Can AI Help Courts be Fair and Just?

Unlocking the Positive Effects of Justice on Economic Development

Daniel L. Chen
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Roadmap

1. AI to understand, diagnose, and address injustice
2. Economic impacts of judicial state capacity
   1. Physical capital (digital infrastructure)
   2. Human capital (training)

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Judicial Analytics and Law *J of Artificial Intelligence & Law 2018*

Justice: **equal treatment before the law** $(y = f(X) + \varepsilon, a \to X)$
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, ...

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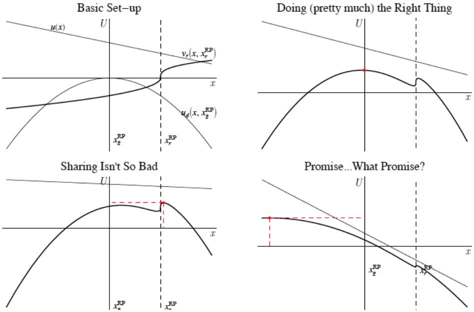
Machine Learning and Rule of Law *Computational Analysis of Law* 2018

- 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

Natural Laboratory to Study Normative Judgments

U.S. Circuit Courts

- All 380K cases, 1M judge votes, from 1891-
- 2B 8-grams, 5M citation edges across cases

U.S. District Courts

- 1M criminal sentencing decisions
- 2.5M opinions from 1923-

U.S. Supreme Court

- Speech patterns in oral arguments from 1955-
- Identical introductory sentences

U.S. Immigration Courts
Prosecutors
WW1 Courts martials
Chile, India, Kenya, Peru, Pakistan, Brazil, Croatia, Czech, Indonesia

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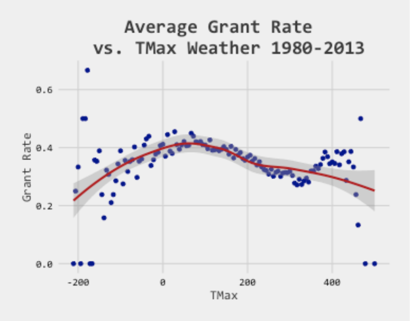
The weather

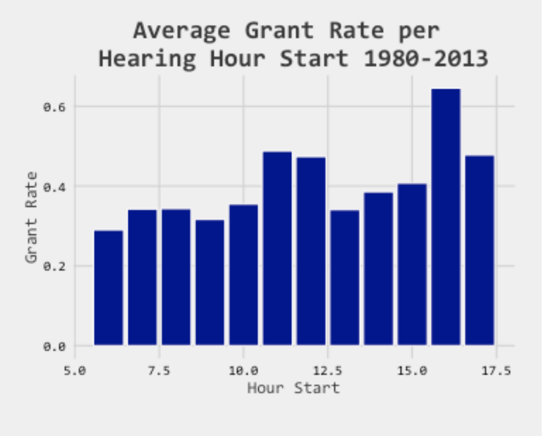
Judges deny refugees asylum when the weather is too hot or too cold



Chen and Eagel, ACM AI & Law 2017

Time of Day

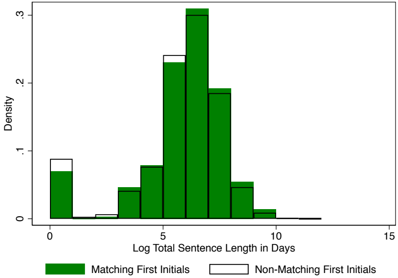
They grant asylum more before lunch and less after.



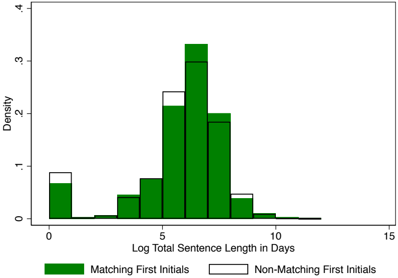
1M decisions

The defendant's name

They assign longer sentence lengths to defendants whose first initial matches their own.



First Letter of First Name



First Letter of Last Name

Kyklos 2024

The defendant's birthday

When they do the opposite and give the gift of leniency

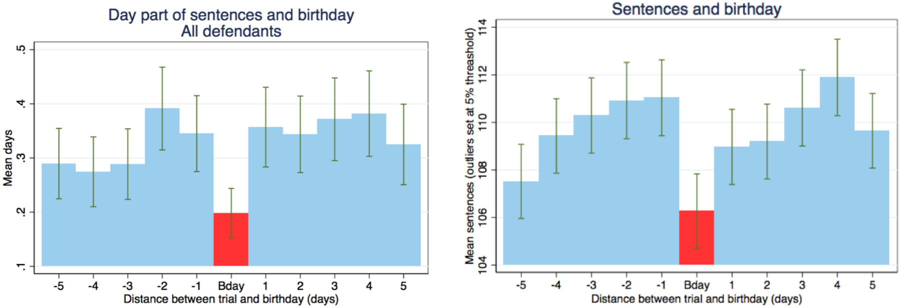
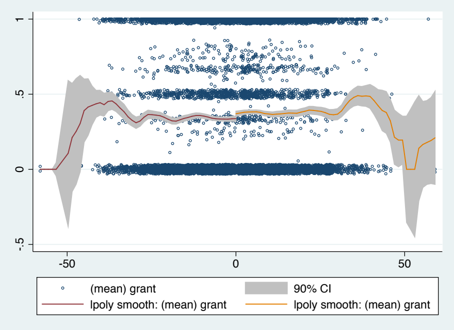


Figure: US and French judicial leniency on defendant birthdays

Chen and Philippe, J Econ Behavior & Org 2023

NFL Football

Judges are more lenient the day after their team wins, rather than loses.



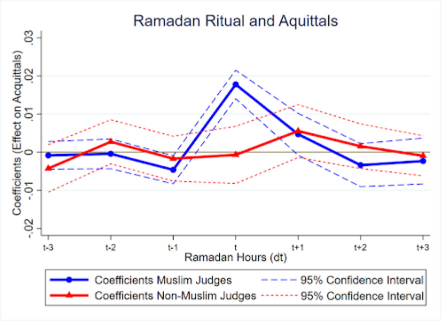
Judges Affected if Born in the Same State of NFL team

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

Ramadan

Muslim judges are more lenient the longer is Ramadan

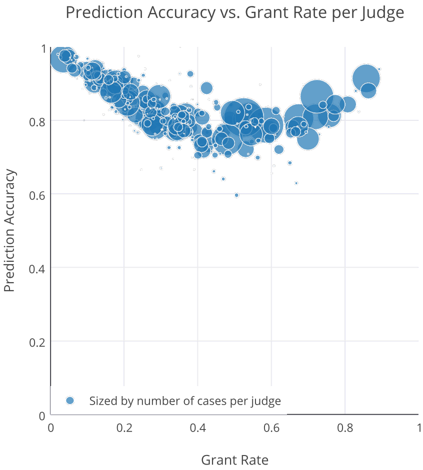


Pakistan and India

Mehmood, Seror, Chen, Nature Human Behavior 2023

Snap judgments

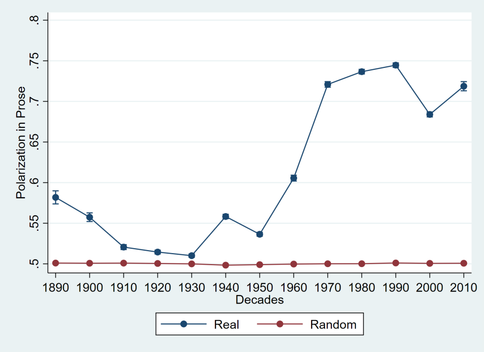
We can use machine learning to predict asylum decisions with 80% accuracy the date the case opens.. and when it closes.



