Can AI Help Courts be Fair and Just?

Unlocking the Positive Effects of Justice on Economic Development

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Radcliffe Institute for Advanced Study at Harvard

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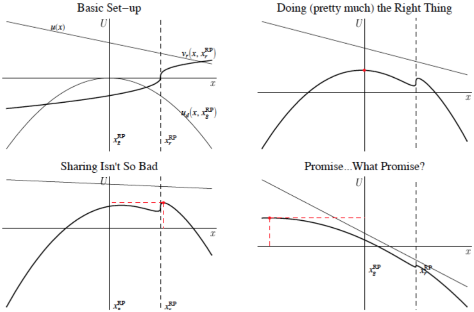
Machine Learning and Rule of Law *Computational Analysis of Law* 2018

- 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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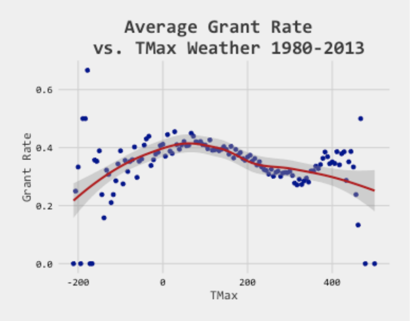
The weather

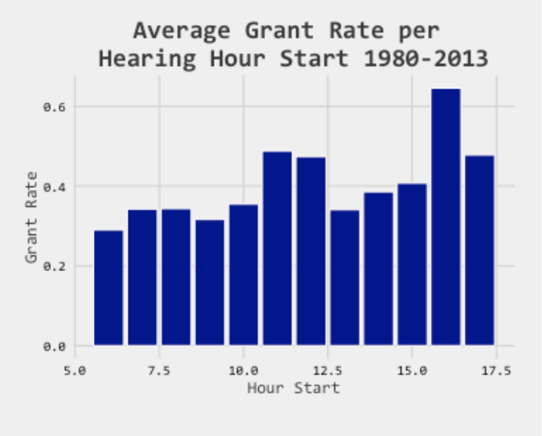
Judges deny refugees asylum when the weather is too hot or too cold



Chen and Eagel, ACM AI & Law 2017

Time of Day

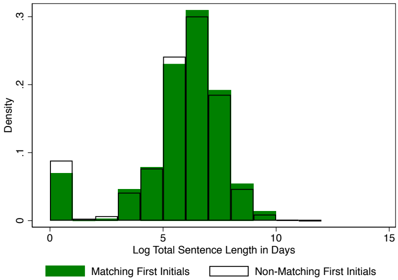
They grant asylum more before lunch and less after.



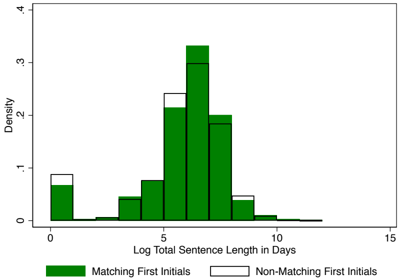
1M decisions

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

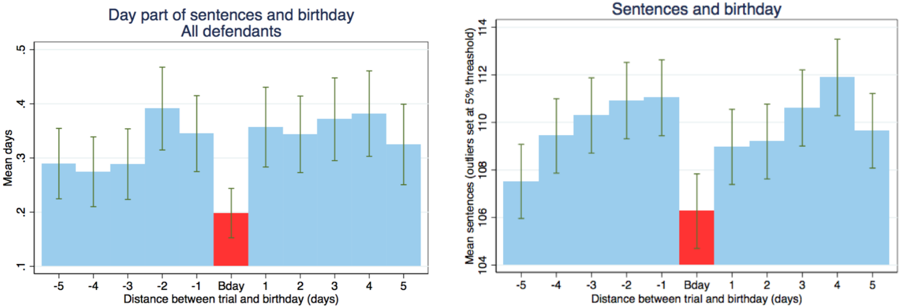
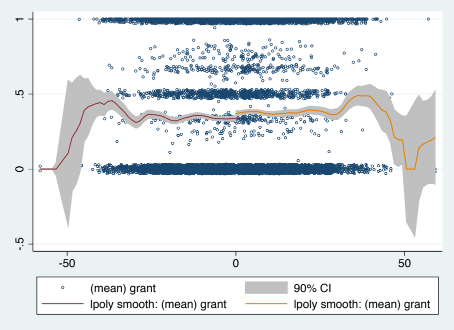


Figure: US and French judicial leniency on defendant birthdays

Chen and Philippe, J Econ Behavior & Org 2023

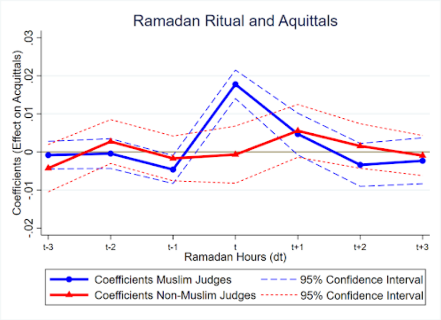
NFL Football

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



Ramadan

Muslim judges are more lenient the longer is Ramadan

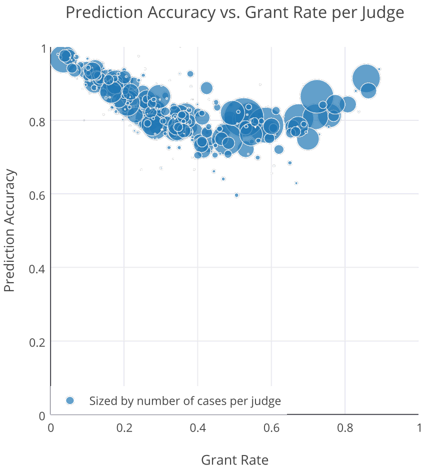


Pakistan and India

Mehmood, Seror, Chen, Nature Human Behavior 2023

Snap judgments

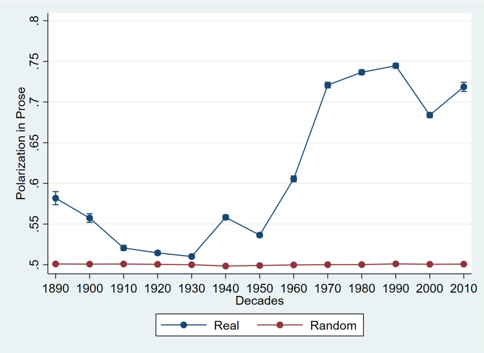
We can use machine learning to predict asylum decisions with 80% accuracy the date the case opens.. and when it closes.



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

Motivated reasoning

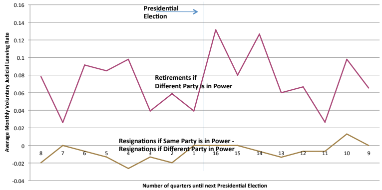
.. and predict partisan identity with 75% accuracy using judges' opinions

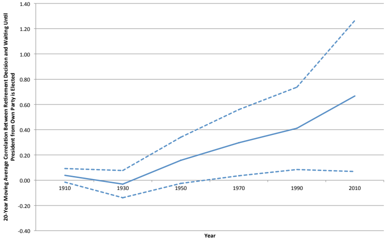


Lu and Chen, Plos-ONE R&R

The Disavowal of Decisionism in American Law

and motivated decision-making reflected in the timing of exits

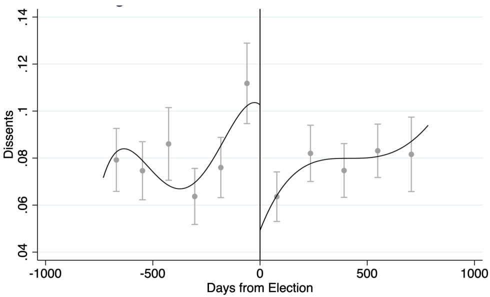


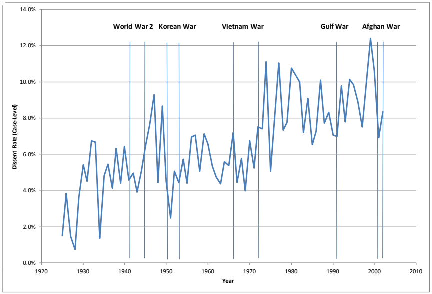


Strategic Retirements around Presidential Elections are also Growing

Chen and Reinhart, Rev Law & Econ 2024

Elections and wartime also affect decisions





Berdejo and Chen, J Law & Econ 2017

Gambler's Fallacy

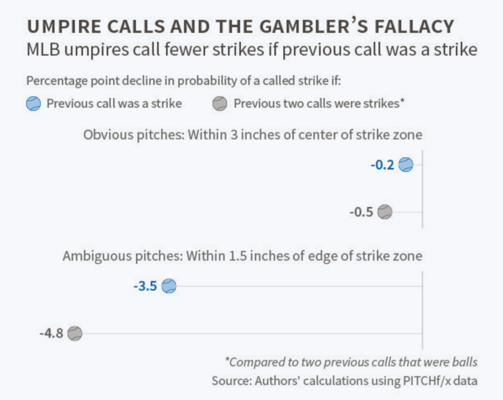
How people often imagine a sequence of coin flips:

0101001011001010100110100

A real sequence of coin flips:

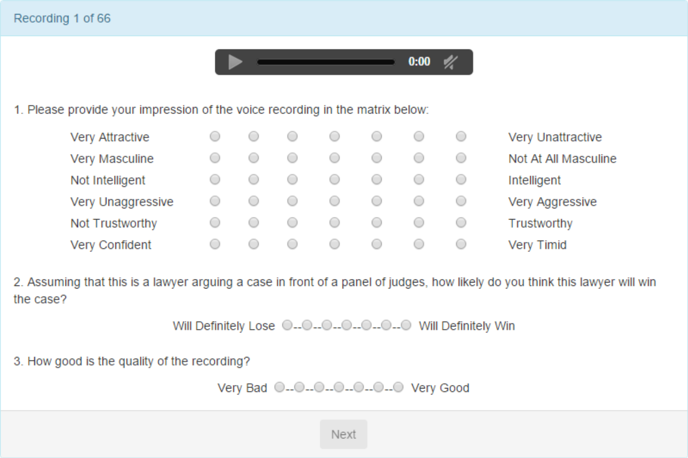
0101011111011000001001101

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


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

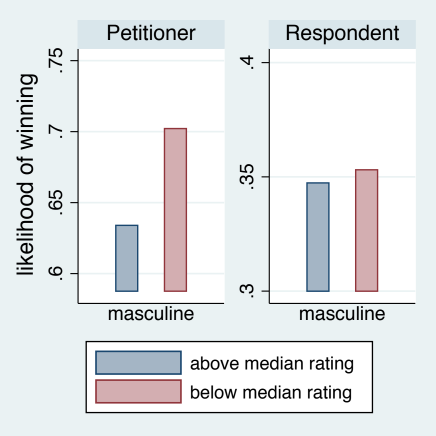
3. How good is the quality of the recording?

Very Bad — Very Good

Next

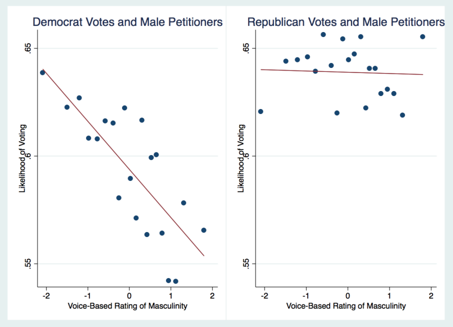
"Mr. Chief Justice, (and) may it please the Court?"

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



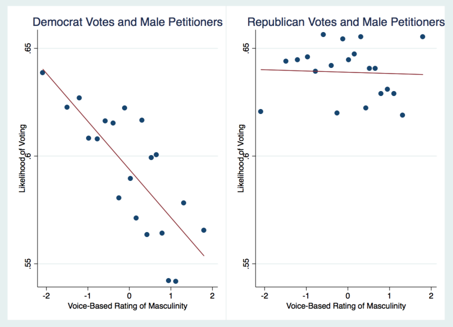
Chen, Halberstam, and Yu, Plos-ONE 2016

Democrats vote against masculine-sounding lawyers



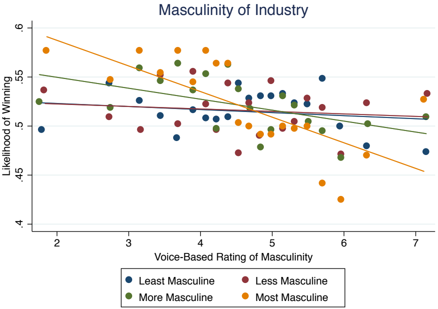
Profit-maximizing firms would tend to erode this correlation

Democrats vote against masculine-sounding lawyers



Profit-maximizing firms would tend to erode this correlation

Negative correlation is stronger in more masculine industries



consistent with their perceiving masculine-sounding lawyers as winners

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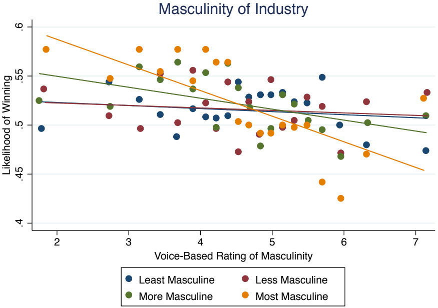

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De-Biasing Experiment Reduces Misbeliefs

