←--DD
Persuasion: **D**R←--R	Other-ing: **D**D←--R	Sectism: **D**D←--D

◂ Identification : Circuit × YearQuarter × Party Fixed Effects (stability w/ Judge FE, Topic FE)

Mitosis of Ideology

How can we observe normative innovation?

Rights Revolutions ("How conservatives weaponized the First Amendment" *New York Times 2018*)

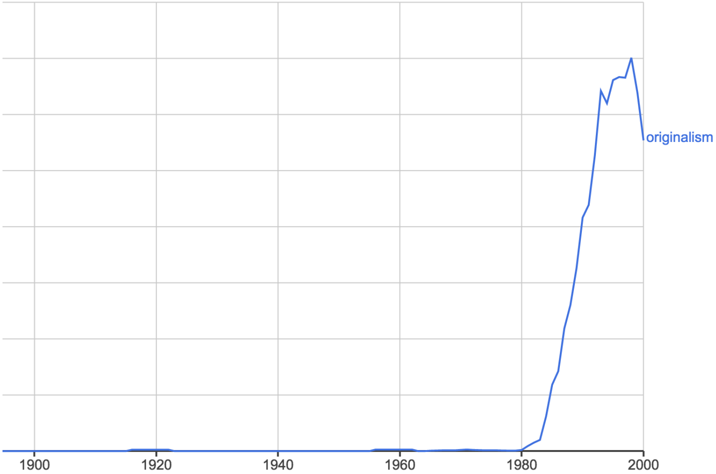
../../GentzkowShapiroTaddy_CircuitCourts/Paper/

First Amendment more phrase polarized for Republicans; Due process, labor, economics for Democrats

More predictable if using a set of magic words (concatenated vocabulary)

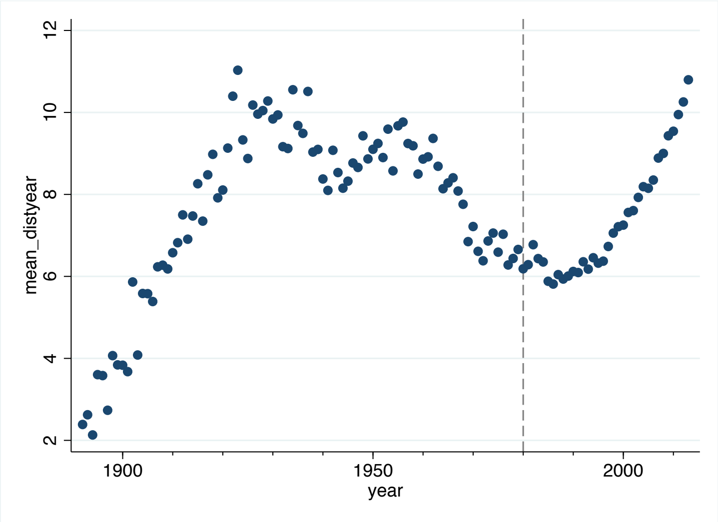
Does concatenated vocabulary cause social change?

Originalism (example of neologism, phrase concatenation, “sparsity”)



- The word "originalism" was coined by Paul Brest in 1980.
- Here is the famous passage: *"By “originalism” I mean the familiar approach to constitutional adjudication that accords binding authority to the text of the Constitution or the intentions of its adopters."*

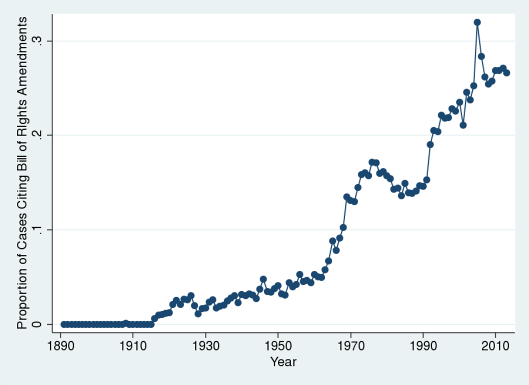
Measuring Originalism



time distance to cited case growing since 1980

"We are all Orignalists now"

Figure: Trend in Citing Bill of Rights Amendments



Citing Bill of Rights began inflection in 1970s

Does concatenated vocabulary $\Longleftrightarrow$? Vote concatenation?

Vote Polarization by Legal Topic and Party

	Dissent Vote						
	Criminal	Civil Rght	1st Amend	Due Process	Privacy	Labor	Econ
Minority	0.00959**	0.0112*	0.0382+	0.00826**	0.0143	0.00307	0.00534*
	(0.00254)	(0.00545)	(0.0227)	(0.00255)	(0.0208)	(0.00486)	(0.00237)
Minority	0.00285	0.0184+	-0.0267	0.00483	-0.0254	0.0235*	-0.00174
*** Dem**	(0.00445)	(0.00989)	(0.0408)	(0.00468)	(0.0205)	(0.00945)	(0.00474)
N	171019	46179	3278	179019	424	37262	232199
Case FE	X	X	X	X	X	X	X
Judge FE	X	X	X	X	X	X	X
Cluster	Judge	Judge	Judge	Judge	Judge	Judge	Judge

Democrats issue more minority dissent in Civil Rights and Labor. Republicans in 1st Amend and Econ.