Dunn, Sagun, Sirin, and Chen, ACM AI & Law 2017

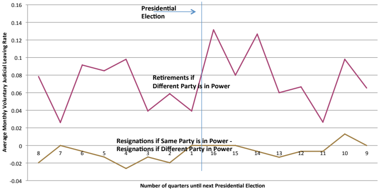
Motivated reasoning

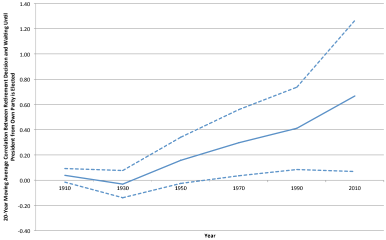
.. and predict partisan identity with 75% accuracy using judges' opinions



The Disavowal of Decisionism in American Law

and motivated decision-making reflected in the timing of exits



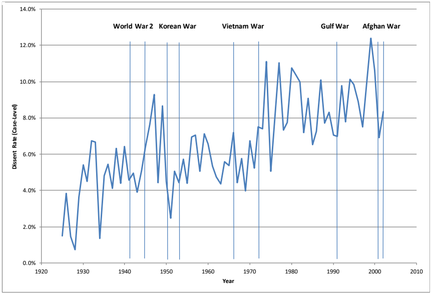


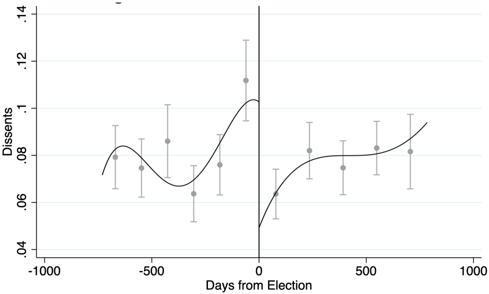
Strategic Retirements around Presidential Elections

are also Growing

Chen and Reinhart, Rev Law & Econ 2024

Wartime and elections also affect decisions





Berdejo and Chen, J Law & Econ 2017

Dissents increase during a state's primary election

	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
- U.S. Senate elections also elevate dissents, only via dissenter's state

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Priming Ideology I: Why Do Presidential Elections Affect U.S. Judges, European Econ Review, 2024

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)

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	[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)

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
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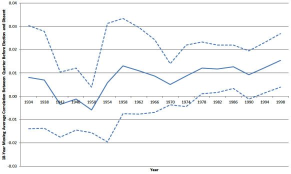
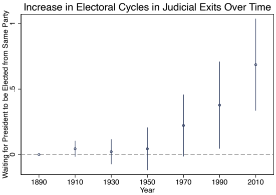
Polarization Increasingly Affect U.S. Judges

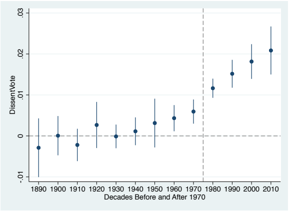
Electoral Cycles in Dissents



Strategic Retirements



Minority dissent (DRR or RDD)



Priming Ideology II, International Econ Review, R|R

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)
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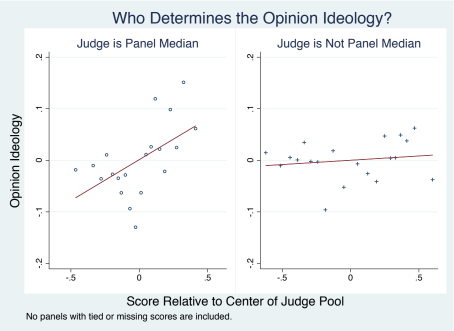
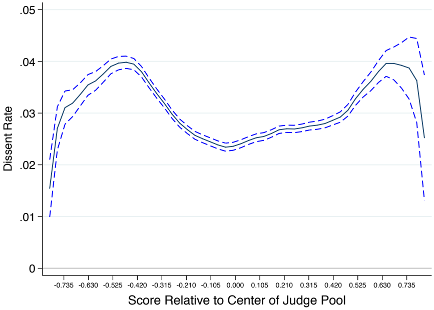
Non-Confrontational Extremists *Chen, Michaeli, Spiro, European Econ Review 2023*





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

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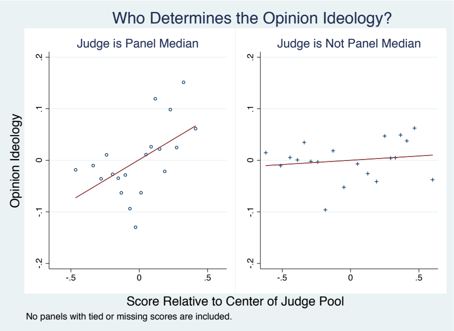

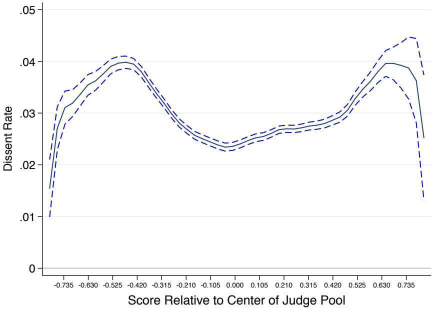

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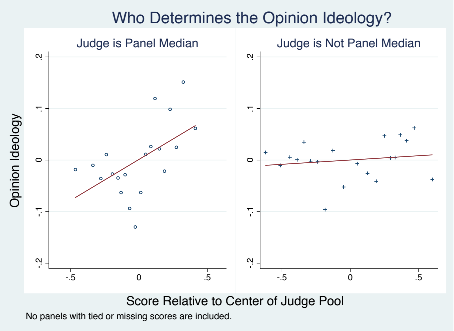

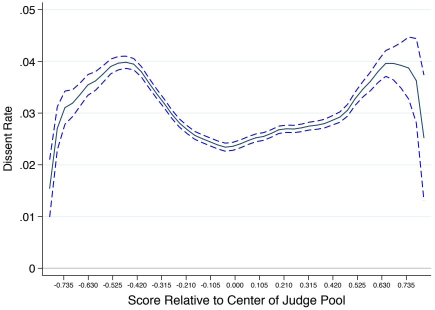

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- But extremists "cave-in" on dissents

Gambler's Fallacy

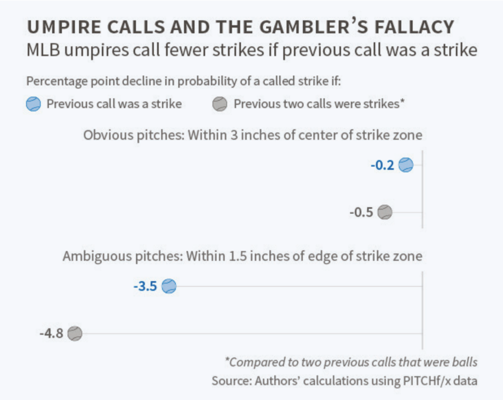
How people often imagine a sequence of coin flips:

010100101100101010011010 0

A real sequence of coin flips:

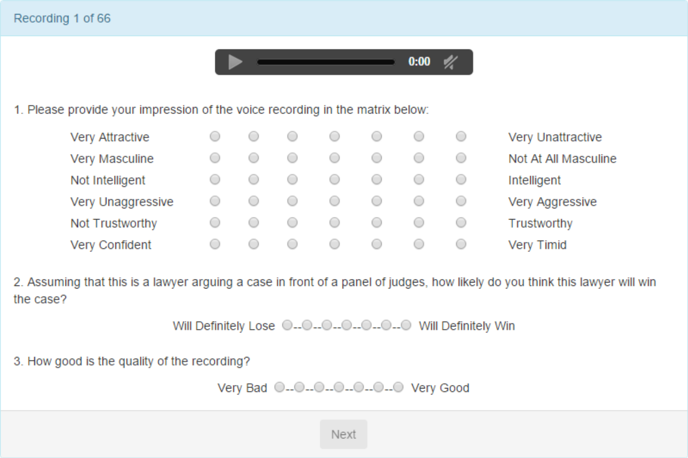
0101011111011000001001101

Up to 5% of decisions reversed due to the gambler's fallacy



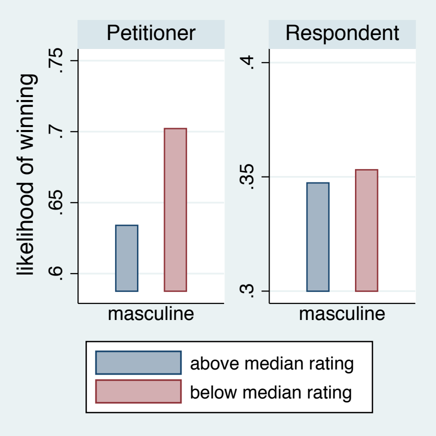
Chen, Moskowitz, and Shue, Quarterly J Econ 2016

In the US Supreme Court, the first sentence of the lawyers oral arguments are identical



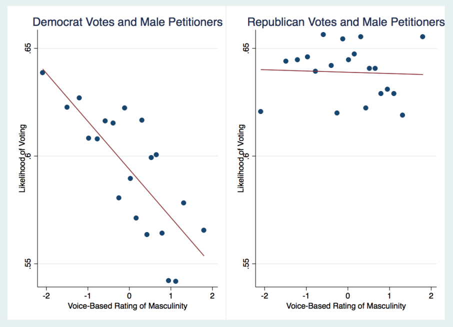
"Mr. Chief Justice, (and) may it please the Court?"