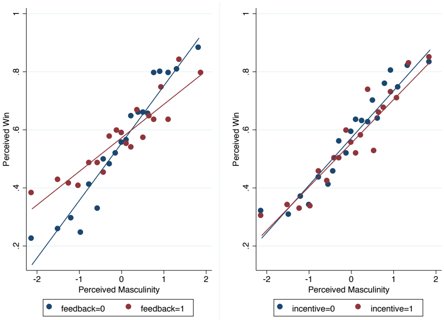

Figure: Feedback ($p < 0.01$), Incentives

Incentives Further Erodes Misbeliefs

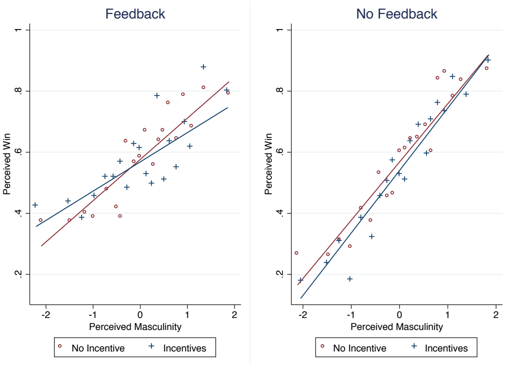

Figure: Incentives ($p < 0.05$) with Feedback

identifying a taste for masculine-sounding lawyers

Incentives Further Erodes Misbeliefs

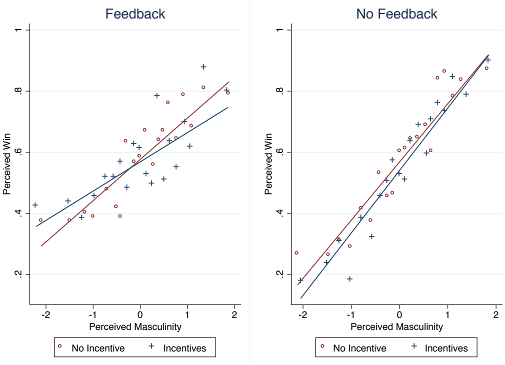

Figure: Incentives ($p < 0.05$) with Feedback

identifying a taste for masculine-sounding lawyers

Gender

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

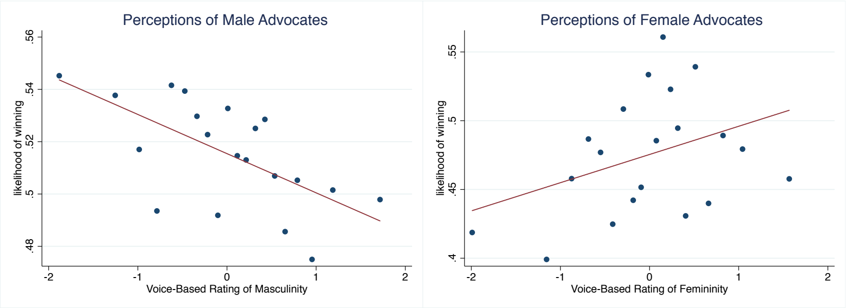

Figure: Extends: Less masculine males and more feminine females ↑win

- 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

- Random forest also selects perceptions

Besides voice, there is text

- Females: Migraine, hysterical, morbid, obese, terrified, unemancipated, battered
- Males: Reserve, industrial, honorable, commanding, conscientious, duty

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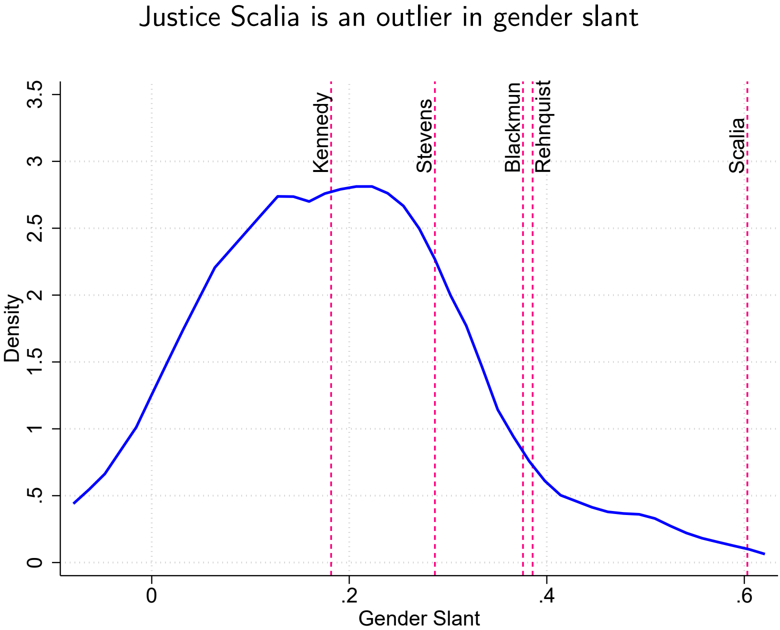
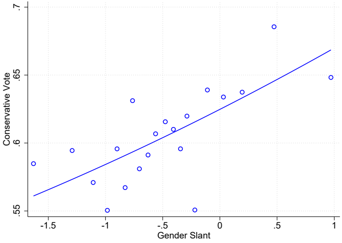
We can do this judge by judge

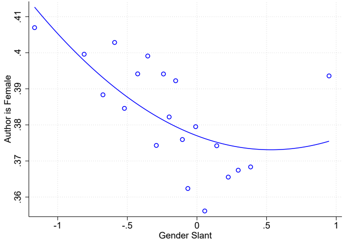


In the Circuit Courts, judges with more gender slant..

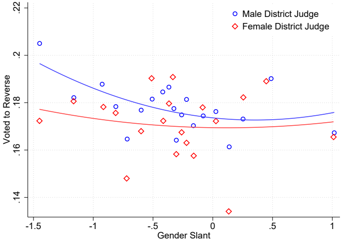
Vote against women's rights issues



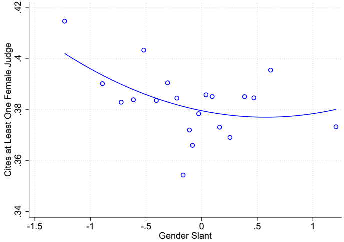
Assign fewer opinions for females to author



Reverse male judges less often



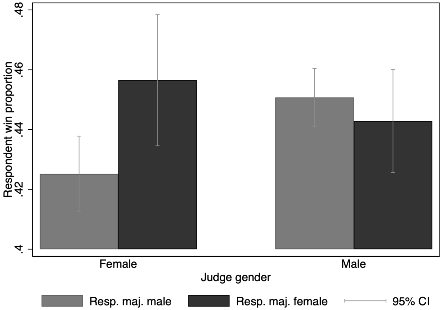
Cite female judges less often

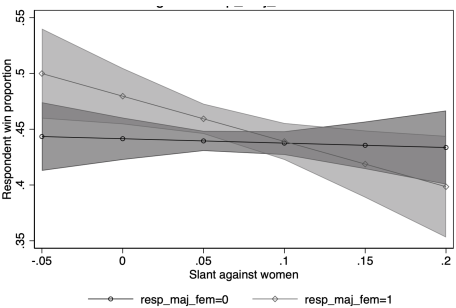


Ash, Chen, and Ornaghi, American Econ J: Applied 2024

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

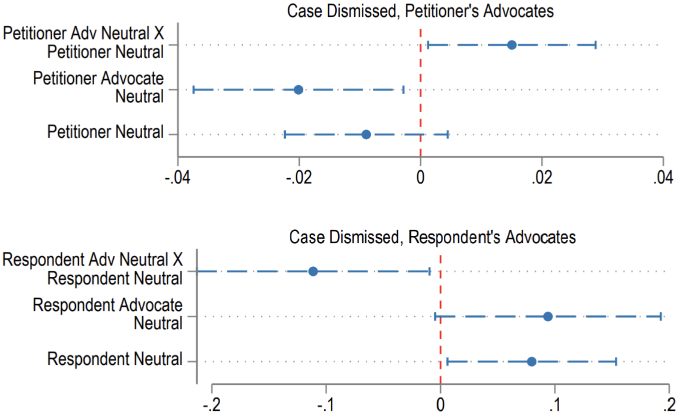
Judges favor defendants who share their last name

	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



Bhupatiraju, Chen, Joshi, Neis, European J Empirical Legal Studies R&R

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)?

Five Ways for ML to Diagnose Judicial Inattention

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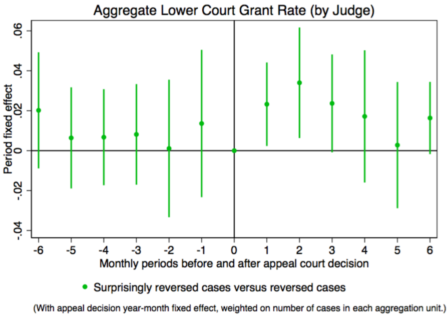
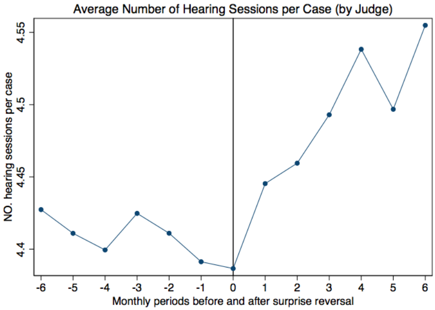
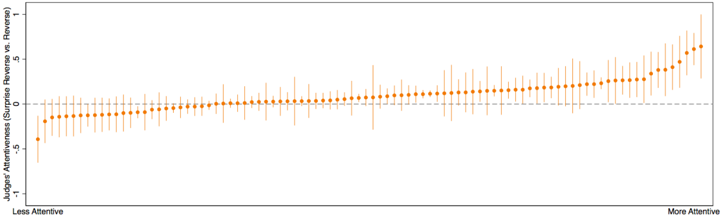
After "Surprise" Reversals, Judges Grant More Asylum and Hold More Hearing Sessions

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





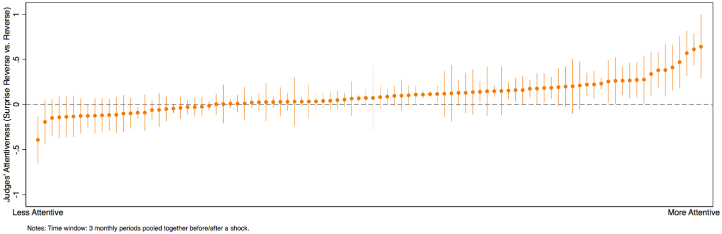
Judges Vary in Responsiveness to Reversal



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

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

Judges Vary in Responsiveness to Reversal



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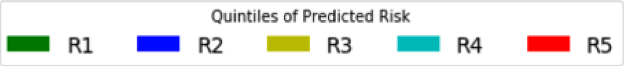
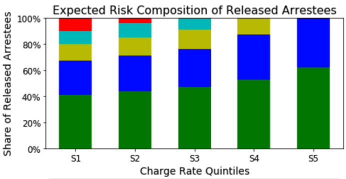
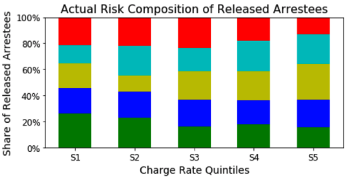


Robot Prosecutors



- If defendants released based only on risk score, the harshest prosecutors would only be releasing low-risk defendants.

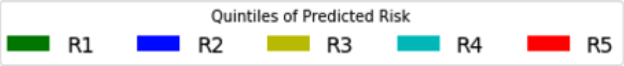
Human Prosecutors



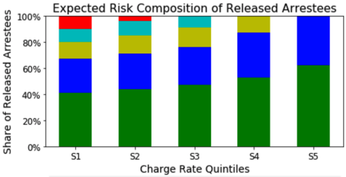
- Distribution of risk scores for released defendants is similar for most lenient and least lenient prosecutors.

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

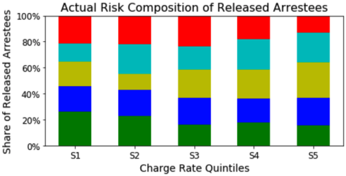
See also *Kleinberg, Lakkaraju, Leskovec, Ludwig, Mullainathan, Quarterly J Econ 2017*



Robot Prosecutors



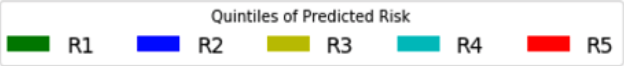
Human Prosecutors



- If defendants released based only on risk score, the harshest prosecutors would only be releasing low-risk defendants.
- 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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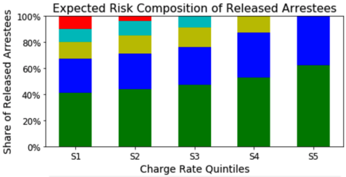

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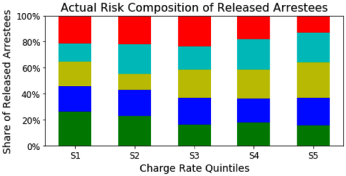

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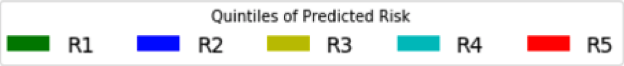

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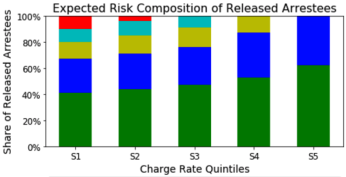

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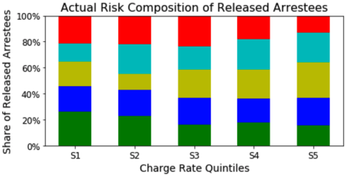

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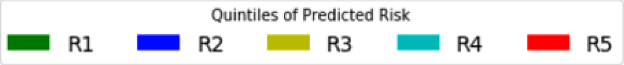

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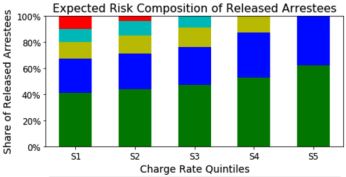

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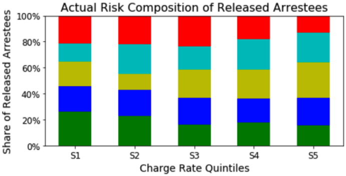

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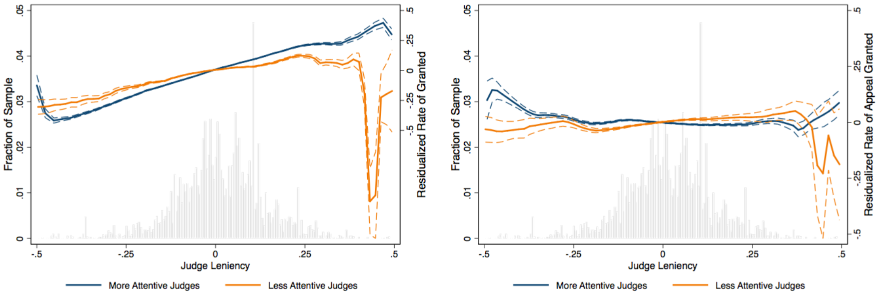
Left Figure: Judges have strong habits

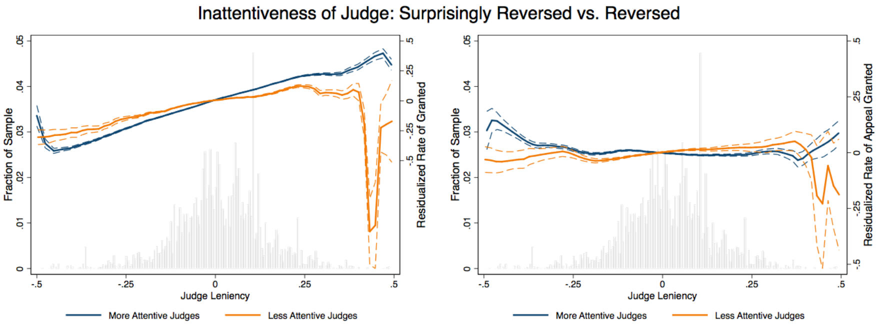
A judge who is generally lenient in other cases is likely to be lenient in a given case