Echoes Democrat prose polarization in Labor, Republican prose polarization in 1st Amend.

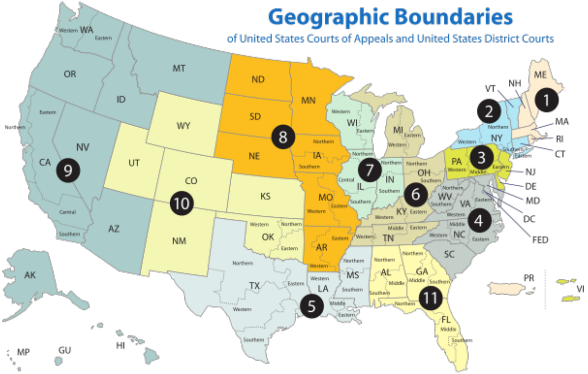
Does legal precedent $\Longleftrightarrow$? social change?

Measuring the Impacts of Legal Precedent

Circuit	District	SCOTUS	Asylum	New Orleans DA
Priming	Economics	Masculinity	Gambler's Fallacy	Implicit Egoism
Motivated Cognition	Mood	Mimicry	Mood	Indifference
Deontological	Interpellation	Vocal Bias	Time of Day	Interpellation
Implicit Bias	Stereotypes	Visual Cues	Snap Judgments	Heirarchy
Economics	In-group Bias			In-group Bias

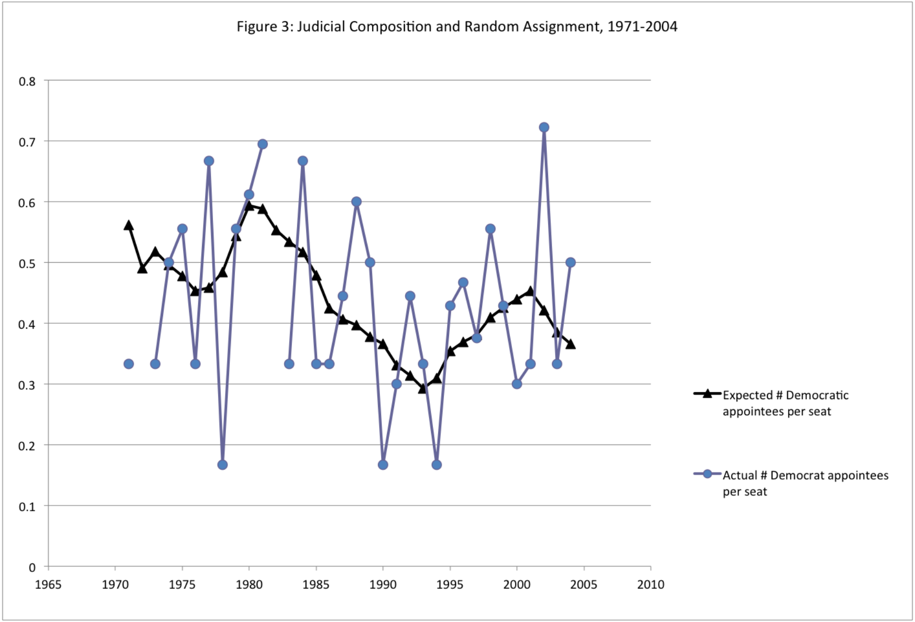
India	France
Implicit Bias	Interpellation
In-group Bias	

Random Variation in Precedent



- **Random** assignment of judges
  - Judge characteristics **predict** decisions
- Binding precedent **within** circuit
  - 98% of decisions are final

Graphical Intuition of "coin flip"



Data

- Chicago Judges Project (Sunstein et al. 2006; Heise and Sisk 2012; other smaller samples)
  6000+ hand-coded cases in 26 polarized legal areas

Civil Rights	Property	Constitutional	Constitutional
sexual harassment	eminent domain	free speech	abortion
affirmative action	corporate veil piercing	campaign finance	Establishment Clause
sex discrimination	contracts	First Amendment	Free Exercise Clause
Title VII	environmental protection	Eleventh Amendment	capital punishment
desegregation	NEPA	standing	criminal appeals
gay rights	punitive damages	federalism	
disability rights	National Labor Review Board	FCC	