Male petitioners below median in masculinity rating are 7 percentage points more likely to win



Chen, Halberstam, and Yu, Plos-ONE 2016

Democrats vote against masculine-sounding lawyers



Profit-maximizing firms would tend to erode this correlation

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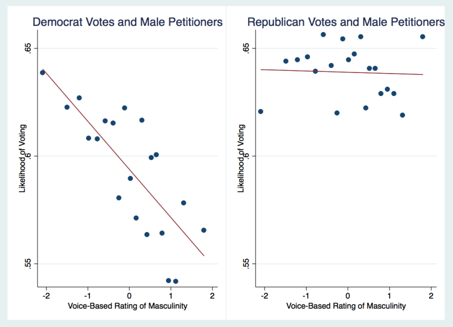

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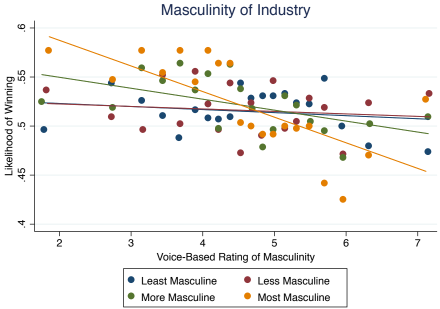
Negative correlation is stronger in more masculine industries



consistent with their perceiving masculine-sounding lawyers as winners

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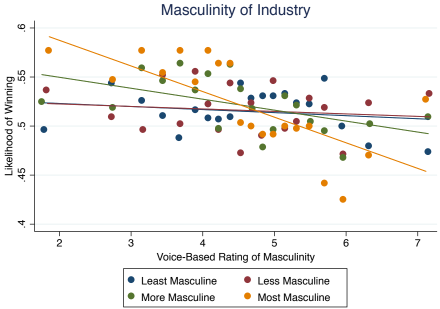

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De-Biasing Experiment Reduces Misbeliefs

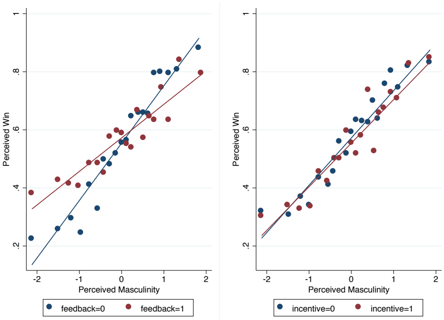

Figure: Feedback ($p < 0.01$), Incentives

Incentives Further Erodes Misbeliefs

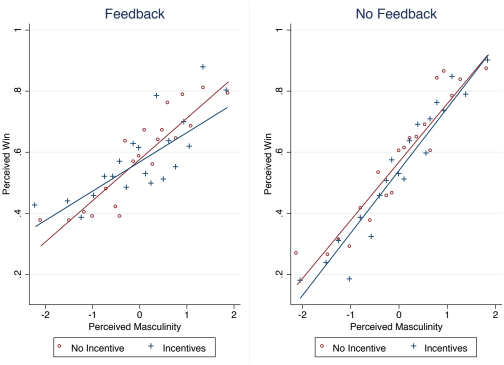

Figure: Incentives ($p < 0.05$) with Feedback

identifying a taste for masculine-sounding lawyers

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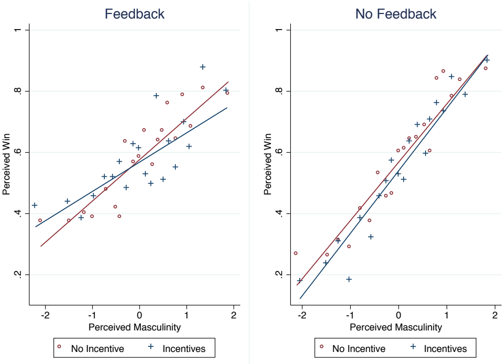

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Gender

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

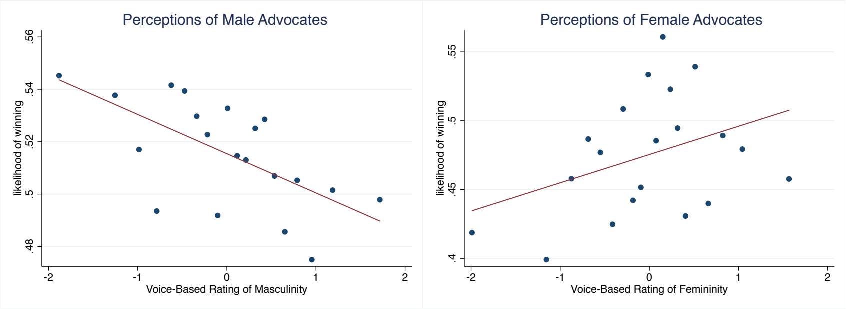

Figure: Extends: Less masculine males and more feminine females ↑win

- masculine = - feminine

Robust to Lawyer Characteristics and the Best ML Prediction 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

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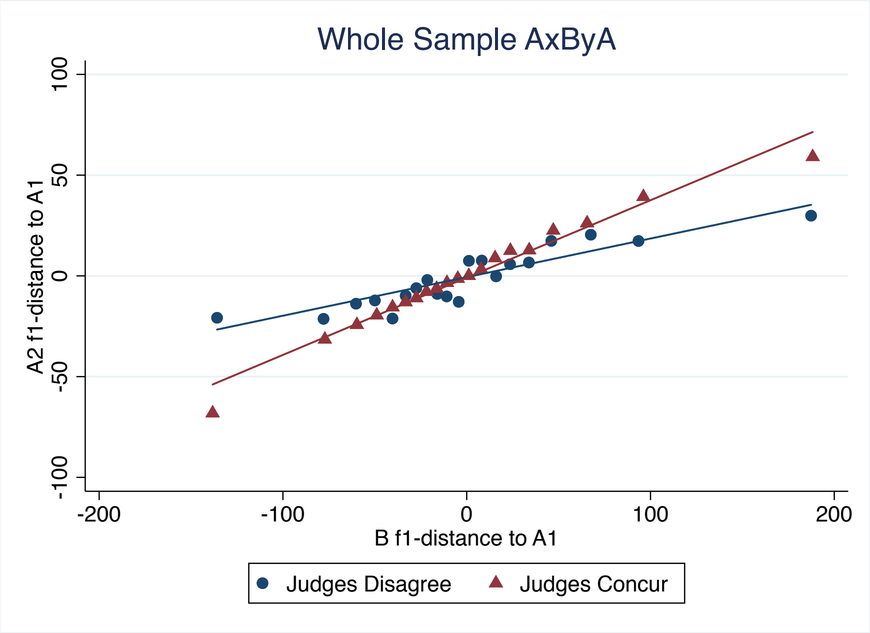
Speaking convergence predicts decisions



.. and winning lawyers

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)

Figure: Convergence predicts winning lawyer

Besides voice, there is text

- Google translate
  - "he/she is a doctor" (turkish) -> "he is a doctor" (english)
  - "he/she is a nurse" (turkish) -> "she is a nurse" (english)
- A truck driver should plan his route carefully.
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"Attitudes that affect our understanding, actions, and decisions in an unconscious manner" Implicit bias (Kirnan institute OSU)