Inattentiveness of Judge: Surprisingly Reversed vs. Reversed



(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

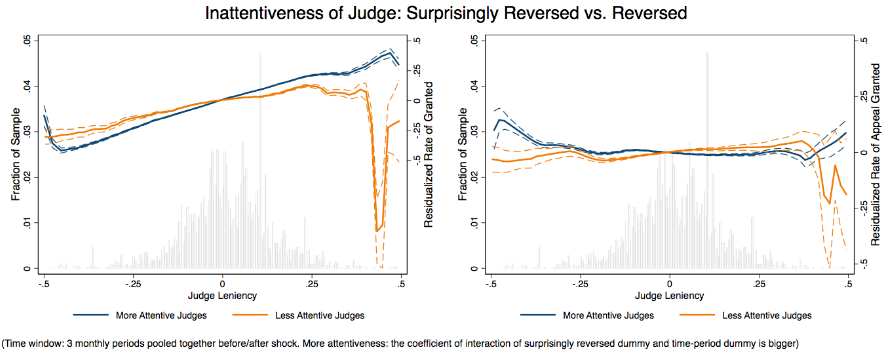


(Time window: 3 monthly periods pooled together before/after shock. More attentiveness: the coefficient of interaction of surprisingly reversed dummy and time-period dummy is bigger)

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

Right Figure: Assess implicit risk ranking



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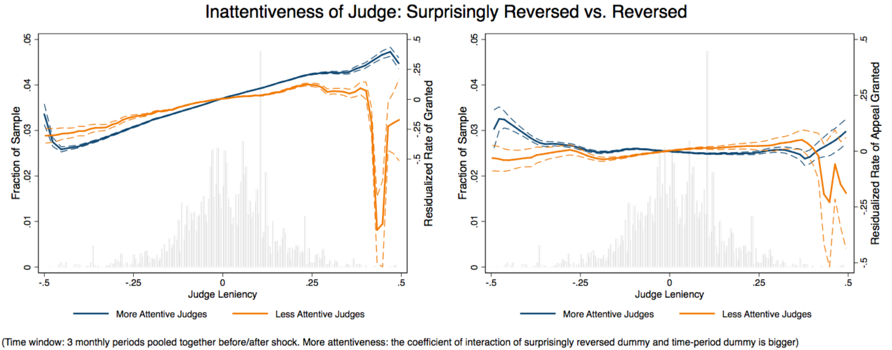
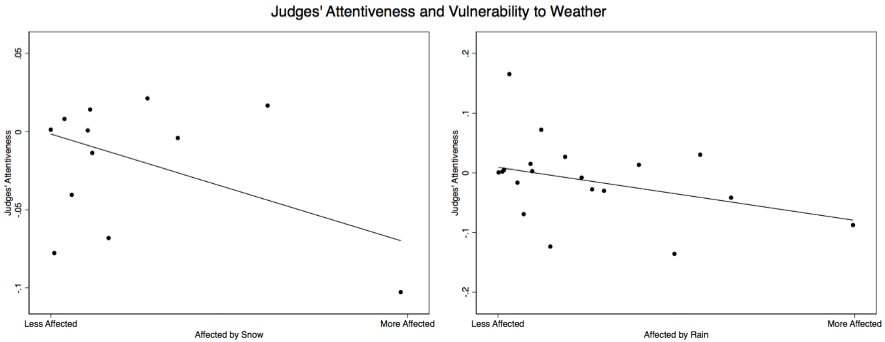
.. but not less attentive judges

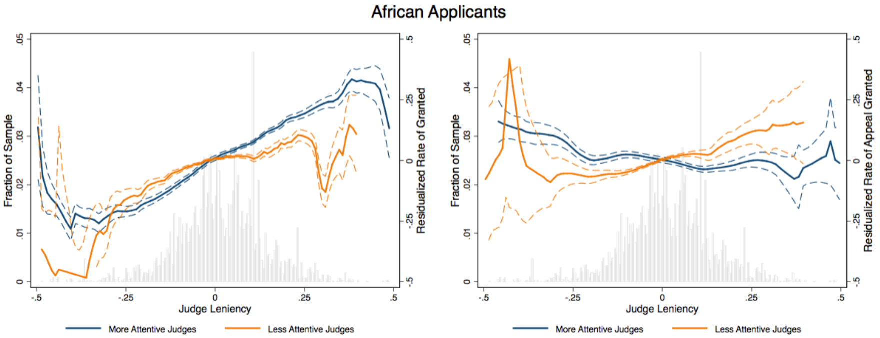


.. who may be more prone to other extraneous factors

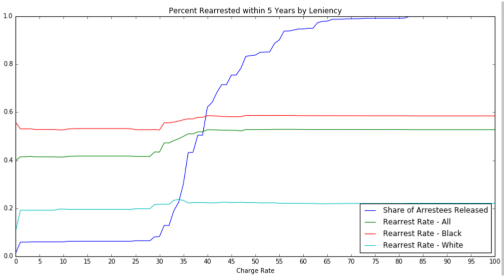
.. such as weather

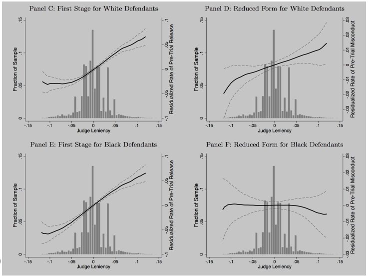


Difference in Indifference for asylees from the Global South



Using ML to Understand how Screeners Screen





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

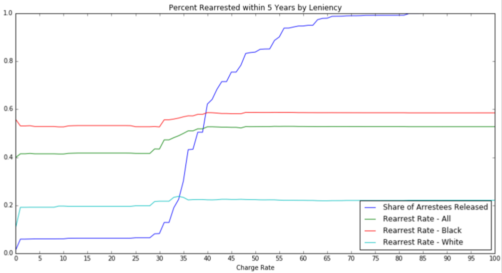
Algorithms as Prosecutors: Identifying Characteristics Noisy to Human Prosecutors

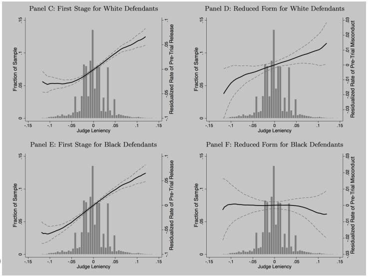
- Judges released along "right" diagonal for Whites but not Blacks (right)

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

Why "wrong diagonal" for Black defendants?

Using ML to Understand how Screeners Screen





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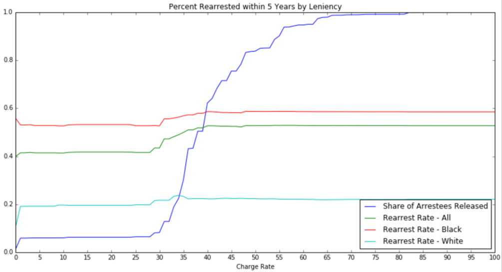

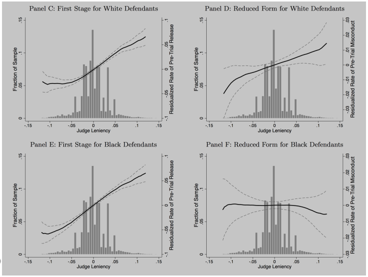

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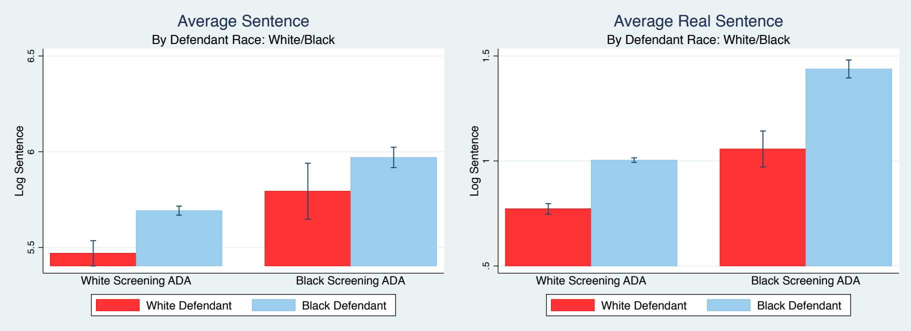
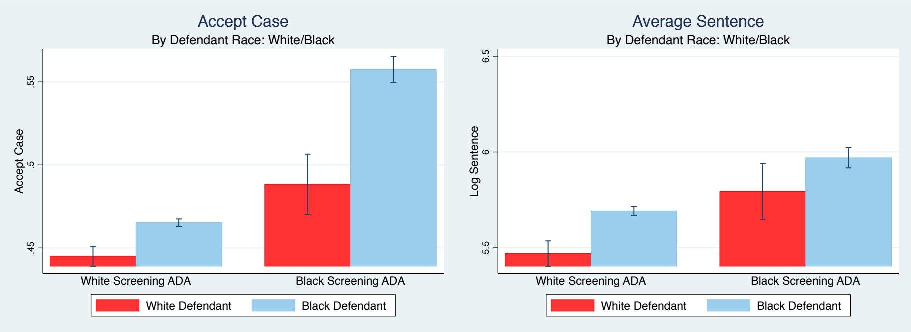
WHY "WRONG DIAGONAL" FOR BLACK DEFENDANTS?

1. Screening Increases Racial Sentencing Gap



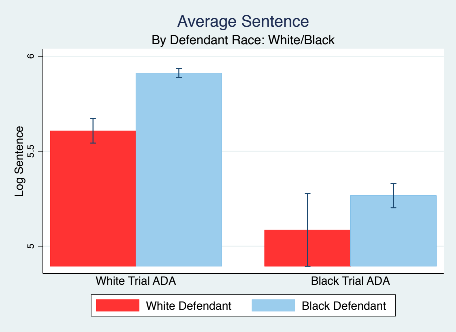
- Since black defendants are less likely to be declined, "real" racial disparity magnifies (on right)
  - Is statistical discrimination the reason for disparate screening?

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



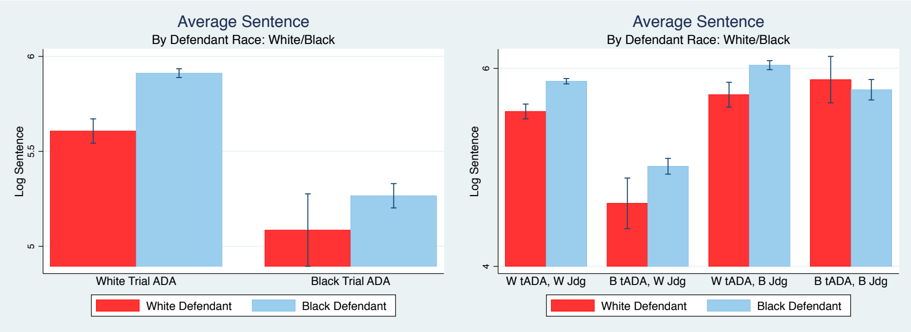
- White and black screeners let in different cases
  - If targeting the most severe ones, white screener cases should have *longer* sentences

3. White Trial Prosecutors Obtain Longer Sentences



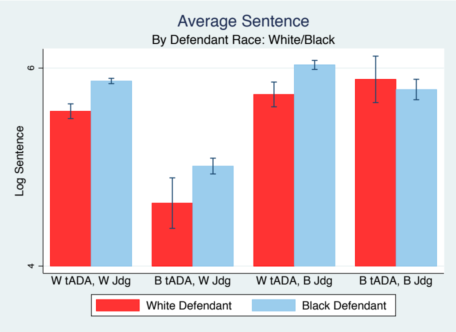
- Most District Attorneys are elected; want to appear tough-on-crime (Pfaff 2016)
- Why are white trial prosecutors more effective in this goal?

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 × 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 Color FE		X
First Letter Match × Hair Color FE		X
First Letter Match × 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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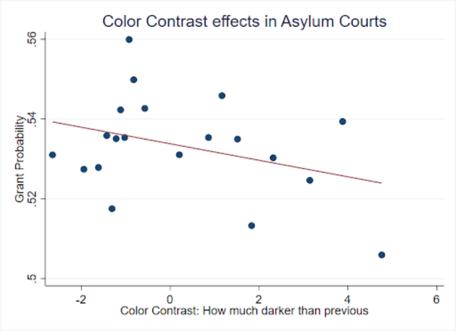
The Judicial Superego: Implicit Egoism, Internalized Racism, and Prejudice, Kyklos 2024

Relativity of Racial Perception

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



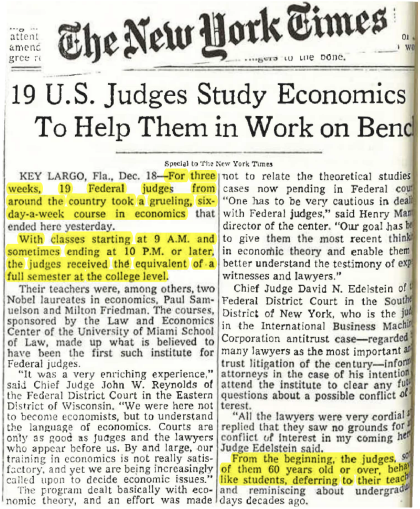
See also *Ludwig and Mullainathan, Quarterly J Econ 2024*

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 Bencl

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.

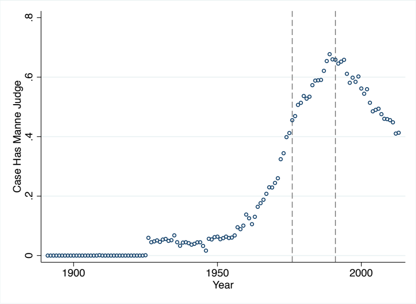
"It was a very enriching experience," said Chief Judge John W. Reynolds of the Federal District Court in the Eastern District of Wisconsin. "We were here not to become economists, but to understand the language of economics. Courts are only as good as judges and the lawyers who appear before us. By and 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 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 futu questions about a possible conflict of terest.