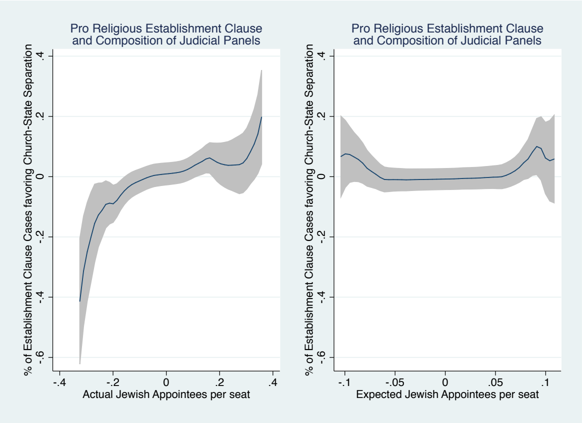
- Federal Judicial Center biographies

  e.g., party, religion, race, gender, college, law school, graduate law degree, year of birth, ABA rating, wealth, appointed when President and Congress majority were from same party, appointed by president from opposing party, prior judiciary experience, prior law professor, prior government experience, previous U.S. attorney, previous asst U.S. attorney

Dissent is roughly half-driven by shared personal features.

What Matters, Chen, Cui, Shang, Zheng, JMLR, NIPS 2016

Biographies Predict Church-State Separation *Chen and Lind*, in review

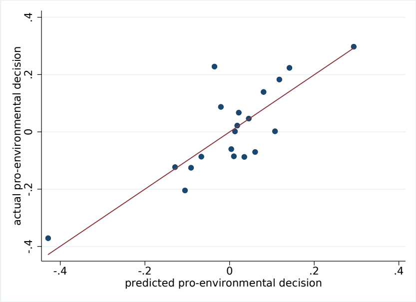


Minority religion judges prefer separate church and state

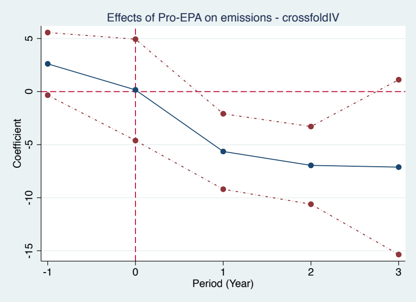
$$\begin{cases} Law_{ct} = \alpha_{ict} + \phi Z_{ct} + \gamma_1 X_{ict} + \gamma_2 W_{ct} + \eta_{ict} \text{ (machine learning step)} \\ Y_{ict} = \alpha_{ict} + \rho Law_{ct} + \beta_1 X_{ict} + \beta_2 W_{ct} + \varepsilon_{ict} \text{ (causal inference step)} \end{cases}$$

Sparse Models and Methods for Optimal Instruments, Belloni, Chen, Chernuzhukov, Hansen, ECMA 2012

Impact of Environmental Decisions *Ash and Chen*

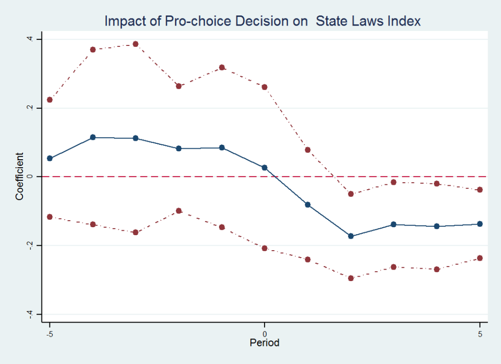


Calibration plot



Rulings in favor of EPA regulations reduce air pollution

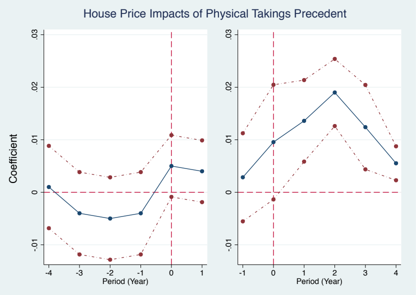
State Compliance with Abortion Jurisprudence

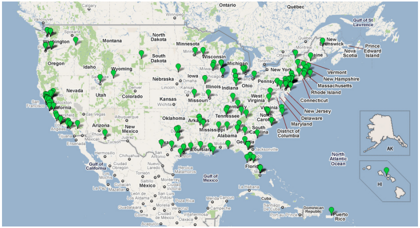


- Index of state laws (Blank et al. 1996)
  - (i) regulations requiring mandatory delay,
  - (ii) banning the use of Medicare payments to fund abortion,
  - (iii) requiring parental notification
- Immediately observed after 1 year
- Pro-choice precedent causes 18% smaller likelihood in *each* regulation in *each* state
- No lead effect: state laws are not changing in advance of the Circuit precedent

Can Policies Affect Preferences, Chen, Levonyan, Yeh, in review

Local vs. Precedential Impacts of Takings (Power)