- Does implicit bias exist?
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- Does it affect real-world decisions?
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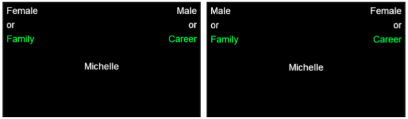
- Subjects asked to assign words to categories



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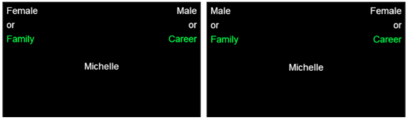

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Challenges of studying implicit attitudes

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  - Sunstein et al. 2006, Boyd, Epstein, and Martin 2010, Kastellec 2013, Glynn and Sen 2015
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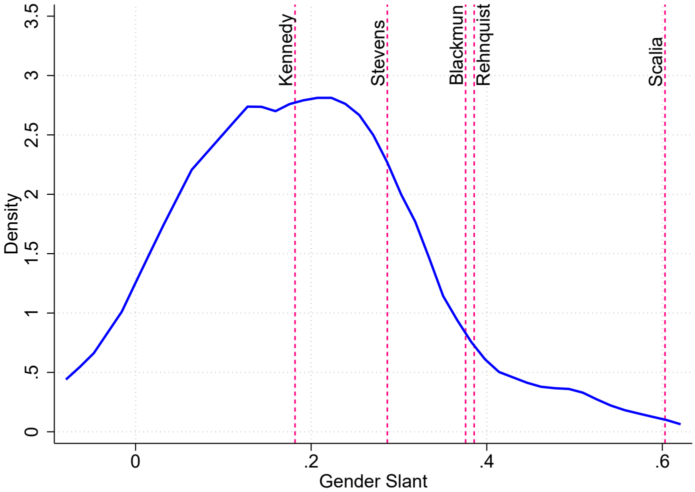
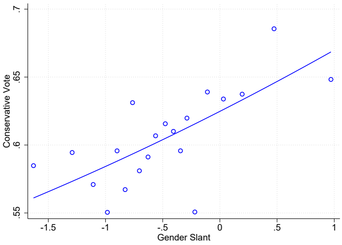
We can do this judge by judge

Justice Scalia is an outlier in gender slant

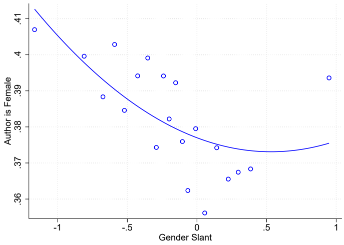


In the Circuit Courts, judges with more gender slant..

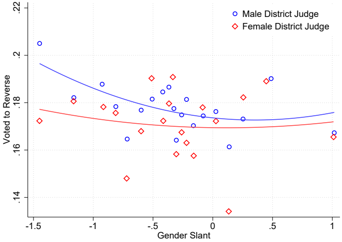
Vote against women's rights issues



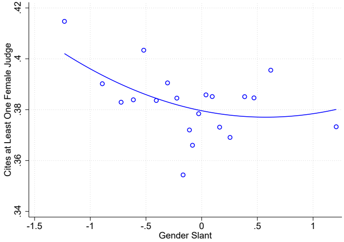
Assign fewer opinions for females to author



Reverse male judges less often



Cite female judges less often



Ash, Chen, and Ornaghi, American Econ J: Applied 2024

Daughters Reduce Gender Slant

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

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

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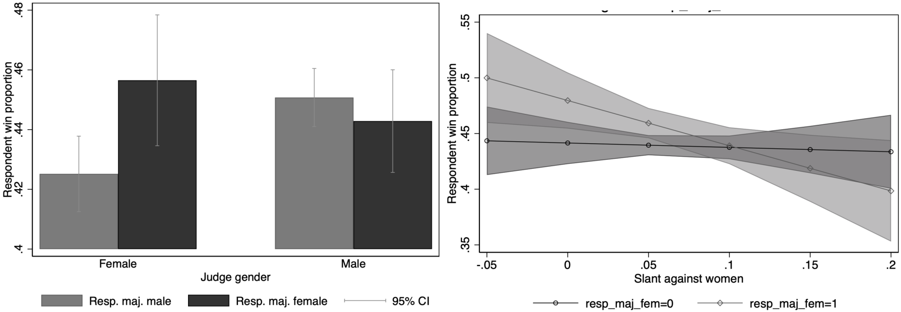
Prejudice in Practice

The results extend to Kenya: Judges favor defendants of their own ethnicity and gender



ruling against women when they exhibit stereotypical gender writing biases

India In-Group Bias

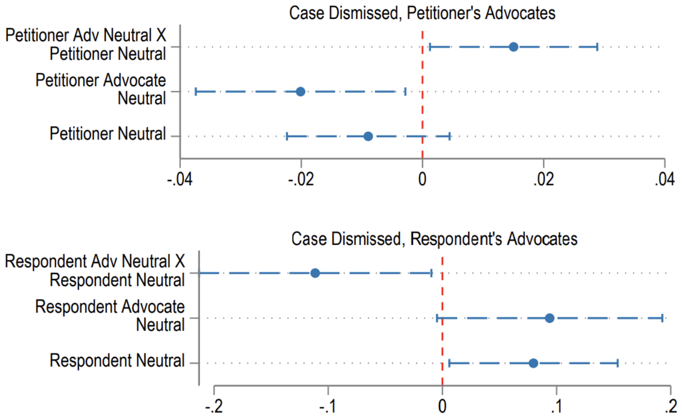
Judges favor defendants who share their last name

	Acquitted	
	(1)	(2)
Same Last Name	0.0176**	-0.0010
	(0.0083)	(0.0045)
Same Last Name * Rare Name		0.0398**
		(0.0176)
N	2142697	2142697
Court-Year FE	Y	Y
Judge FE	Y	Y
Charge FE	Y	Y
Last Name FE	Y	Y

Ash, Asher, Bhowmick, Bhupatiraju, Chen, Devi, Goessmann, Novosad, Siddiqi, Review Econ Stat 2024

Caste Aside?

Exacerbating the disadvantages that low-caste litigants face



Five Ways for ML to Diagnose Judicial Inattention

1. Early predictability
2. Behavioral anomalies
3. Inattentiveness to appellate reversals
4. Implicit risk rankings of asylees closer to random
5. Is indifference greater for some refugees (e.g., from Global South)?

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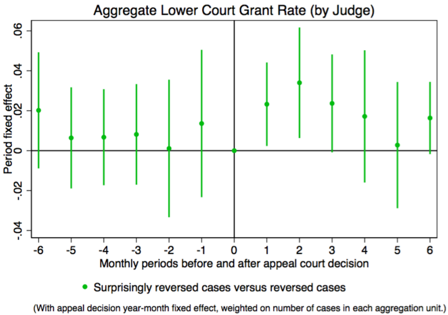
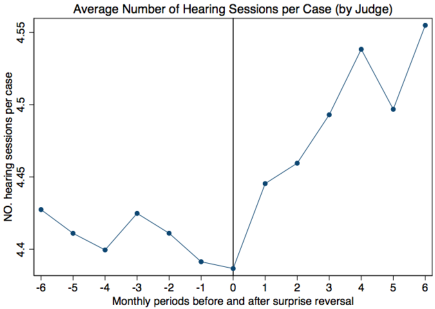
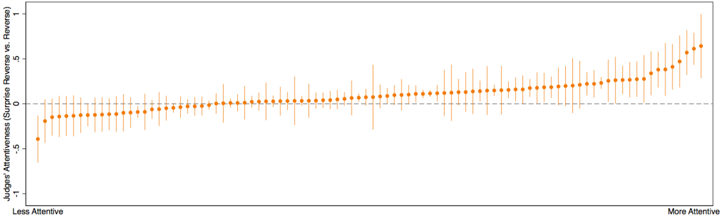
After "Surprise" Reversals, Judges Grant More Asylum and Hold More Hearing Sessions

Surprise Reversal is a reversal of a decision that was predicted to be "Affirm"





Judges Vary in Responsiveness to Reversal



Notes: Time window: 3 monthly periods pooled together before/after a shock.

Do less attentive judges have implicit risk rankings closer to random?