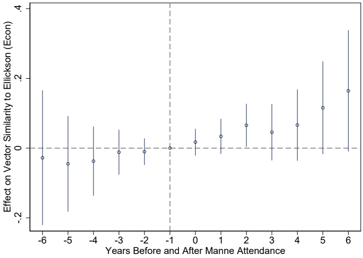
"All the lawyers were very cordial a replied that they saw no grounds for a conflict of interest in my coming her Judge Edelstein said.

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



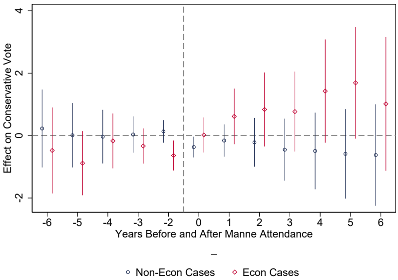
The results of these seminars were dramatic

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

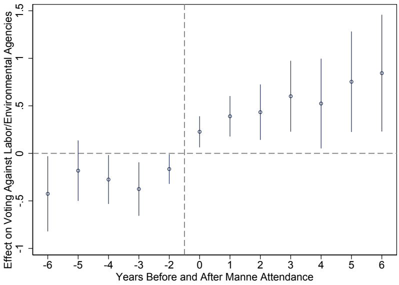


The results of these seminars were dramatic

We can see economics trained judges changing how they decided



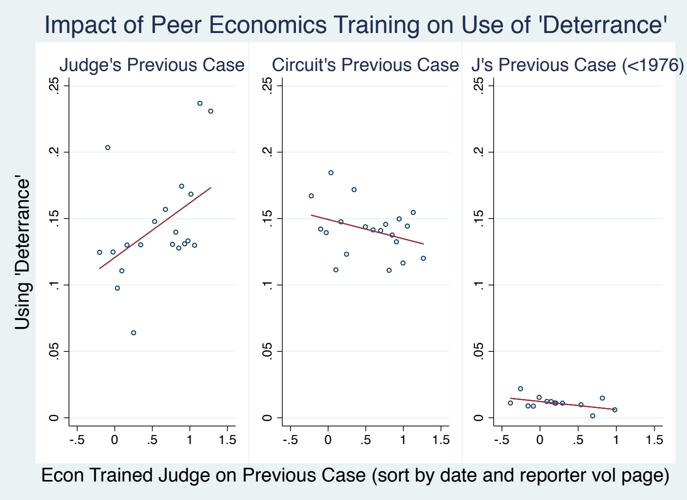
Econ vs Non-Economics Cases



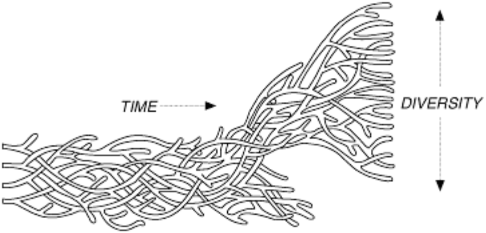
on Labor/Environmental Cases

Impacting their peers

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



The Geneology of Ideology



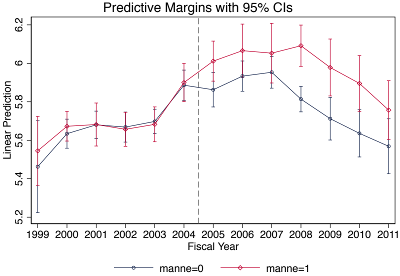
$$P_m = \frac{d_{m \to m}}{d_{\to m} + \delta} \Big/ \frac{d_{m \to \cancel{m}} + \delta}{d_{\to \cancel{m}} + \delta}$$

Scoring Memetic Phrases

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

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

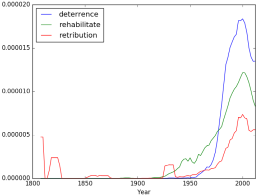
	Life	Months	Life	Months
	(1)	(2)	(3)	(4)
Minority	*0.00395******	*20.84******	*0.00388******	*20.34******
	(0.000770)	*(1.979)*	*(0.00102)*	*(2.170)*
*** Economics**	**0.00401****	**5.413*****	**0.00379****	**3.180***
	(0.00157)	**(2.044)**	**(0.00170)**	**(1.910)**
*** Republican**			0.000641	**4.096****
			(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

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

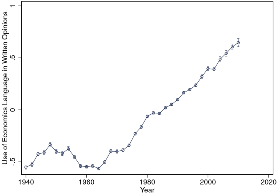
Chen, Nagarathinam, and Reinhart

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

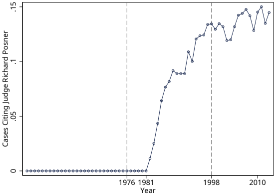
Word Frequency in Opinions



Economics style

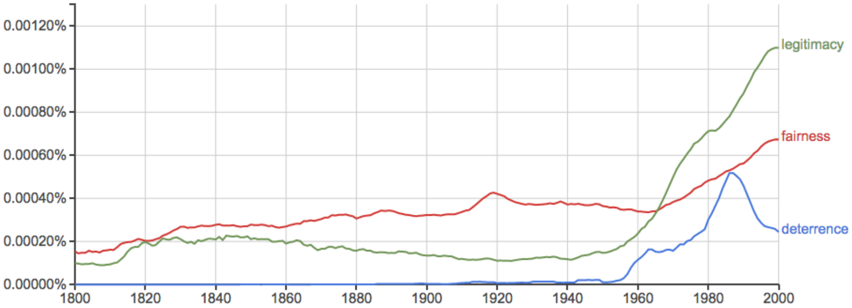


Citation to Richard Posner



◂ Massive build-up of prisons

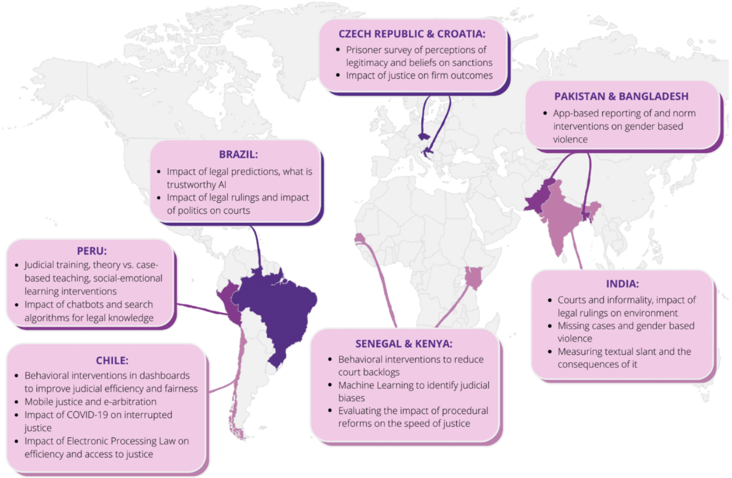
AI and the Next Transformation of Law?



Word Frequency in Google Books

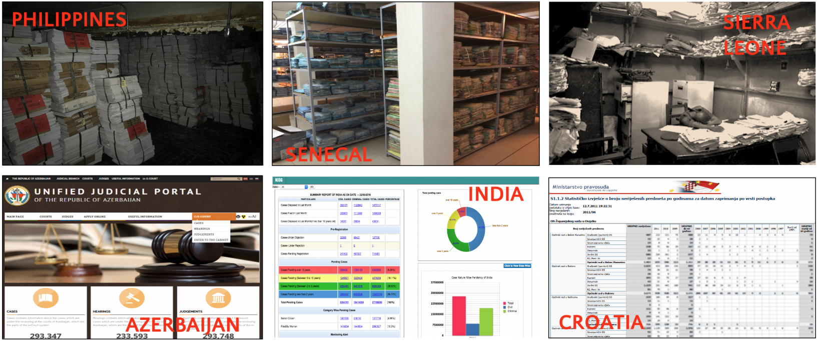
- ~~retribution, rehabilitation,~~ deterrence, legitimacy, fairness

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.

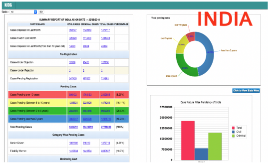
Data Ecosystems

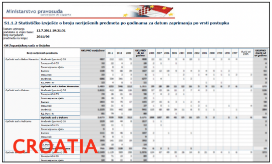


- Recent innovations have opened up new opportunities for delivery of justice
  - Increasingly digitized large-scale datasets
  - ML applications to produce interpretable data from unstructured text
  - Predictive models of decision-making to better understand biases and address them with digital interfaces

Ramos-Maqueda and Chen, World Development R&R

Data Ecosystems





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  - Predictive models of decision-making to better understand biases and address them with digital interfaces

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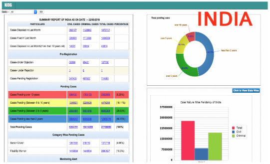

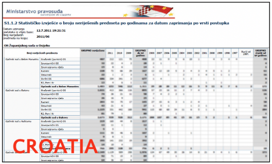

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Ramos-Maqueda and Chen, World Development R&R

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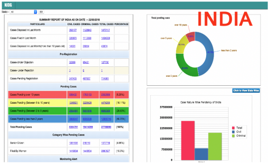

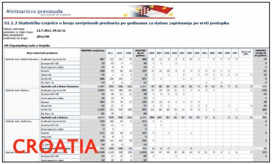

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Recommending Actions to Each Other

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All Centers
Geospatial Analysis
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Type of Case

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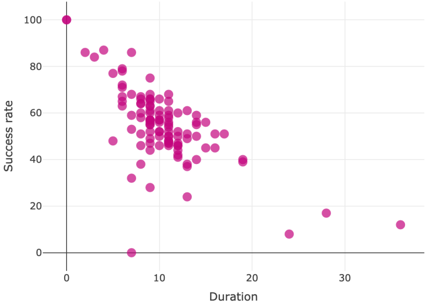
Year of 2014 – 2020

X: Duration
Y: Success rate

Show 25 entries

Search:

	Legal Aid Center	Number of cases	Success rate (%)	Duration of cases (days)	Avg. monthly caseload
1	CERCADO DE LIMA	2950	39	19	36
2	CHINCHA ALTA	972	47	12	19
3	MUNICIPALIDAD PROVINCIAL DE SATIPO	951	64	8	19
4	ICA	3648	60	9	36
5	AREQUIPA	1110	67	8	21
6	AMBO	85	58	11	8
7	HUANCAYO	1232	71	6	23



oTreeJustice

OR, AS MANAGEMENT TOOL, OBSERVING REGRESSIONS THAT THEY RUN

Recommending Actions to Each Other

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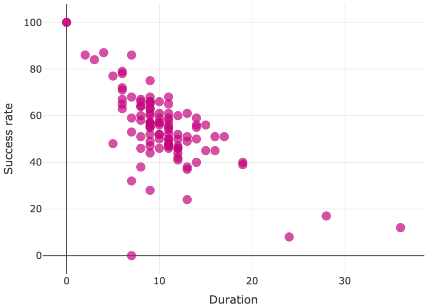

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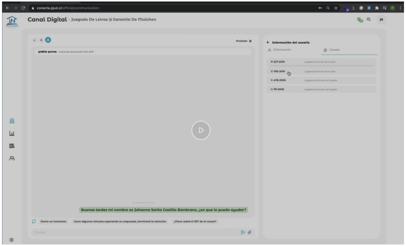
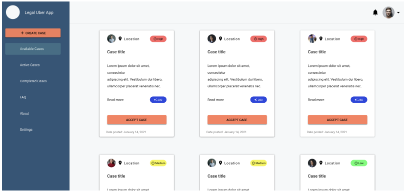
E-Justice Innovations

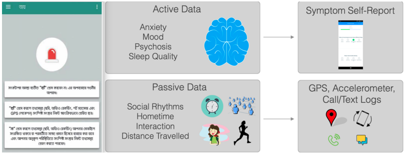
WhatsApp access to virtual courts



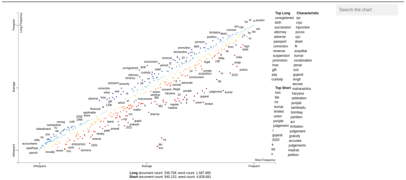
Uber-ization of case backlog



Apps for missing cases

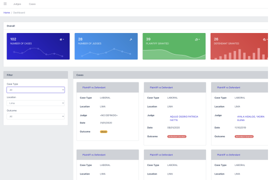


Open access legal search engines

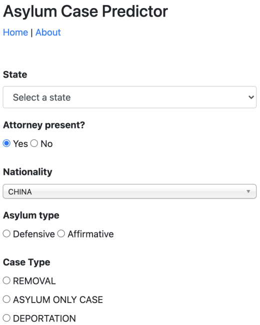


Human-Centric

Personalized case-based teaching



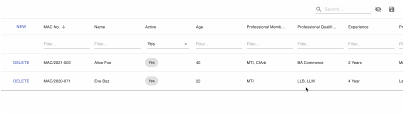
Predicted self



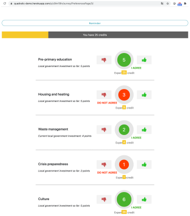
Building Capacity

Open source no-code tools for

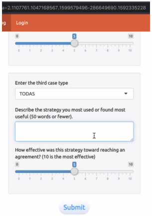
Data entry and decision-support



Understanding justice needs



Learning best practices



Increasing recognition-respect

Chen, Schonger, and Wickens
J Behavioral & Experimental Finance 2016

Economic development & legal institutions are associated

A 20% decrease in case duration is associated with a 10% increase in GDP per capita
(Penn World tables)

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“Endless adjournments of cases on frivolous grounds” are a major cause of case backlog (Chief Justice Maraga 2019)

- Nation-wide experiment using the first digitized daily court records
  - Developed an algorithm to identify the greatest source of court delays
  - T1: provide actionable information
  - T2: + accountability
  - Control: status quo (no information), RCT across all 123 court stations

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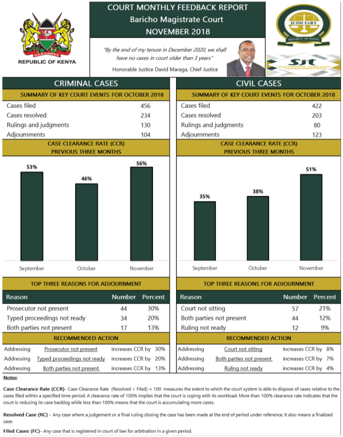
Actionable Recommendations



REPUBLIC OF KENYA

COURT MONTHLY FEEDBACK REPORT
Baricho Magistrate Court
NOVEMBER 2018

"By the end of my tenure in December 2020, we shall have no cases in court older than 3 years"

Honorable Justice David Maraga, Chief Justice

CRIMINAL CASES

SUMMARY OF KEY COURT EVENTS FOR OCTOBER 2018	
Cases filed	456
Cases resolved	234
Rulings and judgments	130
Adjournments	104

CASE CLEARANCE RATE (CCR) PREVIOUS THREE MONTHS

September	October	November
53%	46%	56%

TOP THREE REASONS FOR ADJOURNMENT

Reason	Number	Percent
Prosecutor not present	44	30%
Typed proceedings not ready	34	20%
Both parties not present	17	13%

RECOMMENDED ACTION

Addressing Prosecutor not present increases CCR by 30%
Addressing Typed proceedings not ready increases CCR by 20%
Addressing Both parties not present increases CCR by 13%

CIVIL CASES

SUMMARY OF KEY COURT EVENTS FOR OCTOBER 2018	
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35%	38%	51%

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Reason	Number	Percent
Court not sitting	57	21%
Both parties not present	44	12%
Ruling not ready	12	9%

RECOMMENDED ACTION

Addressing Court not sitting increases CCR by 8%
Addressing Both parties not present increases CCR by 7%
Addressing Ruling not ready increases CCR by 4%

Notes:

Case Clearance Rate (CCR)- Case Clearance Rate (Resolved ÷ Filed) × 100 measures the extent to which the court system is able to dispose of cases relative to the cases filed within a specified time period. A clearance rate of 100% implies that the court is coping with its workload. More than 100% clearance rate indicates that the court is reducing its case backlog while less than 100% means that the court is accumulating more cases.