No lead effect

Zip code origin distinguishes local v. precedential effects

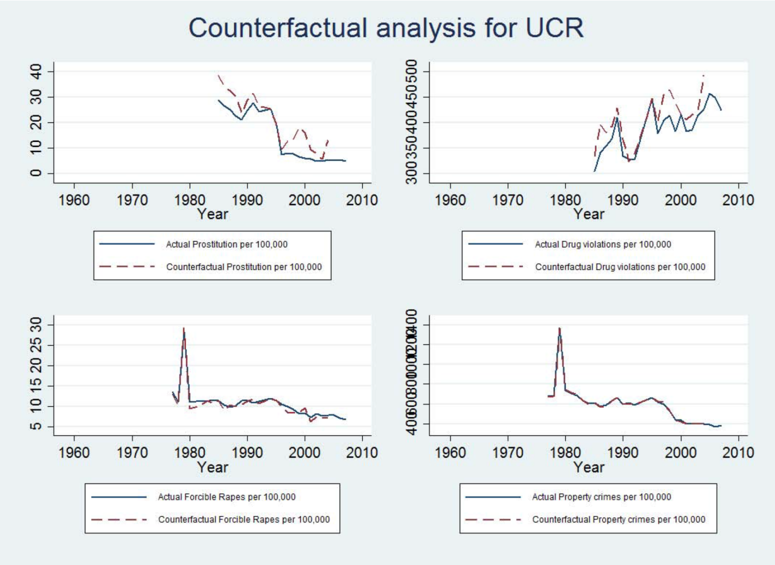
Law_{ct} + **Local**Law_{zct}

Government Expropriation Increases Economic Growth and Racial Inequality, Chen and Yeh, EJ, invited to resubmit

Sexual Harassment Law Increases Female Labor Share

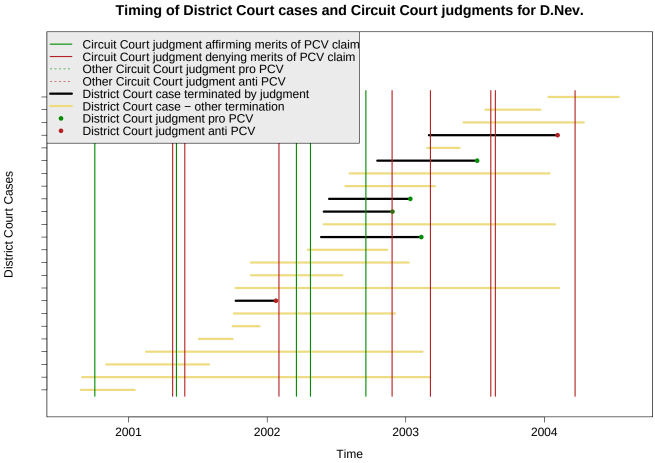
	β_3	Joint F
A. Add Circuit-Specific Trends	0.016	8.35
B. Drop θ_c, θ_t	0.016	8.17
C. Only $1\left[M_{ct-n} > 0\right]$, F_{ict}	0.017	8.08
D. Add $\mathbf{E}(\frac{N_{ct}}{M_{ct}})$	0.016	8.31
E. Add State Fixed Effects	0.016	8.00
F. No CPS Weights	0.013	16.49
G. Add 2-year Lead	0.021	19.25
H. Drop 1 Circuit		
Circuit 1	0.015	6.57
Circuit 2	0.017	14.22
Circuit 3	0.016	13.81
Circuit 4	0.017	17.12
Circuit 5 (TX, LA, MS)	0.007	37.15
Circuit 6	0.017	6.61

Impact of First Amendment Free Speech *Chen and Yeh*, in review



See also *Bhuller, Havnes, Leuven, Mogstad, ReStud 2013*

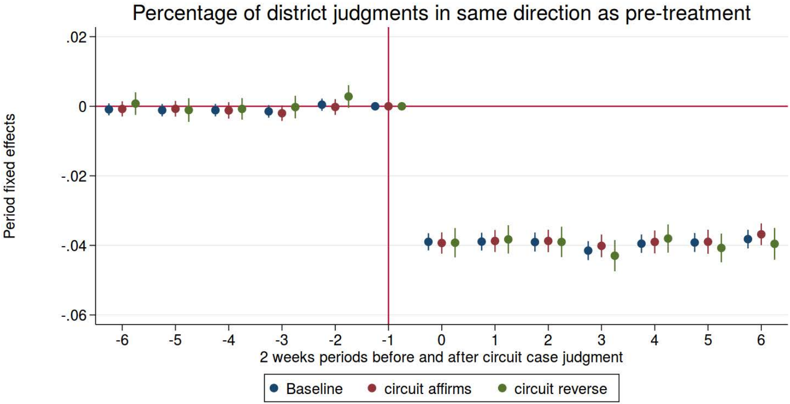
Judicial Compliance to Circuit Precedents *Chen, Frankenreiter, Yeh,* EI R&R



1. Consider only cases pending at the time of the circuit court decisions
2. Instrument for the direction of the appellate case

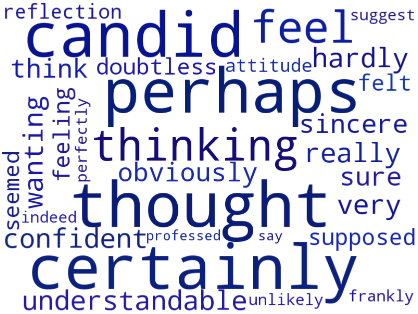
Judicial Overreaction to Appeals

Using all District cases merged to Circuit cases:



Large spillover effects to **presence** of a legal decision

Judicial Sentiment...