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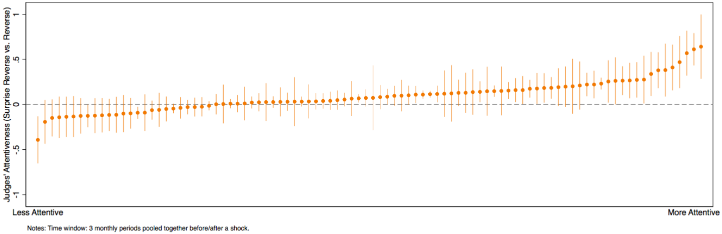

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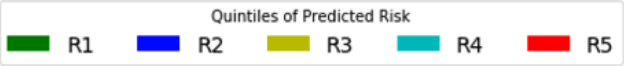
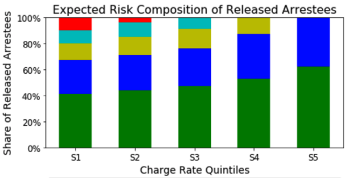


Robot Prosecutors



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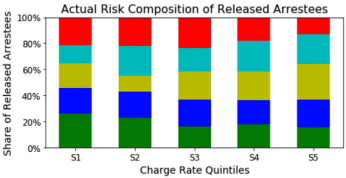
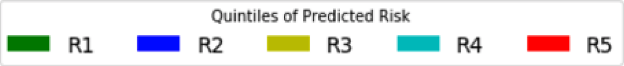
Human Prosecutors



- Distribution of risk scores for released defendants is similar for most lenient and least lenient prosecutors.

- Are the lenient asylum judges, only denying the 'riskiest' applicants
  - i.e., seeing the lowest reversal rates (of their asylum denials)?

See also *Kleinberg, Lakkaraju, Leskovec, Ludwig, Mullainathan, Quarterly J Econ 2017*



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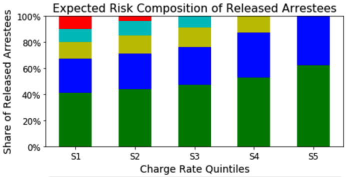

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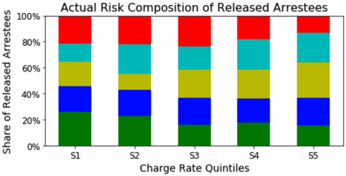

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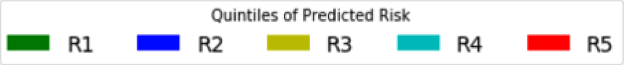

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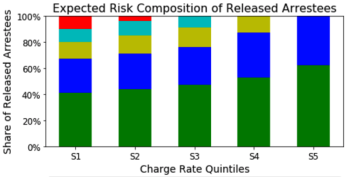

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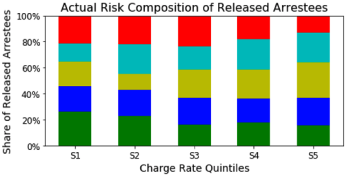

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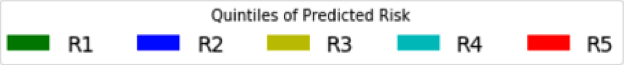

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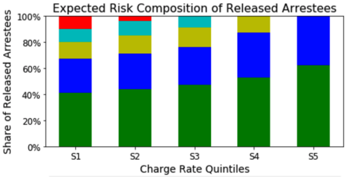

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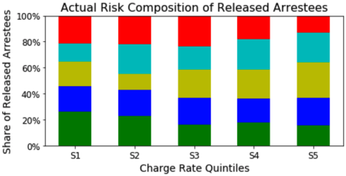

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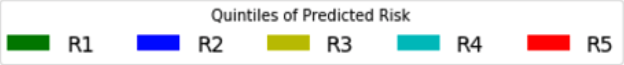

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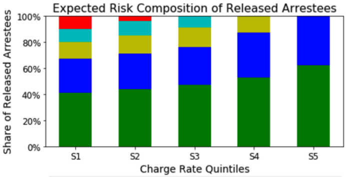

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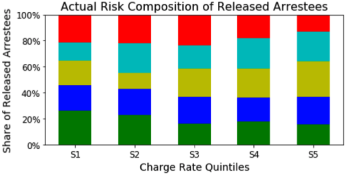

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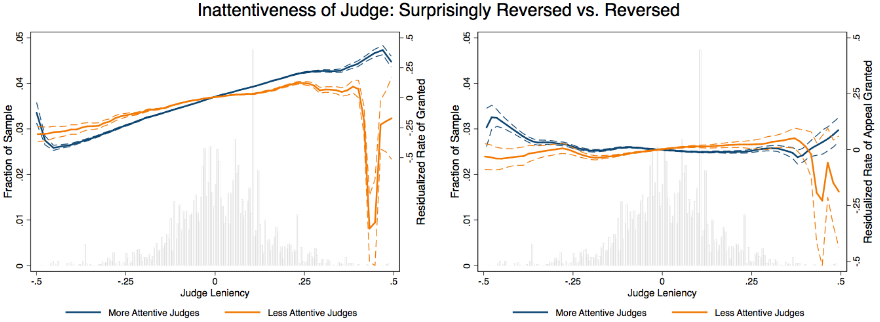
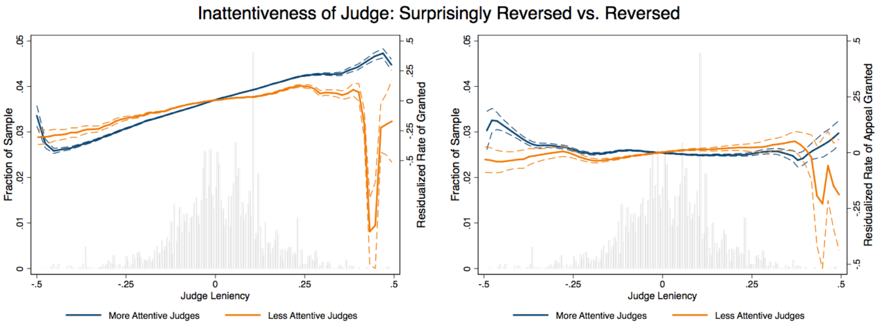
Left Figure: Judges have strong habits

A judge who is generally lenient in other cases is likely to be lenient in a given case



(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)

Right Figure: Assess implicit risk ranking



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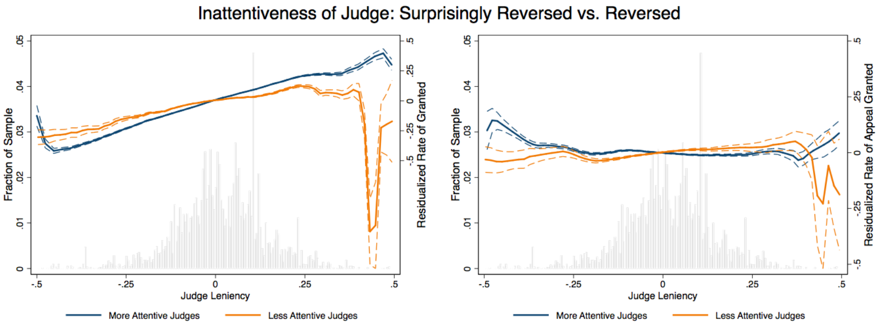
If judges are 'ordering' their asylees, the most lenient judge letting in the most applicants should be rejecting only the "least safe" applicants

Their appeal success should be lower, which we see among more attentive judges

Right Figure: Assess implicit risk ranking

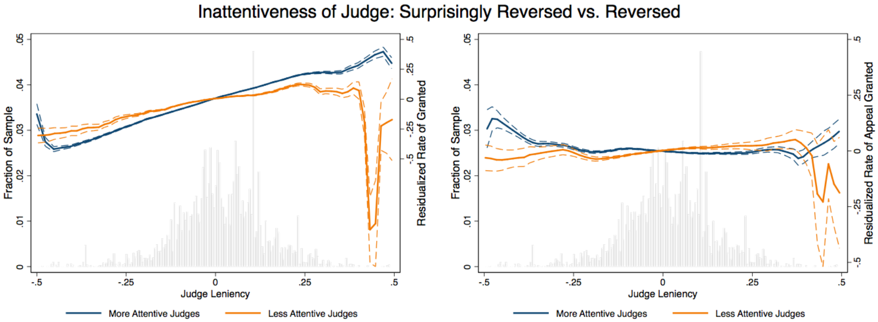


(Time window: 3 monthly periods pooled together before/after shock. More attentiveness: the coefficient of interaction of surprisingly reversed dummy and time-period dummy is bigger)