Resolved Case (RC) - Any case where a judgement or a final ruling closing the case has been made at the end of period under reference. It also means a finalized case.

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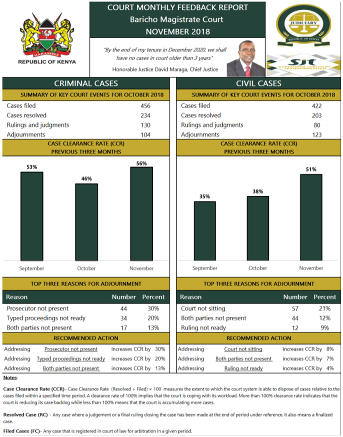
Can AI reduce information frictions

Improve the functioning of courts

Unlock the positive effects of justice on economic development?

Actionable Recommendations



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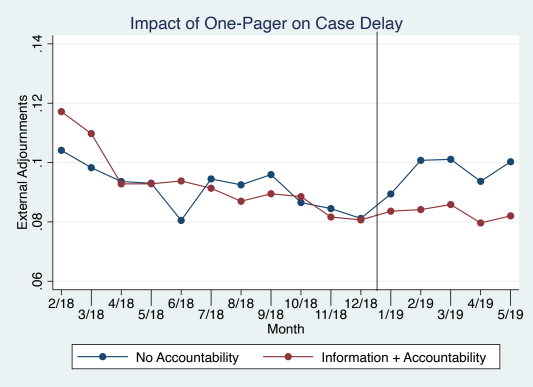
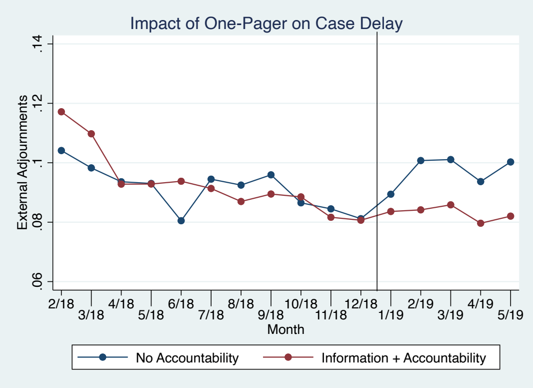
Accountability reduced adjournments



- Effect size suggests 20 percent impacts
- Compound effects: adjournments for another hearing
  - The mean number of hearings per case is 4.63
- Translates into a reduction of 107 days in trial length, or 22%

Accountability reduced adjournments



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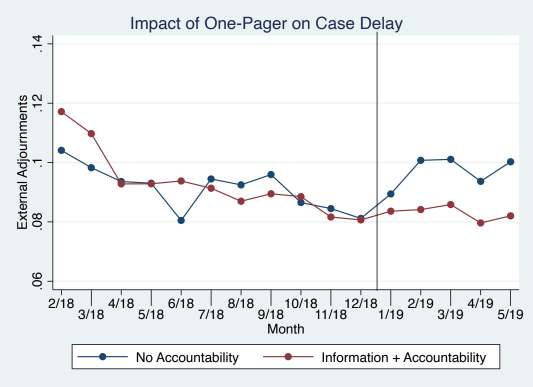

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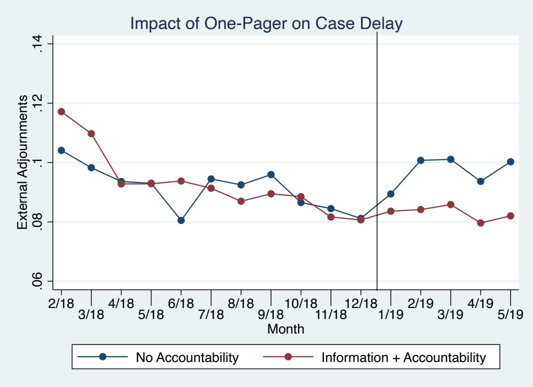

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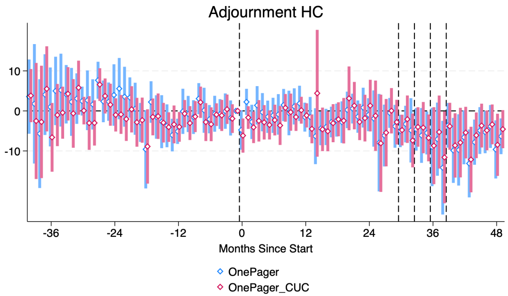
The effects persist



Long-term impact

Elevating to 30% reduction in time to disposition over four years

	Time to Disposition	Commercial Cases Filed Per Day Per Court
OnePager * Post	-244.8*	0.27
	(135.4)	(0.17)
OnePager_CUC * Post	-322.4*	0.41**
	(176.5)	(0.20)
Court FE	Yes	Yes
Day FE	Yes	Yes
Control Group mean	1103.6	0.61
SD	1481.6	2.36
Observations	183068	62883

along with an increase in access to justice

No adverse impacts of increased speed on proxies for quality

	(1) Judgement Length	(2) Cases in text	(3) Laws in text	(4) Number citations
OnePager * February 2019	-2.75	-0.87	0.23	-0.01
	(160.75)	(0.66)	(0.55)	(0.09)
OnePager CUC * February 2019	-38.67	-0.07	0.06	-0.10
	(179.62)	(0.82)	(0.54)	(0.10)
OnePager * March 2019	194.00	0.09	0.32	0.05
	(142.12)	(0.38)	(0.50)	(0.05)
OnePager CUC * March 2019	107.30	0.54	0.67	0.22
	(179.59)	(0.52)	(0.60)	(0.25)
OnePager * April 2019	186.91	0.73	0.56	0.13*
	(193.18)	(0.68)	(0.73)	(0.07)
OnePager CUC * April 2019	-29.20	0.89	0.49	-0.07
	(229.49)	(0.60)	(0.82)	(0.09)
OnePager * May 2019	-4.81	-0.76	0.51	0.08
	(221.05)	(0.67)	(0.69)	(0.07)
OnePager CUC * May 2019	-92.43	0.17	0.86	-0.11
	(236.63)	(0.78)	(0.80)	(0.09)
OnePager * After June 2019	143.04	-0.04	0.36	0.08
	(151.46)	(0.75)	(0.69)	(0.07)
OnePager CUC * After June 2019	70.80	0.82	0.07	-0.05
	(194.39)	(0.87)	(0.66)	(0.09)
OnePager * Month Before	-4.36	0.24	-0.26	0.08
	(172.62)	(0.45)	(0.72)	(0.07)
OnePager CUC * Month Before	206.14	1.45**	0.35	0.14
	(194.22)	(0.61)	(0.68)	(0.14)
Observations	137,376	137,376	137,376	137,231
R-squared	0.111	0.141	0.126	0.034
Mean Dep Var	2023	3.273	5.128	1.350
(SD)	2643	6.558	13.51	12.82

Speed of Justice & Citizen Satisfaction

What suggestions do you have for improving court facilities and services?

	Judge neutral	Judge led proceedings well	Suggestion Speed	Suggestion Quality
OnePager * 2019	0.04	0.00	-0.06*	-0.06***
	(0.07)	(0.07)	(0.03)	(0.02)
OnePager_CUC * 2019	-0.09	-0.04	-0.04	-0.05***
	(0.07)	(0.06)	(0.04)	(0.02)
OnePager * 2015	0.29	0.33	-0.05	0.01
	(0.27)	(0.32)	(0.03)	(0.04)
OnePager_CUC * 2015	0.26	0.31	-0.00	0.02
	(0.26)	(0.30)	(0.03)	(0.04)
Observations	12,612	13,847	15,199	15,199
R-squared	0.875	0.903	0.227	0.176

We find a reduction in complaints about speed and quality.

What is the long-term impact on trust?

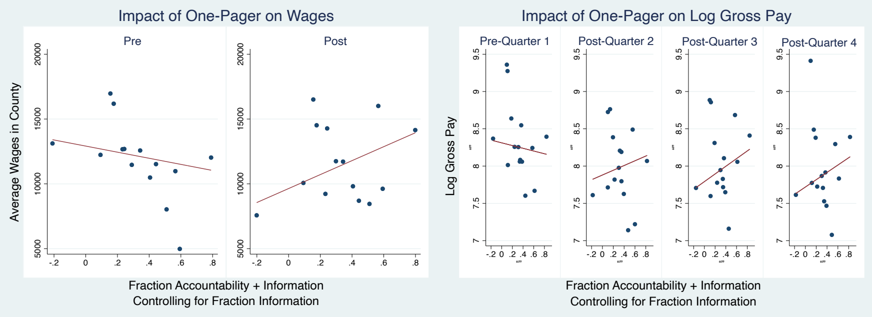
Trust courts

	All	Likely user	Not Likely user
OnePager * Wave 2	9.99*	16.37**	4.67
	(5.34)	(6.35)	(6.55)
OnePager_CUC * Wave 2	4.41	3.28	5.31
	(5.02)	(5.65)	(7.04)
OnePager * Wave 1	4.45	4.94	3.48
	(5.89)	(6.66)	(6.43)
OnePager_CUC * Wave 1	1.33	-1.86	4.98
	(6.42)	(6.82)	(7.27)
OnePager * Before	7.41	9.34	6.37
	(6.69)	(7.60)	(7.25)
OnePager_CUC * Before	1.94	-1.79	5.93
	(6.19)	(7.29)	(6.87)
Observations	9,315	4,791	4,484
County fixed effects	YES	YES	YES
Time FE	YES	YES	YES
Mean control group	55.78	54.50	57.62
SD control group	31.16	31	31.33

- Afrobarometer survey: "How much do you trust Courts of law?" (0=Not at all, 1=Just a little, 2=Somewhat, 3=A lot).

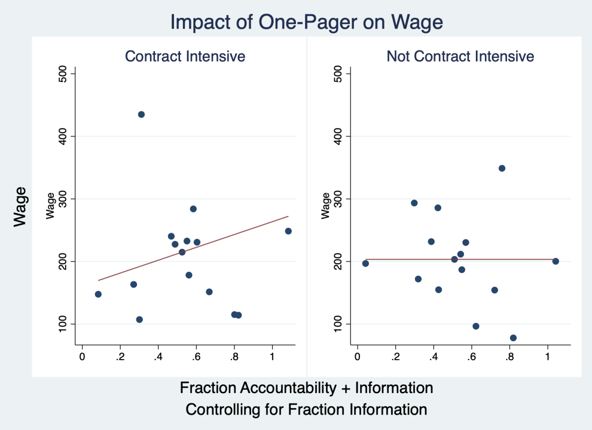
Speed of Justice & Economic Outcomes (VAT, KIHBS)

Kenya Continuous Household Survey measures wages, industry, contracts



Wages of individuals in the county is associated with proportion of treated court stations in a county

Contract Intensity



The effects are larger in contract-intensive industries.

Increase in Formal Contracts

Robust to different trimming of the wages, or using the log of wages, or using other measures of wage

	(1) Wage	(2) Wage Trim 3 sd	(3) Log Wage	(4) Total Gross Pay	(5) Extensive Margin	(6) Written Contract
%OnePager*Post*CI	61.61	63.25	0.37	59.99	0.022	0.06**
	(46.95)	(45.94)	(0.32)	(59.51)	(0.033)	(0.03)
%OnePagerCUC*Post*CI	76.18**	74.91**	0.33*	110.21*	0.005	0.06**
	(34.96)	(35.45)	(0.18)	(57.14)	(0.026)	(0.03)
%OnePager*Post	52.40	45.80	0.26	69.39	0.016	0.02
	(36.93)	(37.56)	(0.35)	(64.07)	(0.037)	(0.02)
%OnePagerCUC*Post	106.88**	103.29**	0.55	173.95**	-0.008	0.04
	(44.29)	(44.23)	(0.35)	(67.44)	(0.029)	(0.02)
Observations	6,857	6,827	6,857	3,574	34,887	34,154
County fixed effects	YES	YES	YES	YES	YES	YES
Quarter FE	YES	YES	YES	YES	YES	YES
CI	YES	YES	YES	YES	YES	YES
Mean control group	261	261	8.225	436.4	0.0921	0.143
SD control group	319.3	319.3	1.819	462.4	0.289	0.350

Individuals in the KCHSP are asked whether their labor contract is a written contract, a verbal agreement, an implied contract, or not a contract. We find **more written contracts** after the reform, which is indicative of citizens feeling more confident asking for contracts. (Kenyan Employment Act)

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%OnePager*Post*CI	61.61	63.25	0.37	59.99	0.022	0.06**
	(46.95)	(45.94)	(0.32)	(59.51)	(0.033)	(0.03)
%OnePagerCUC*Post*CI	76.18**	74.91**	0.33*	110.21*	0.005	0.06**
	(34.96)	(35.45)	(0.18)	(57.14)	(0.026)	(0.03)
%OnePager*Post	52.40	45.80	0.26	69.39	0.016	0.02
	(36.93)	(37.56)	(0.35)	(64.07)	(0.037)	(0.02)
%OnePagerCUC*Post	106.88**	103.29**	0.55	173.95**	-0.008	0.04
	(44.29)	(44.23)	(0.35)	(67.44)	(0.029)	(0.02)
Observations	6,857	6,827	6,857	3,574	34,887	34,154
County fixed effects	YES	YES	YES	YES	YES	YES
Quarter FE	YES	YES	YES	YES	YES	YES
CI	YES	YES	YES	YES	YES	YES
Mean control group	261	261	8.225	436.4	0.0921	0.143
SD control group	319.3	319.3	1.819	462.4	0.289	0.350

Individuals in the KCHSP are asked whether their labor contract is a written contract, a verbal agreement, an implied contract, or not a contract. We find **more written contracts** after the reform, which is indicative of citizens feeling more confident asking for contracts. (Kenyan Employment Act)

Can digital platforms offering free legal information improve justice systems?