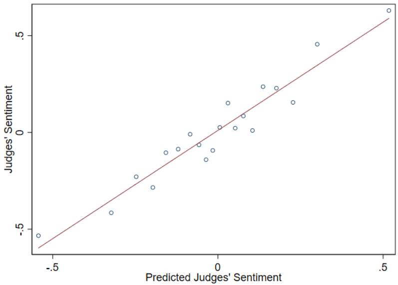


Positive

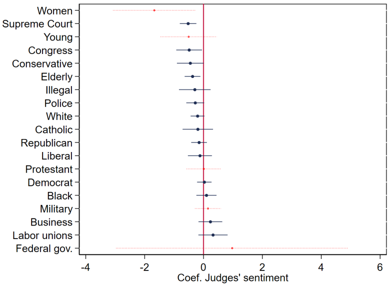
Negative

in embedding space

...renders temporary backlash *Galletta, Ash, Chen, in review*



Calibration plot



in ANES (by topic)

Broad Sketch

- District Cases $\rightarrow$
- District Judge Bio $\rightarrow$
- Circuit Case Appeal $\mathbf{1}[\mathrm{M}_{\mathrm{ct}} > 0] \rightarrow$
- **Circuit Judge Bio** $\rightarrow$
- **Circuit Case Decision** $Law_{ct} \rightarrow$
- **Precedential Effects (e.g., State Laws)** $\rightarrow$
- Promulgation (e.g., News) $\rightarrow$
- Outcomes
  - Law_{ct} distinguishes pro *vs.* anti *What if Roe v. Wade decided opposite?*
  - $Law_{ct} + \mathbf{1}[\mathrm{M}_{\mathrm{ct}} > 0]$ distinguishes pro *vs.* none *What if no Roe v. Wade?*

Experimental TOT_{direct} * P($\text{exp}_{\text{direct}}$) + Spillovers TOT_{indirect} * P($\text{exp}_{\text{indirect}}$)

The Construction of Morals, Chen and Yeh, JEBO 2014

Heads or Tails or No Coin?

Dummying for the presence of a case also permits the identification of additional counterfactuals.

- β_1 captures the effect of progressive precedent where the counterfactual is a conservative precedent
- $\beta_1 + \beta_2$ captures the effect of progressive precedent where the counterfactual is no precedent
- β_2 captures the effect of conservative precedent where the counterfactual is no precedent.
- $\beta_1 \mathit{Law}_{ct} + \beta_2 \mathbf{1}[\mathrm{M}_{\mathrm{ct}} > 0]$
  - High frequency data could distinguish $\mathbf{1}[\mathrm{M}_{\mathrm{ct}} > 0]$ when appeal is filed vs. when precedent issued.

Common Law Interpretation

Hard cases (compliers) precede easy cases (always/never-takers)

- Compliers are (hard) decisions affected by judicial biography
- β_{1n} captures hard cases n years ago; their subsequent effects at $t = 0$ can be decomposed into delayed direct effects and to subsequent easy cases that cite these hard cases.
- $\sum_{n=0}^{\infty} \beta_{1n} = \sum_{n=0}^{\infty} TOT_{ct}^{n} = \sum_{n=0}^{\infty} LATE_{ct}^{n}$

Exclusion Restriction

- Randomization check
  - 2-3 weeks before oral argument, computer randomly assigns
  - or panels are set up on a yearly basis, and ensured that judges are not sitting together too often
- Judge panels announced very late
  - No differential rate of settlement when judges are known earlier
- Supported by orthogonality checks of judicial characteristics vs. pre-determined district case features and random strings tests
- Not accounting for vacation, sick leave, senior status, en banc, remand, and recusal can lead to the inference that judges are not randomly assigned. Treat these as Rubin-ignorable.

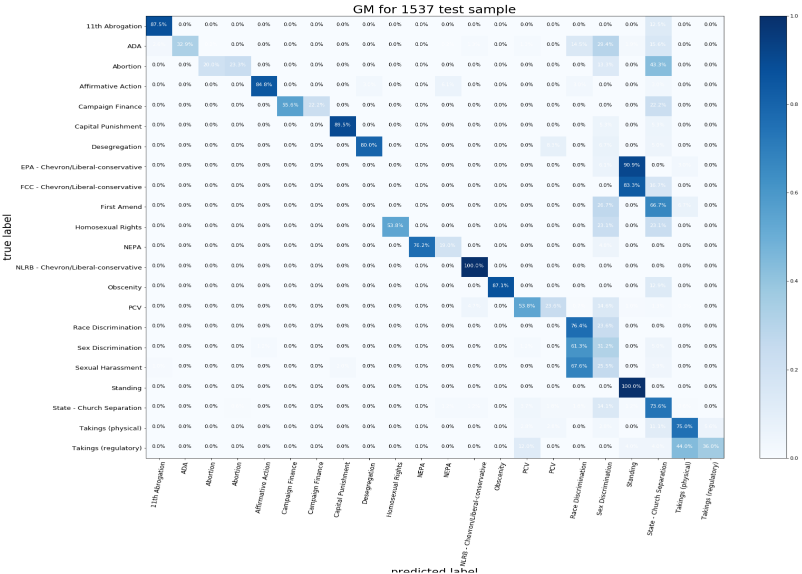
- Exclusion restriction
  - Judge identity not usually announced in newspapers
  - Impacts likely only through policy
  - No stock market response to judge identity when panels are revealed