If judges are 'ordering' their asylees, the most lenient judge letting in the most applicants should be rejecting only the "least safe" applicants

Their appeal success should be lower, which we see among more attentive judges

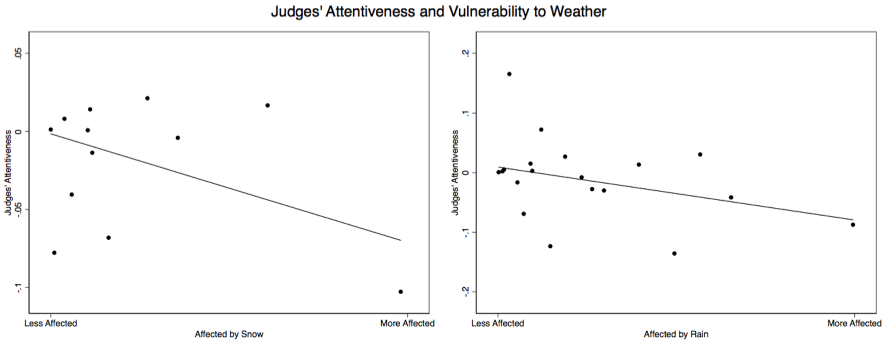
.. but not less attentive judges



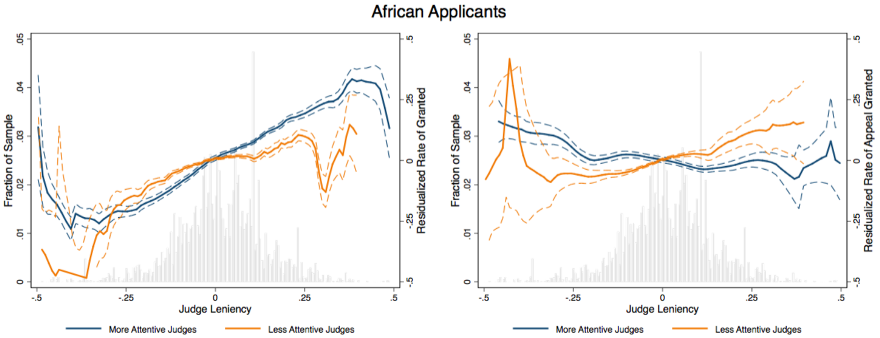
(Time window: 3 monthly periods pooled together before/after shock. More attentiveness: the coefficient of interaction of surprisingly reversed dummy and time-period dummy is bigger)

.. who may be more prone to other extraneous factors

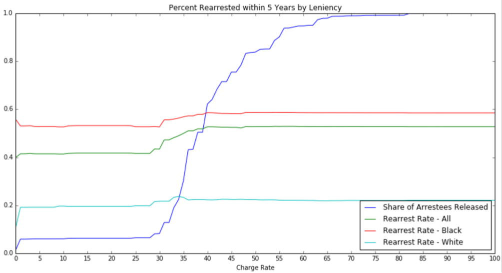
.. such as weather

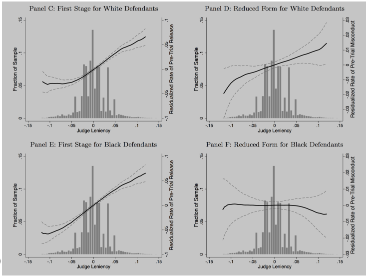


Difference in Indifference for asylees from the Global South



Using ML to Understand how Screeners Screen





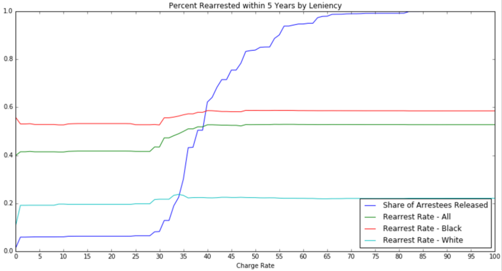
Actually, flat for Whites, *upward* slope for Blacks (left)

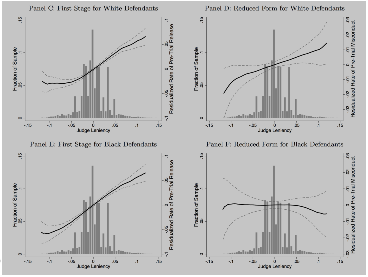
Algorithms as Prosecutors: Identifying Characteristics Noisy to Human Prosecutors

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

in *Arnold, Dobbie, Yang, Quarterly J Econ 2017*

Using ML to Understand how Screeners Screen





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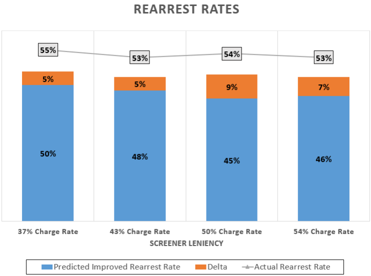
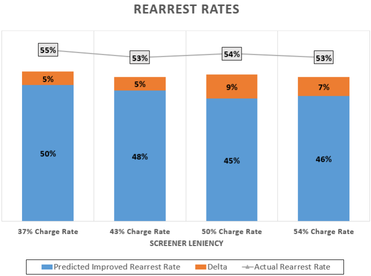
Potential Reduction in Rearrest from Using ML



- Racial disparities did not increase with the model
  - Consistent with "wrong" slope for Black defendants

WHY "WRONG DIAGONAL" FOR BLACK DEFENDANTS?

Potential Reduction in Rearrest from Using ML



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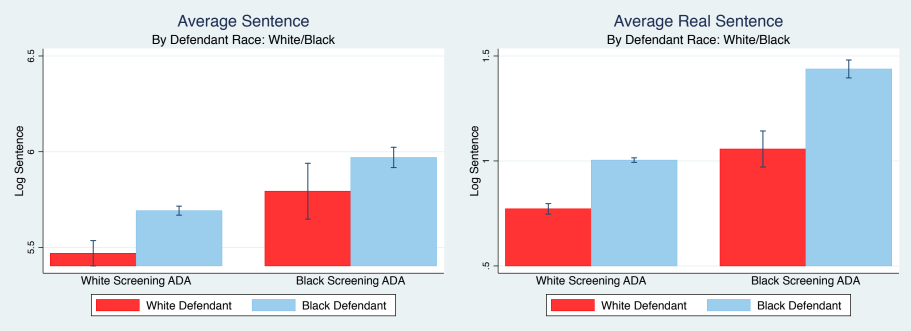
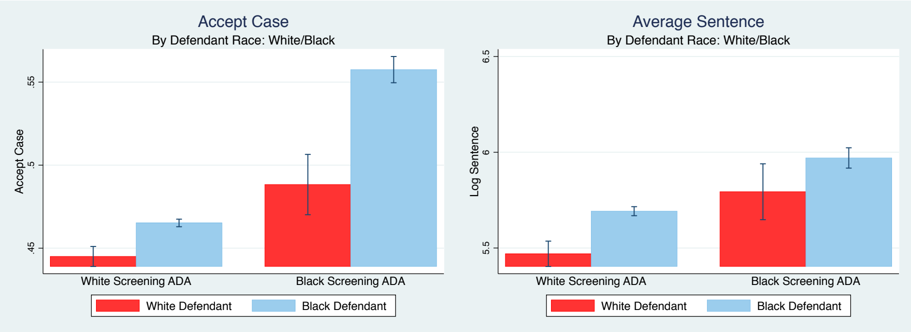
WHY "WRONG DIAGONAL" FOR BLACK DEFENDANTS?