"bring knowledge of the law to the common people"

Keyword searches for automatic determination of most relevant clauses and judgments

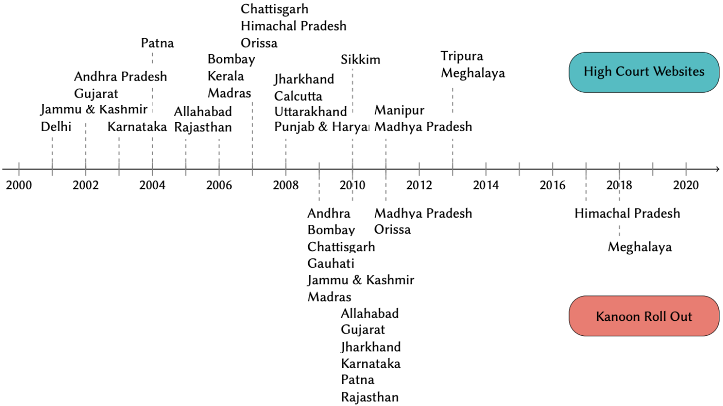


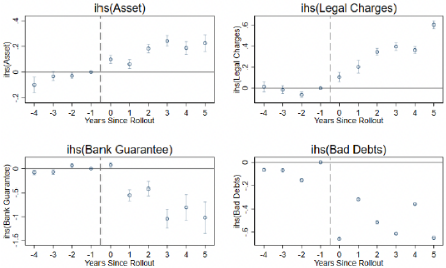
Figure: Roll Out Years for High Court Websites (top) and Kanoon (bottom)

Today, it is a "first-stop" for lawyers, 6 min per page, 2.9 M search queries and 1.5 M sessions per month

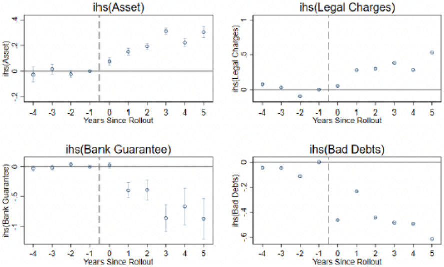
Event study analysis of firm financials

$$Y_{cfst} = \alpha + \sum_{j=2}^{4} \beta_j (lag_j)_{cfst} + \sum_{k=1}^{4} \gamma_k (lead_k)_{cfst} + \mu_s + \delta_f + \lambda_t + \epsilon_{cfst}$$

Firms with at least one case



General equilibrium



Sizeable impacts on assets and reduction of bad debt reinforce the findings of a 12% increase in employment in an RCT of free legal information to South African firms. (Bertrand and Crepon 2021)

Highlight the potential for open source / open access tools to be transformative for development

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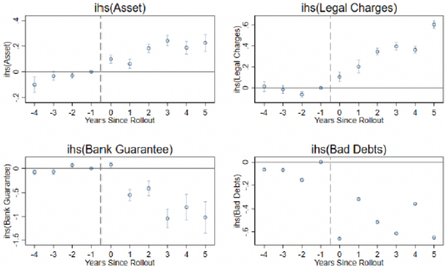

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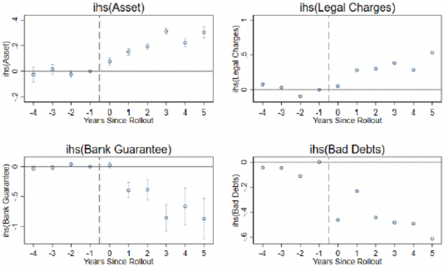

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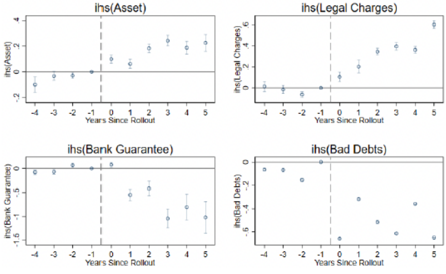

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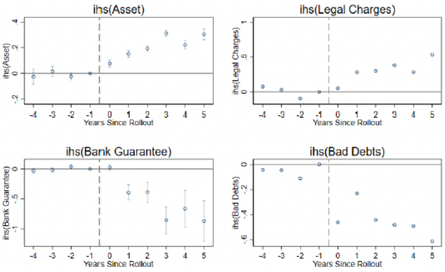

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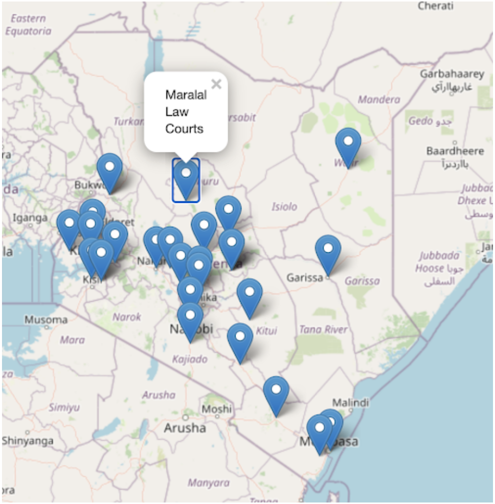
Highlight the potential for open source / open access tools to be transformative for development

Court Building

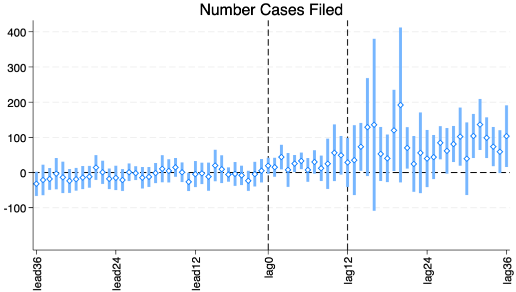
In 2012, Kenya began one of the largest court construction programs on record



Half had exogenous delays in construction

Court Building

Completed courts experienced 60% more cases filed per day



Succession, Commercial, Property

Court Performance

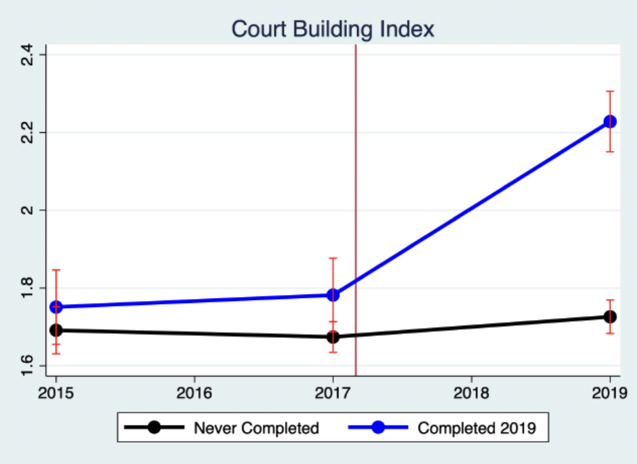
Completed courts reduced case delay by 25%

	(1) Time to Disposition	(2) Number Judges	(3) Time to Disposition
$CompletedCourt^{1+}$	-119.2*	0.48***	-140.5**
	(59.9)	(0.13)	(58.9)
$CompletedCourt^{0}$	-13.5	0.13	-19.4
	(52.1)	(0.15)	(49.7)
$CompletedCourt^{-1}$	-17.6	0.19	-22.6
	(50.3)	(0.15)	(53.0)
Number Judges			38.3**
			(16.6)
Control Group mean	483.6	1.92	483.6
Observations	125245	33602	125245

Impact of Completed Courts

Completed courts increased court satisfaction and access to justice

particularly for the disadvantaged



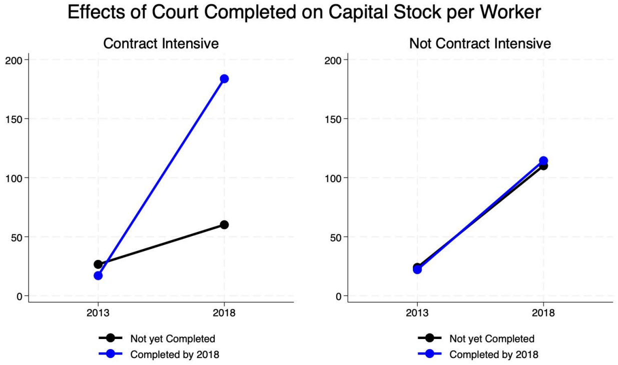
The share of litigants with only primary school education grows by 16 percentage points

Transforming the courts to being more nationally representative

Firm Investment

Increased investment by firms by 37%

especially in contract intensive industries



- a total added investment of USD 100 million, more than double the costs of the program (USD 45.5 million)

Building Courts: Effects on Access to Justice and Economic Development

WE SEE THAT COURT SPEED MATTERS

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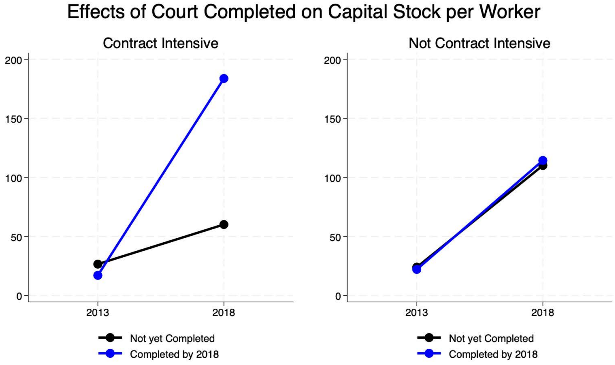

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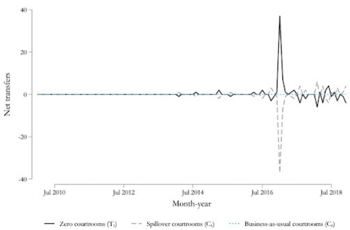
Building Courts: Effects on Access to Justice and Economic Development

WE SEE THAT COURT SPEED MATTERS

Court Speed Matters

Transferred cases result in Judge changes

Figure 12: Density of transfers by month

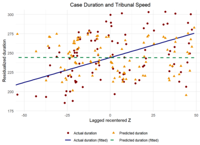


that increase case duration by 30%

	Days in court	Disposed within 1 year	Number of Hearings	Duration of Hearings
Judge changed	169*	-0.24**	3.1*	83***
	(93)	(.11)	(1.8)	(25)
Mean dep. var.	503	0.47	8.1	234
Observations	601540	601775	600268	397902
Month FE	Y	Y	Y	Y
F-test p-value	.12	.063	.085	.049

What is the impact of delay on litigants' outcomes?

Firms randomly assigned to 1σ faster panels



Testing empirically the identification assumptions:

- **Tribunal assignment matters for case duration**: there is a steep positive correlation between tribunal speed and case duration (blue line)
- **Tribunal assignment is random**: there is no correlation between duration predicted by baseline case characteristics and tribunal speed (green dotted line)

Increase productivity by 10%

	Log Sales		
	t-1	t0	t+1
Tribunal Speed	-0.008	0.049	0.099***
	(0.025)	(0.034)	(0.034)
1st Stage F-stat	41	41	41
Y mean (level)	9.401	9.053	8.735

Court Speed Matters

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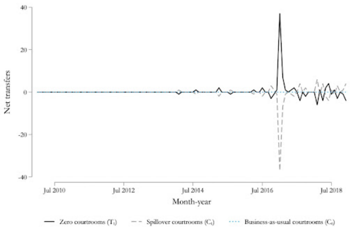
Figure 12: Density of transfers by month



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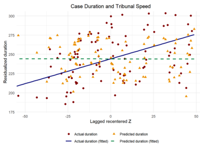

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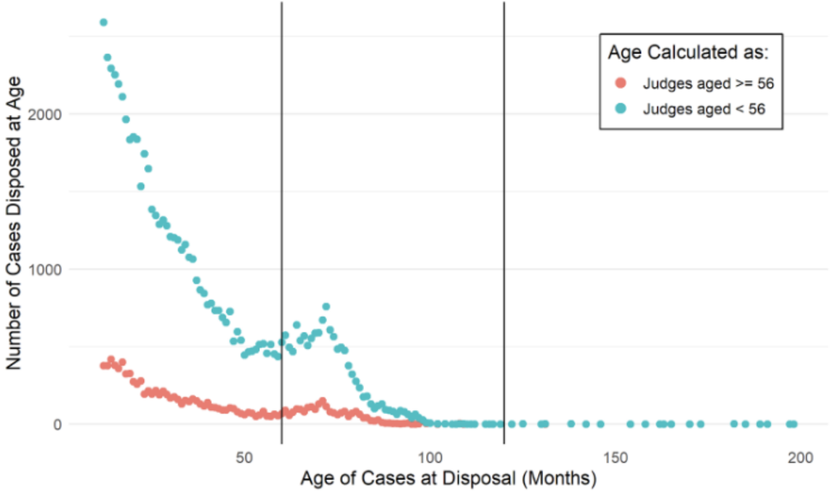
How to increase court effectiveness?

Judges respond to productivity quotas

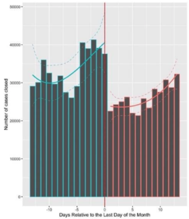


many case types get extra points if case is older than 5 years

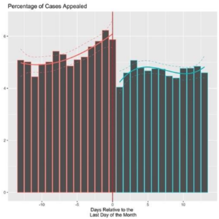
Judges respond to productivity quotas

resolving cases hastily at the end of month

Impact of Judicial Productivity Quotas on Firm Outcomes in Croatia



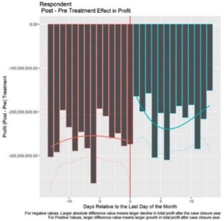
Cases Closed by the days of the month



% Appeals by Case Closing Date

Observe: Judges close more cases towards end of the month

- **RDD:** Cases decided at end of month are more likely to be appealed
- **RDD:** Respondent firms have worse outcomes when their cases are decided at end of month



Post - Pre Treatment Effect for Defendant Firm

but hastened decisions are more likely to be appealed and adversely impact firms

Is there a smoother way?