The Shareholder Wealth Effects of Delaware Litigation, Badawi and Chen, ALER 2017

Modularity and Extensibility *(automating the Chicago Judges Project)*

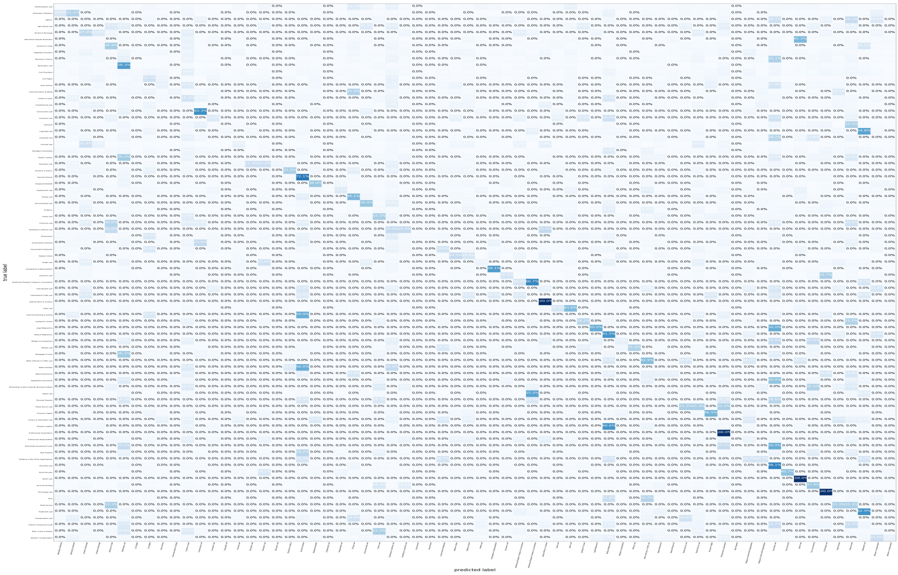
- District Cases $\rightarrow$
- District Judge Bio $\rightarrow$
- Circuit Case Appeal $\mathbf{1}[\mathrm{M_{ct}} > 0] \rightarrow$
- Circuit Judge Bio $\rightarrow$
- **Circuit Case Decision** $Law_{ct} \rightarrow$
- Precedential Effects (e.g., State Laws) $\rightarrow$
- Promulgation (e.g., News) $\rightarrow$
- Outcomes
  - 1. Identifying the nearest cases — *Learning Policy Levers*
  - 2. Fast decision classification — *Automated Fact-Value Distinction, Cao, Ash, Chen*
  - 3. Document embedding — *Does Dicta Matter, Ash, Chen*
  - 4. Judge embedding using own corpora — *Deep IV in Law, Ash, Chen, Huang, Wang*

Learning Policy Levers *Ash, Chen, Delgado, Fierro, Lin*



correctly identifies 15 of 22 Chicago Judges Project areas

Learning Policy Levers (baseline just using text)



Chicago Judges Project as training, classifies 35 out of 82 topics correctly in 5% sample

Fast decision classification

Liberal vs. Conservative decisions can be predicted by text $\sim$ facts or reasonings salient to judge

Campaign Finance	advertis influenc outcom vote, argument appel consid definit, challeng present, case controversi district, disclosur sourc	Expens, inform elector mean provis, compel court went histori, buckley court limit
Capital Punishment	duti make reason, Involuntari, materi reason probabl, mental health	consid mitig, Attack, Inelig, counti jail
EPA	act impos, board character, Chevron, Elimin, interst transport hazard wast	factor demonstr, id statut silent ambigu respect, requir provis

(Note: Buckley held that **limits on election spending are unconstitutional**)

Fast decision classification (baseline)

AUC	Logistic Regression with tf-idf
11th Abrogation	0.845
Abortion	0.642
ADA	0.751
Affirmative Action	0.653
Campaign Finance	0.876
Capital Punishment	0.650
EPA	0.72
FCC	0.96
First Amend	0.695
Homosexual Rights	0.873
NEPA	0.783
NLRB	0.715
Obscenity	0.855
Piercing Corp Veil	0.719
Sex Discrimination	0.752
Title 7	0.78