1. Screening Increases Racial Sentencing Gap



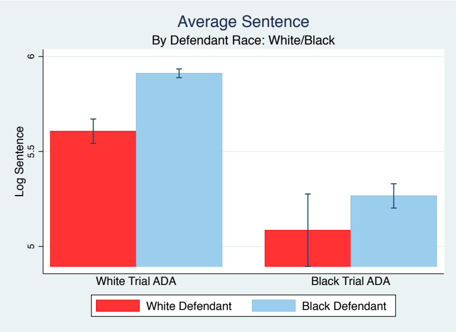
- Since black defendants are less likely to be declined, "real" racial disparity magnifies (on right)
  - Is statistical discrimination the reason for disparate screening?

2. White Prosecutors Screen-In Fewer Cases that result in Shorter Sentences



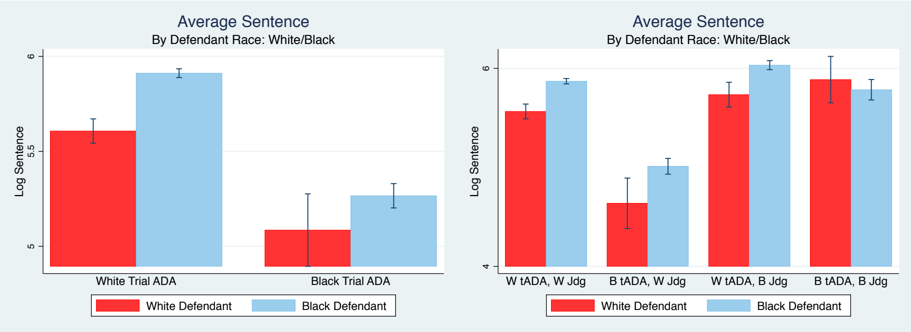
- White and black screeners let in different cases
  - If targeting the most severe ones, white screener cases should have *longer* sentences

3. White Trial Prosecutors Obtain Longer Sentences



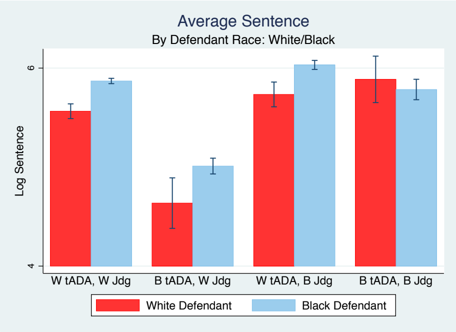
- Most District Attorneys are elected; want to appear tough-on-crime (Pfaff 2016)
- Why are white trial prosecutors more effective in this goal?

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 (on right) render similar average sentences as White trial prosecutors do

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



- Hard to explain as statistical discrimination

Revealed Preference Indifference

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

- Name letter effects appear only for African Americans labeled "Negro" and not for "Black"
  - robust to controls for skin, hair, eye color
  - highlights the potential for labels to increase recognition and respect

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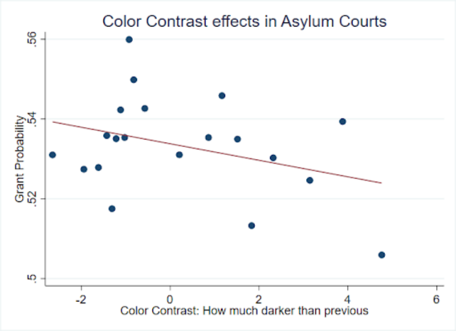
Relativity of Racial Perception

Judges deny refugees asylum, the darker the applicant's skin tone is relative to that of the prior applicant



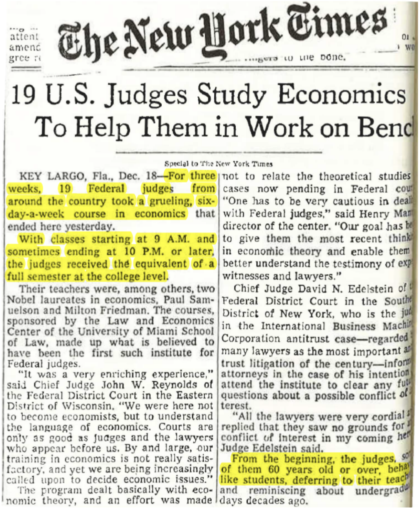
See also *Ludwig and Mullainathan, Quarterly J Econ 2024*

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

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



The New York Times

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

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."

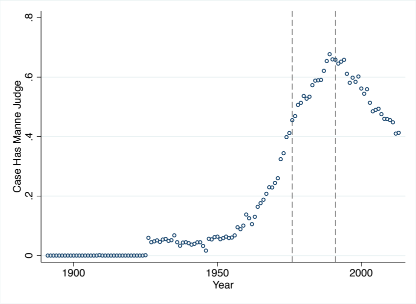
The program dealt basically with economic theory, and an effort was made not to relate the theoretical studies to cases now pending in Federal cou

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

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

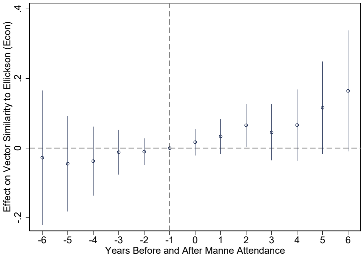
"All the lawyers were very cordial replied that they saw no grounds for conflict of interest in my coming her Judge Edelstein said.

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



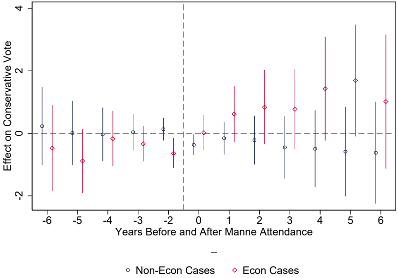
The results of these seminars were dramatic

We can see economics language used in academic articles became prevalent in opinions.

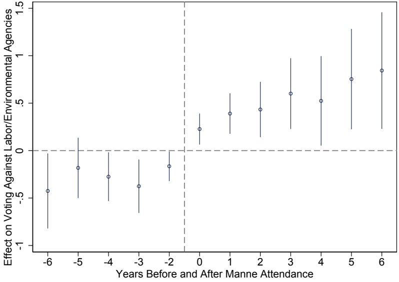


The results of these seminars were dramatic

We can see economics trained judges changing how they decided



Econ vs Non-Economics Cases



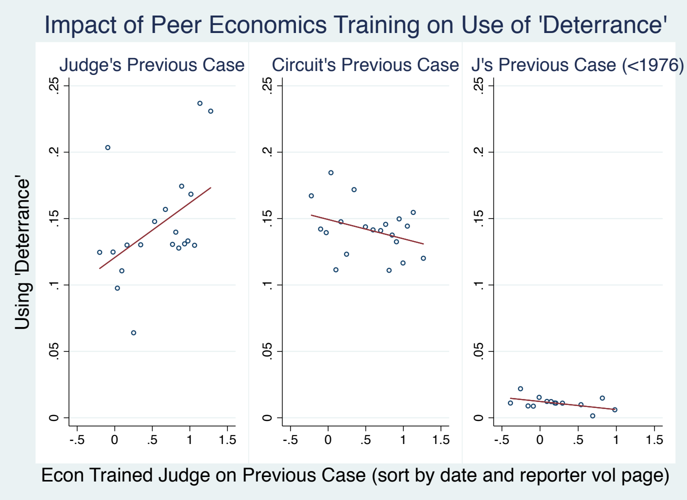
on Labor/Environmental Cases

Peer Impacts on Never-Attenders

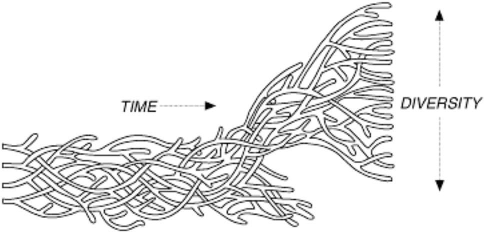
	Ellickson Average	
	(1)	(2)
Econ Case	0.0300***	0.0294***
	(0.00524)	(0.00249)
Post-Manne	**0.0141****	
	(0.00630)	
Econ Case *	0.00170	
Post-Manne	(0.00919)	
Econ Training on	-0.00559	**0.00513***
Previous Case	(0.0106)	**(0.00292)**
N	143144	486673
adj. R-sq	0.042	0.042
Circuit-Year FE	X	X
Judge FE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

Impacting their peers

We can see economic language traveling from one judge to another and across legal areas.