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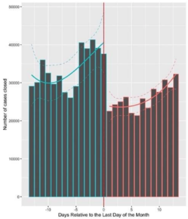

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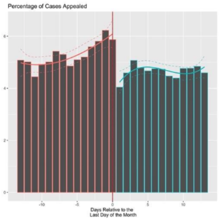

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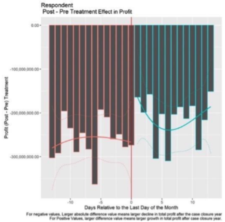


Post - Pre Treatment Effect for Defendant Firm

but hastened decisions are more likely to be appealed and adversely impact firms

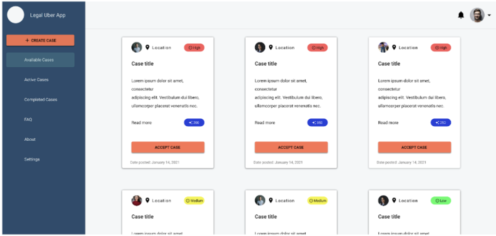
Is there a smoother way?

Dynamic Point Sytems?

Apply sharing economy principles of low transaction costs, coordination of information networks and better resource allocation and utilization.

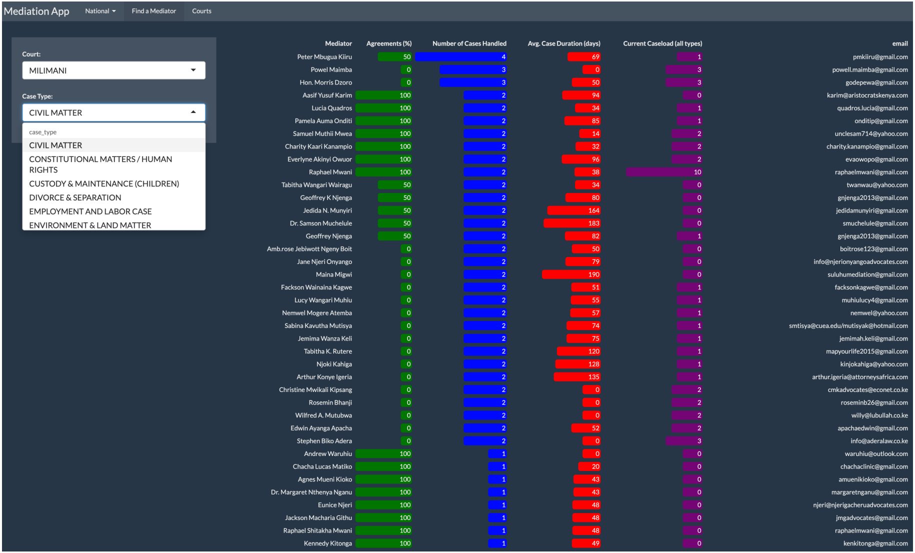
Legal Uber App

The web app will display a dashboard interface that allows the supply side user (clerk or judge) to view case availability. Case priority can be determined by how long the case has been idle and in which region it exists. These factors can influence not only the prioritization of a case but also the reward that is offered for taking the case. Participants can volunteer into an incentive scheme that allows them to earn points as they complete the cases. These points can then be spent on various rewards like access to interns, working from home allowance, flexible scheduling, and public recognition. Judges and clerks could also share schedules and professional details like their location and expertise with the system which can assist in determining their suitability for the platform.



Improve performance in congested courts by balancing workload across courts, without incurring cost of hiring new staff.

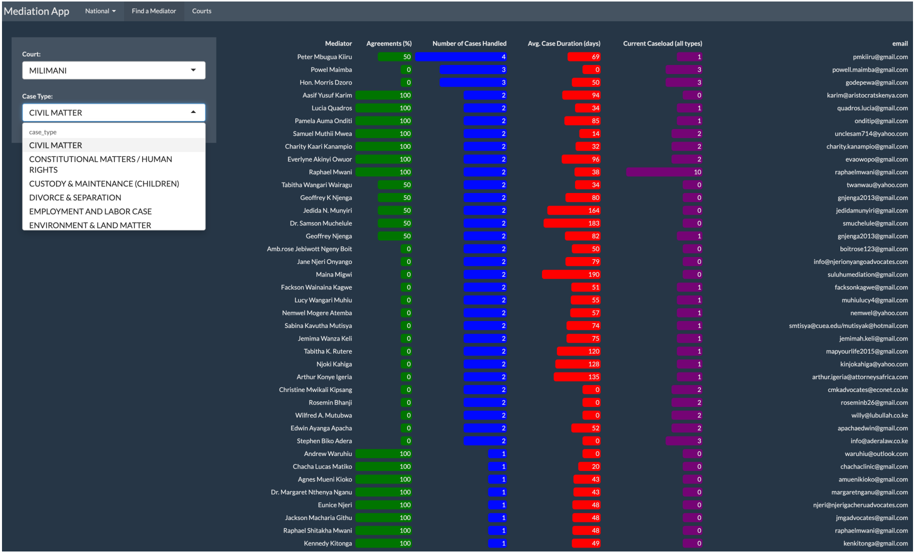
Recommending Mediators to Cases based on Value-Added?



Mediator	Agreements (%)	Number of Cases Handled	Avg. Case Duration (days)	Current Caseload (all types)	email
Peter Mbugua Kiiru	50	4	69	1	pmkiiru@gmail.com
Powel Maimba	0	3	0	3	powell.maimba@gmail.com
Hon. Morris Dzoro	0	3	50	3	godepewa@gmail.com
Aasif Yusuf Karim	100	2	94	0	karim@aristocratskenya.com
Lucia Quadros	100	2	34	1	quadros.lucia@gmail.com
Pamela Auma Onditi	100	2	85	1	onditip@gmail.com
Samuel Muthii Mwea	100	2	14	2	unclesam714@yahoo.com
Charity Kaari Kanampio	100	2	32	2	charity.kanampio@gmail.com
Everlyne Akinyi Owuor	100	2	96	2	evaowopo@gmail.com
Raphael Mwani	100	2	38	10	raphaelmwani@gmail.com
Tabitha Wangari Wairagu	50	2	34	0	twanwau@yahoo.com
Geoffrey K Njenga	50	2	80	0	gnjenga2013@gmail.com
Jedida N. Munyiri	50	2	164	0	jedidamunyiri@gmail.com
Dr. Samson Muchelule	50	2	183	0	smuchelule@gmail.com
Geoffrey Njenga	50	2	82	1	gnjenga2013@gmail.com
Amb.rose Jebiwott Ngeny Boit	0	2	50	0	boitrose123@gmail.com
Jane Njeri Onyango	0	2	79	0	info@njerionyangoadvocates.com
Maina Migwi	0	2	190	0	suluhumediation@gmail.com
Fackson Wainaina Kagwe	0	2	51	1	facksonkagwe@gmail.com
Lucy Wangari Muhiu	0	2	55	1	muhiulucy4@gmail.com
Nemwel Mogere Atemba	0	2	57	1	nemwel@yahoo.com
Sabina Kavutha Mutisya	0	2	74	1	smtisya@cuea.edu/mutisyak@hotmail.com
Jemima Wanza Keli	0	2	75	1	jemimah.keli@gmail.com
Tabitha K. Rutere	0	2	120	1	mapyourlife2015@gmail.com
Njoki Kahiga	0	2	128	1	kinjokahiga@yahoo.com
Arthur Konye Igeria	0	2	135	1	arthur.igeria@attorneysafrica.com
Christine Mwikali Kipsang	0	2	0	2	cmkadvocates@econet.co.ke
Rosemin Bhanji	0	2	0	2	roseminb26@gmail.com
Wilfred A. Mutubwa	0	2	0	2	willy@lubullah.co.ke
Edwin Ayanga Apacha	0	2	52	2	apachaedwin@gmail.com
Stephen Biko Adera	0	2	0	3	info@aderalaw.co.ke
Andrew Waruhiu	100	1	0	0	waruhiu@outlook.com
Chacha Lucas Matiko	100	1	20	0	chachaclinic@gmail.com
Agnes Mueni Kioko	100	1	43	0	amuenikioko@gmail.com
Dr. Margaret Nthenya Nganu	100	1	43	0	margaretnganu@gmail.com
Eunice Njeri	100	1	48	0	njeri@njerigacheruadvocates.com
Jackson Macharia Githu	100	1	48	0	jmgadvocates@gmail.com
Raphael Shitakha Mwani	100	1	48	0	raphaelmwani@gmail.com
Kennedy Kitonga	100	1	49	0	kenkitonga@gmail.com

To do so, we need data

Recommending Mediators to Cases based on Value-Added?



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Lucia Quadros	100	2	34	1	quadros.lucia@gmail.com
Pamela Auma Onditi	100	2	85	1	onditip@gmail.com
Samuel Muthii Mwea	100	2	14	2	unclesam714@yahoo.com
Charity Kaari Kanampio	100	2	32	2	charity.kanampio@gmail.com
Everlyne Akinyi Owuor	100	2	96	2	evaowopo@gmail.com
Raphael Mwani	100	2	38	10	raphaelmwani@gmail.com
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Maina Migwi	0	2	190	0	suluhumediation@gmail.com
Fackson Wainaina Kagwe	0	2	51	1	facksonkagwe@gmail.com
Lucy Wangari Muhiu	0	2	55	1	muhiulucy4@gmail.com
Nemwel Mogere Atemba	0	2	57	1	nemwel@yahoo.com
Sabina Kavutha Mutisya	0	2	74	1	smtisya@cuea.edu/mutisyak@hotmail.com
Jemima Wanza Keli	0	2	75	1	jemimah.keli@gmail.com
Tabitha K. Rutere	0	2	120	1	mapyourlife2015@gmail.com
Njoki Kahiga	0	2	128	1	kinjokahiga@yahoo.com
Arthur Konye Igeria	0	2	135	1	arthur.igeria@attorneysafrica.com
Christine Mwikali Kipsang	0	2	0	2	cmkadvocates@econet.co.ke
Rosemin Bhanji	0	2	0	2	roseminb26@gmail.com
Wilfred A. Mutubwa	0	2	0	2	willy@lubullah.co.ke
Edwin Ayanga Apacha	0	2	52	2	apachaedwin@gmail.com
Stephen Biko Adera	0	2	0	3	info@aderalaw.co.ke
Andrew Waruhiu	100	1	0	0	waruhiu@outlook.com
Chacha Lucas Matiko	100	1	20	0	chachaclinic@gmail.com
Agnes Mueni Kioko	100	1	43	0	amuenikioko@gmail.com
Dr. Margaret Nthenya Nganu	100	1	43	0	margaretnganu@gmail.com
Eunice Njeri	100	1	48	0	njeri@njerigacheruadvocates.com
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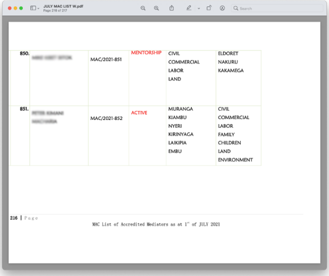
Raphael Shitakha Mwani	100	1	48	0	raphaelmwani@gmail.com
Kennedy Kitonga	100	1	49	0	kenkitonga@gmail.com

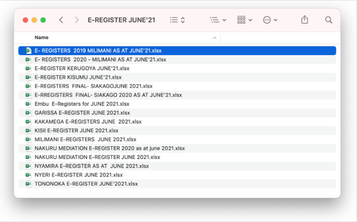
To do so, we need data

Open source decision support

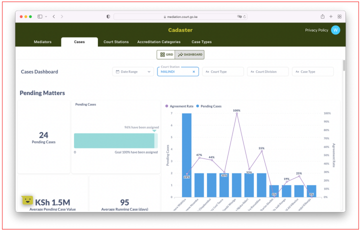
Before: excel spreadsheets



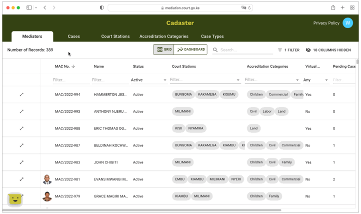
disaggregated and disharmonized



After: decision dashboards

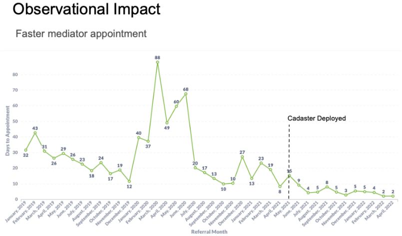


and harmonized data-entry

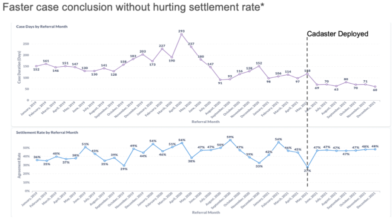


Harmonized data and dashboards

increased speed in appointments



reduced case delay without adverse effects



AEARCTR-0007699, *The Impact of Case Management on Court-Annexed Mediation in Kenya*

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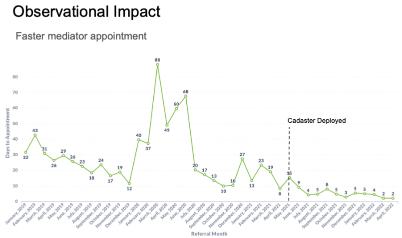

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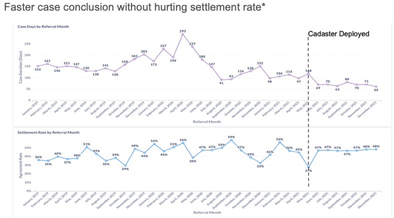

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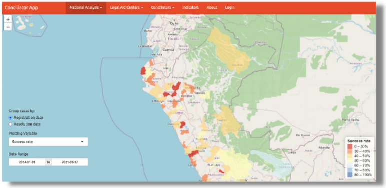
Dashboard RCT improved case outcomes

increased settlement rates

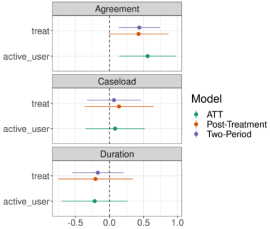
Improving the Quality of Legal Aid: Tech-Enabled Mediation in Peru



Research design: Randomized controlled trial across 80 legal stations in Peru

- **Treatment:** Conciliator App to self-assess performance indicators
- **Control:** No access

App increases agreement rate by 0.5 standard deviations.