Judicial Analytics with 12 TB of data

- Predicting SCOTUS using ideology + circuit + oral + audio + lawyer
  - benchmark political model has 59% accuracy (1891-); surprising lift from implicit gender attitudes

Vunikili, Ochani, Jaiswal, Deshmukh, Ash, Chen, ExLing 2018

- LEGAL GRAMMAR parser (identifying equivalent legal phrases)
  - Identify fact vs. law
  - judicial fact discretion
    - Cardozo defended the right of a judge deliberately to misstate facts in the service of creating pragmatic rules because he believed that "the final cause of law is the welfare of society." (Polenberg HUP 1997)
    - Cardozo's "selection of facts with a freedom bordering on that of a novelist or short-story writer" was one of the keys to his judicial success. (Posner 1990)
- Predicting sentencing harshness (and disparities) using judicial corpora
  - significant reduction in MSE relative to naive prediction (mean) by 24%

Predicting Punitiveness

- Predicting ideology (political donations) using text + audio
  - In rarified Supreme Court setting, audio doubles predictive accuracy relative to text alone

Dialects of Ideology

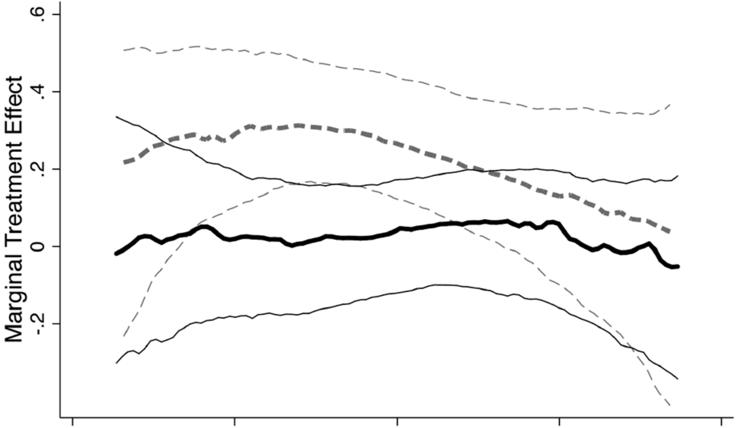
- Predicting asylum appeals and diagnose wrong diagonals
  - Relative to the previous best prediction of 82%, Wikileak cables achieve accuracy of 98%

Difference-In-Indifference

- Predicting REVERSALS (district → circuit; circuit → scotus)
  - achieve accuracy of 72% in supreme court and 79% in circuit courts (using only the text)

Using Machine Learning To Help Judges Write Opinions

Impacts of Hard vs. Easy Cases



Predicted likelihood of reversal based on district court opinion

See also *Heckman and Vytlacil, ECMA 2005*

Do hard cases establish precedent ⇒ social change? (Dashed)

Do surprise decisions overturning precedent ⇒ social change? (Solid)

Judicial Analytics, Recognition, and Dignity

US Circuit	District	SCOTUS	Asylum	New Orleans DA

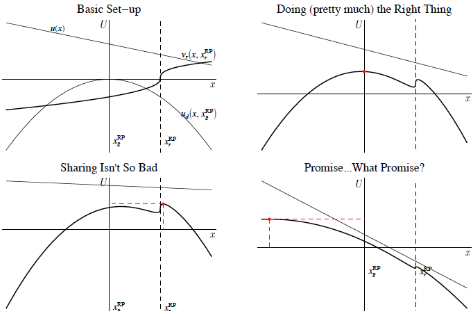
India	Kenya	Philippines	Croatia	Czech	Chile
Implicit Bias	Do behavioral biases replicate?				
In-group Bias	In-group Bias			Interpellation	

- Personalized nudges for judges (instead of checklists) to increase justice?
  - Based off recent decisions and environment: "be less indifferent"
- Measures of social preferences and implicit biases linked to decisions
  - Validate experimental (real-time, oTree) measures
- Survey trust (legitimacy) in the lawmaker (e.g., trust game)
  - Increase EFFICIENCY ***and*** FAIRNESS of law

PERCEIVED LEGITIMACY MOTIVATES OBEDIENCE IRRESPECTIVE OF SANCTION LIKELIHOOD *(Tyler 1997)*

Legitimacy and Perceived Indifference *Review of Law and Economics* 2017

Sympathy and Empathy



Recognition cannot be grounded in application of algorithmic procedures *(Daston and Galison 2010)*

Projects of identity as influential as economic self-interest *(Taylor 1989; 1992)*

Everything has either a price or a dignity. What has a price can be replaced by something else as its equivalent; what, on the other hand, is raised above all price and therefore admits of no equivalent has a dignity. .. humanity insofar as it is capable of morality is that which alone has dignity. *(Kant 1797)*

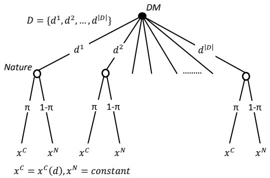
What commands respect is the capacity for morality *(Waldron 2009)*