The Geneology of Ideology



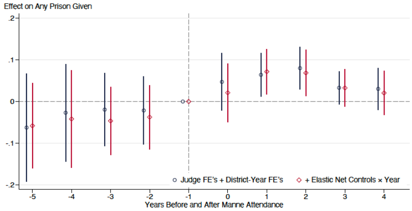
$$P_m = \frac{d_{m\rightarrow m}}{d_{\rightarrow m} + \delta} \Big/ \frac{d_{m\rightarrow \cancel{m}} + \delta}{d_{\rightarrow \cancel{m}} + \delta}$$

Scoring Memetic Phrases

Varma, Parthasarathy, and Chen, ACM AI & Law 2017

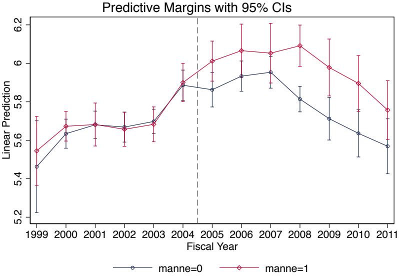
Impacting sentencing

economics trained judges became harsher to criminal defendants



When judges were given discretion in sentencing

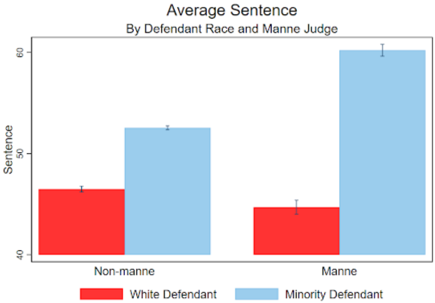
economics trained judges immediately rendered 20% longer sentences relative to the non-economics counterparts.



Ash, Chen, and Naidu, Quarterly J Econ R/R

The Prejudices of Economic Ideology

Economics trained judges are harsher to blacks



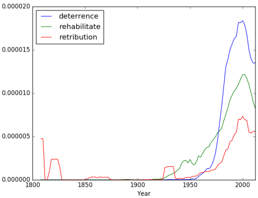
even controlling for political party

Half the magnitude of ingroup bias, which reduces gap by one-third

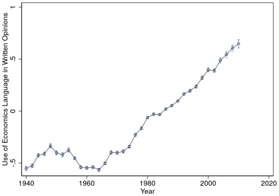
Chen, Nagarathinam, and Reinhart

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

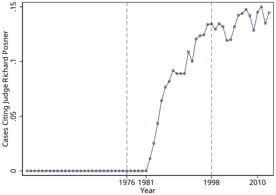
Word Frequency in Opinions



Economics style

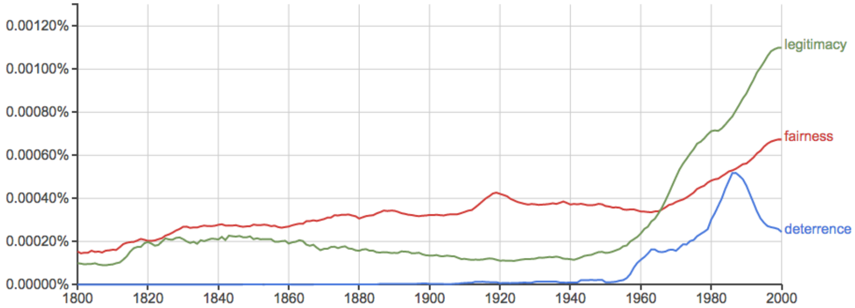


Citation to Richard Posner



◂ Massive build-up of prisons

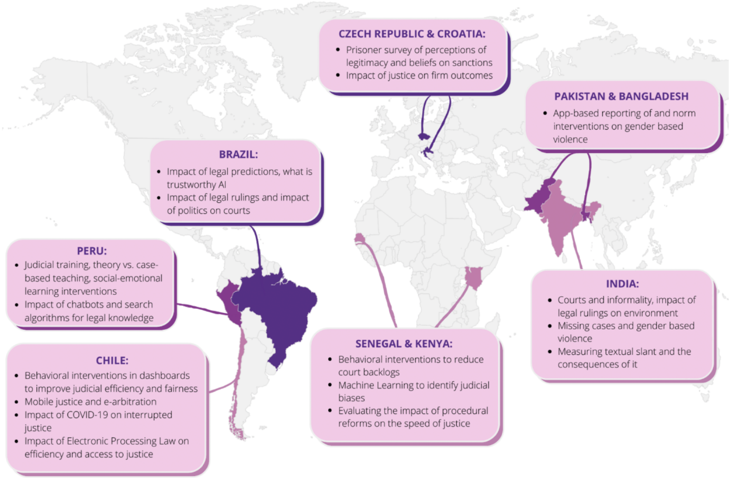
AI and the Next Transformation of Law?



Word Frequency in Google Books

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

AMICUS (Analytical Metrics for Informed Courtroom Understanding & Strategy)

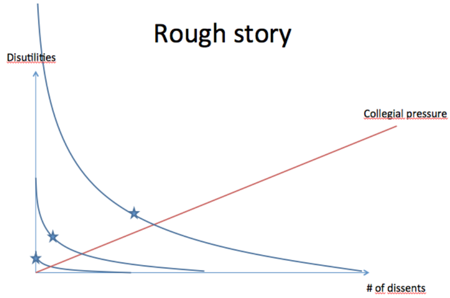


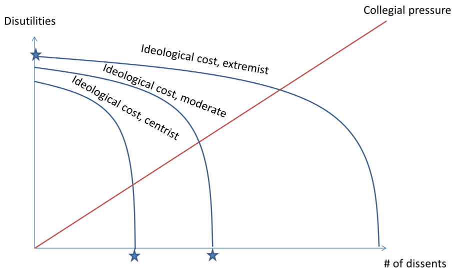
We run law and development RCTs through relationships with government partners who link legal cases to downstream effects for individuals and firms.

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)

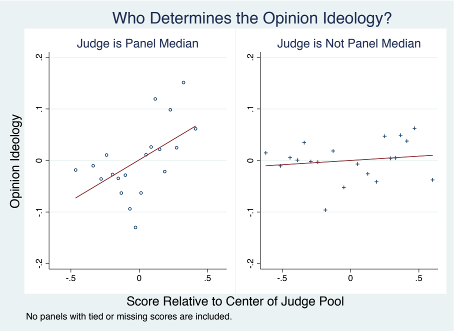
Judicial Perfectionism

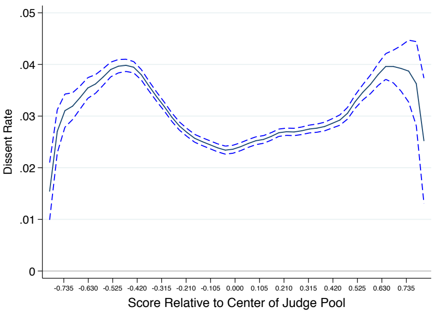




- Convex costs render a bowl shape in dissents
- Concave costs render cave-in on dissents and votes

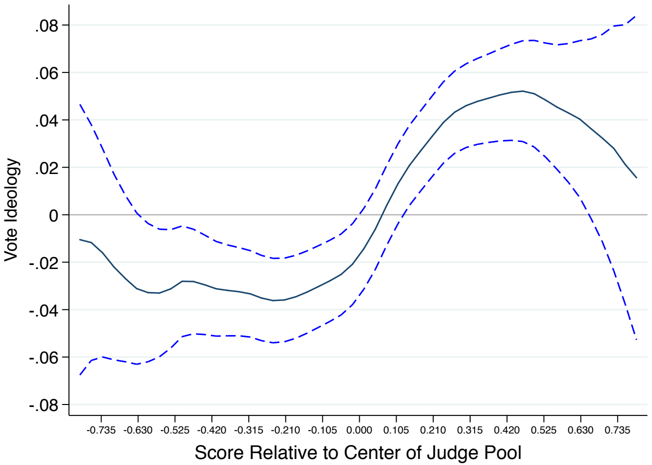
Non-Confrontational Extremists *Chen, Michaeli, Spiro, European Econ Review 2023*





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

Extremists Cave-In in Vote Ideology



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

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

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    - "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)

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