Hypothetical vs. Categorical Imperative

Economic models have thus far focused on the *hypothetical imperative*–preferences over acts because of their consequences–rather than the *categorical imperative*–preferences over acts regardless of their consequences (Kant's axe murderer vignette)

- Agents choose between quantities (in Chicago models)
  - but do not have preferences over *choices* separate from preferences over *quantities*
- Agents choose acts (in Identity models)
  - but do not have preferences over *acts* separate from *consequences of acts*

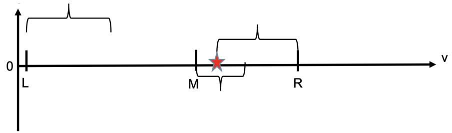
Shredding Criterion for Non-Consequentialist Motivations

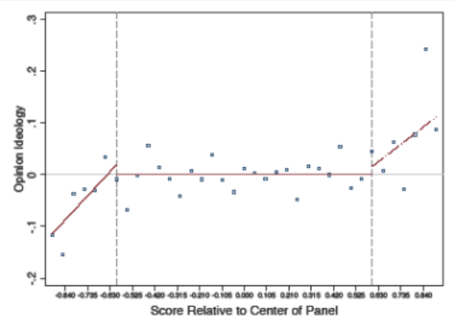


Social Preferences or Sacred Values? Chen and Schonger, in review

Do judges act to increase perceived legitimacy?

Legitimacy in Law *Chen, Michaeli, Spiro*





- How does the quest for legitimacy affect decisions (voting outcomes)?
- Accomodate moderate extremists to gain their vote

AI and Rule of Law

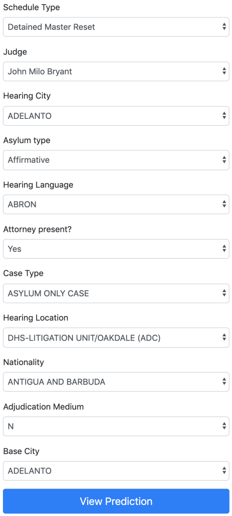
- How can AI increase fairness of law?
  - Observe bias and indifference
- How can AI increase efficiency of law?
  - Assist complex decision-making (triage and causal inference)
- Why are people resistent to AI in law?
  - Value of identity, recognition, and dignity (which AI may increase)

Ergonomic AI *Babic, Chen, Evgeniou, Fayard*

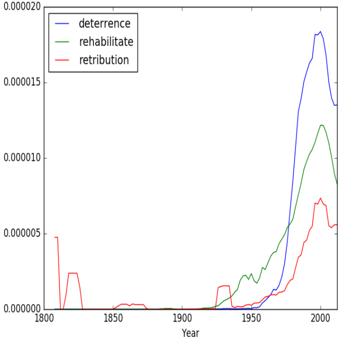
- Leverage self image motives to facilitate adoption of AI
  - Show users their predicted self
  - Compete against the self
  - Projects of self-knowledge and self-improvement *(Taylor 1989; 1992)*
- Auto-complete
  - Minimizes cognitive fatigue
  - Deviation activates Type II thinking
- Nudges
  - "pay more attention" or
  - interpretable machine learning
- Leverage social-image motives
  - Show users others' predictions

App (Screenshot)

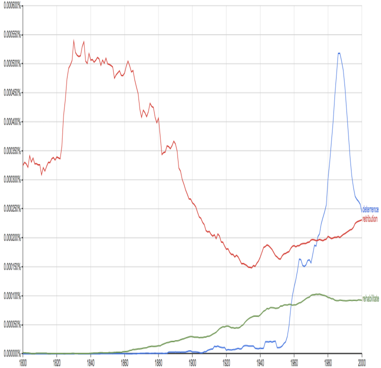
Prediction App (Beta): `https://floating-lake-11821.herokuapp.com/`



The Great Transformation mentalities changed to be more economical (*Polyani 1944*)



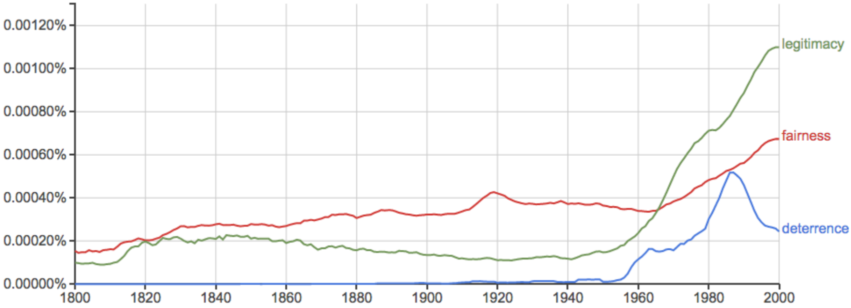
Word Frequency in State Court Opinions



Word Frequency in Google Books

Massive build-up of prisons

AI and the Next Transformation of Law?



Word Frequency in Google Books

- ~~retribution, rehabilitation,~~ deterrence, legitimacy, fairness