RCT 1.2: Coaching or Vertical accountability

RCT 2: Reddit forum using Netflix recommendation system

AEARCTR-0008607, *Improving the Quality of Legal Aid, Rev Law & Econ R&R*

Dashboard RCT improved judicial performance

increased case clearance rates

Information Provision and Court Performance: Experimental Evidence from Chile

Research design: RCT across 55 court stations

- Simple dashboards alleviate the impacts of limited information.
- Courts adjust their decisions and improve court efficiency. Email promotion and feedback increase the timely resolution rate by 0.2 and 0.5 standard deviations, respectively, and hearing programming by 0.7 and 1.3 standard deviations, while they decrease the realized hearings by -1.3 and -1.0 standard deviations for those treated.

simple e-justice interventions enhance judicial state capacity

AEARCTR-0005512, *Information Provision and Court Performance: Experimental Evidence from Chile*

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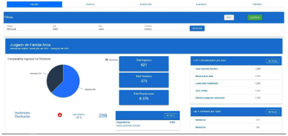

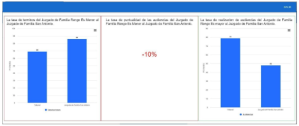

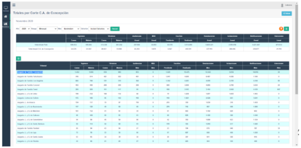

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AEARCTR-0005512, *Information Provision and Court Performance: Experimental Evidence from Chile*

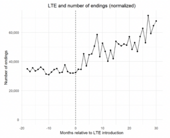
What about e-courts?

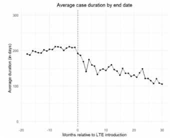
What is the Impact of E-Justice?

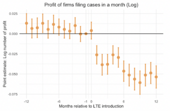
E-filing reduced case duration and increased access to justice, particularly for smaller parties

Peru & Chile Improving the Performance of Justice Services (P162833, P173860)

Question: Can technological innovations improve the performance of courts and the overall wellbeing of litigants?







Intervention:
- Electronic filing of cases (LTE) began in 2016
- Interrupted time-series analysis of LTE courts
- Total number of cases filed and resolved increased
  - Duration of cases significantly decreased
  - Even for non-spurious cases
- Smaller firms have greater access
- Next: What are the impacts on firms?

IE design and timeline:
- Geospatial Impact Evaluation (GIE)
- 2020-

Key Feature : Electronic processing is a common policy intervention; covid accelerates development of e-justice solutions

Impact of e-Access to Justice: Evidence from Chile

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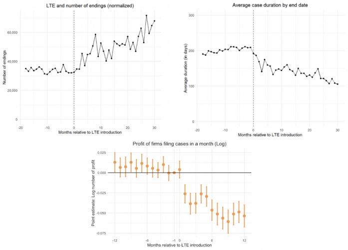

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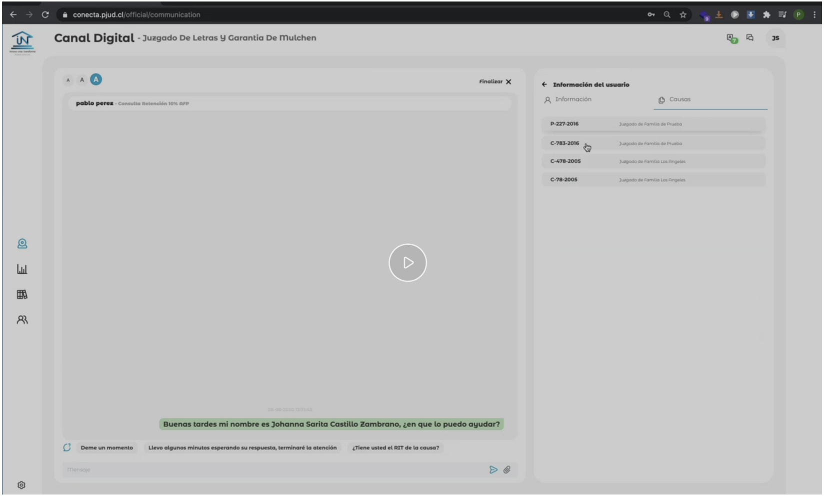
WHAT ABOUT E-COURTS?

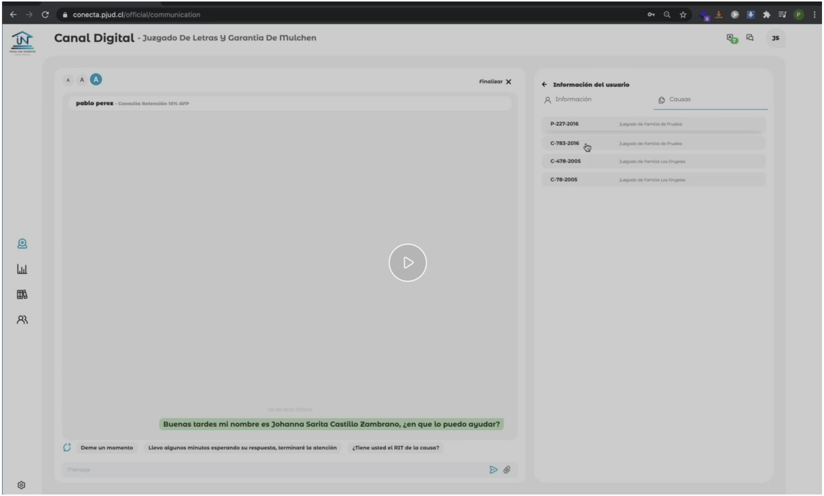
E-Justice during covid: Whatsapp



for Q&A with courts

video and audio also enabled

E-Justice during covid: Whatsapp



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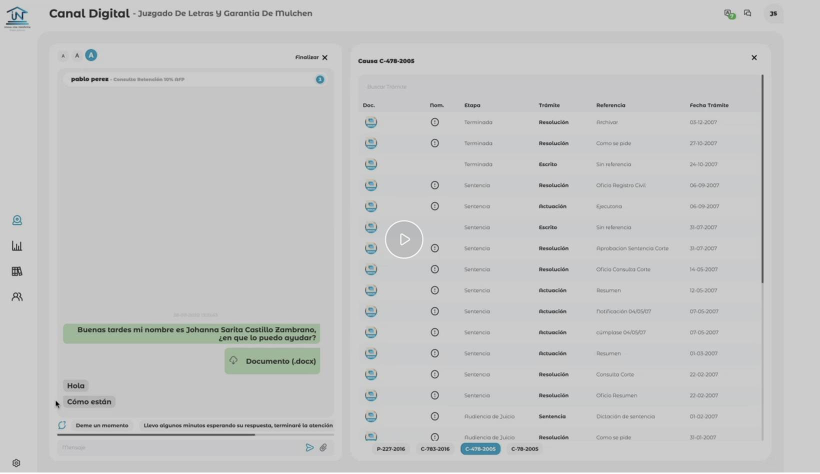
.. Receivers are given text to copy and paste (chatbots/humans?)



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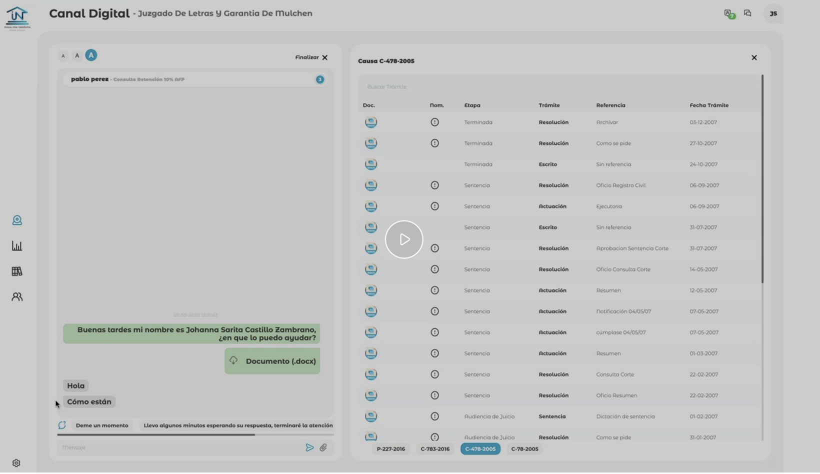

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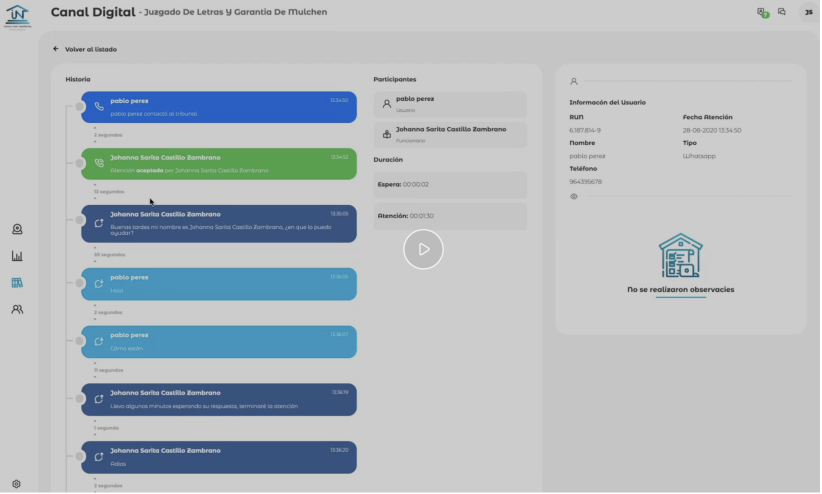
Cases are linked across calls

.. and into the courts (Digital interoperability)



Facilitating downstream analysis on consequences

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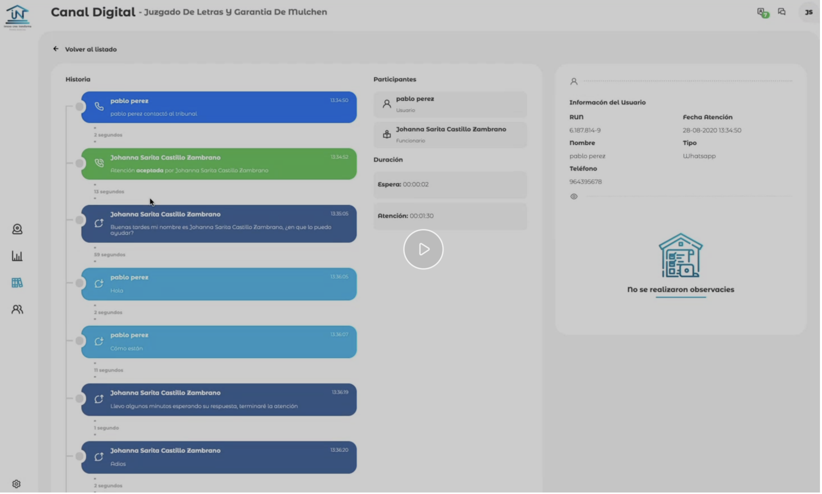

facilitating downstream analysis on consequences

40% of inquiries were gender-related

Rolled out nationally (and advertised on Facebook)

to improve speed of justice

Chatbot & WhatsApp RCT improved dispute resolution and fiscal recovery for the state

Impact of Online Lok Adalats on Judicial Efficiency

With SAMA

Context

- A 2004 study in the US demonstrates that Alternative Dispute Resolution approaches reduced the number of trials (Stipanowich, 2004). We extend this hypothesis to Online Dispute Resolution with the aim to measure its impact on justice outcomes and judicial efficiency.
- This workstream seeks to deploy the technologies developed by Sama to scale up mediation services to poorly served locations in partnership with various state legal service authorities across India.
- Chatbot and WhatsApp performs best and significantly improved settlement rate and fiscal recovery for the state.

Phase 1

- Lok Adalat in September, 2021, Sama, in addition to WhatsApp FAQS, depended on a customer care helpline to resolve 1.1 million traffic violation disputes in Maharashtra.
- We transcribed 400 audio files from made over the customer care helpline and ran Natural Language Processing algorithms to form clusters of different themes of questions.
- These questions are added to the previous set of FAQs used by Sama to create an automated chatbot.

Phase 2

- In the next Lok Adalat, on 12th March, 2022, Sama, we randomize the 5.3 million traffic violations across five treatment arms to determine their impact on settlement rate.
- Five treatment arms were:
  - WhatsApp
  - WhatsApp+ IVR
  - IVR
  - IVR+ Chatbot
  - Chatbot
- Sama achieved a settlement rate of 18% and recovered INR 710 billion for the state.

Phase 3

- 14th May, 2022, Sama will be using IVR + WhatsApp to resolve traffic violation disputes

Table 1: Regression results

	Total Duration	Mean Duration	Total Action Count	Mean Action Count	Total Page Count	Mean Page Count
Chatbot	11.288	3.875	0.209	0.131	0.116	0.076
	(11.48)	(6.43)	(0.40)	(0.30)	(0.06)	(0.05)
IVR	10.518	6.694	1.006	0.850	0.062	0.020
	(16.32)	(9.37)	(1.04)	(1.06)	(0.06)	(0.03)
IVR + Whatsapp	18.907	11.305	0.328	0.054	0.156**	0.080*
	(12.45)	(6.36)	(0.27)	(0.20)	(0.05)	(0.04)
Chatbot + Whatsapp	25.853	17.965	0.574*	0.384**	0.150**	0.113***
	(17.12)	(8.99)	(0.22)	(0.14)	(0.05)	(0.03)
claimamount	-0.009***	-0.005***	-0.000***	-0.000*	-0.000**	-0.000
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Constant	289.371***	196.828***	12.334***	8.415***	2.040***	1.371***
	(9.87)	(5.40)	(0.19)	(0.17)	(0.03)	(0.02)
N	11694	11694	11694	11694	11694	11694
R2	0.078	0.095	0.008	0.003	0.035	0.012
F Statistic	13.61	17.51	16.23	12.36	6.54	4.70

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Chandra, Chen, Nagarathinam, Review of Law & Econ 2024

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Chandra, Chen, Nagarathinam, Review of Law & Econ 2024

Metaverse

Colombia court moves to metaverse to host hearing

By Isabel Woodford

February 24, 2023 11:08 PM GMT+1 · Updated 3 months ago

64 J.L. & Econ. 269 (2021)
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Can we personalize debiasing to the listener/viewer?

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Judicial Analytics for Recognition and Dignity

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- Cognitive science and psychology suggests that humans have limited and imperfect reasoning capacities (Tversky and Kahneman 1986; Eyster 2019)
- Gambler's fallacy, mood, time of day, order, ...
  - highlight fragility of courts
    - "In a crowded immigration court, 7 minutes to decide a family's future" (Wash Post 2/2/14)
- Policy discussion tends to revolve around having AI replace humans or suggest the optimal decision
- Consider instead an incremental approach based on Enlightenment and Romantic ideals of the self: self-knowledge, self-expression

(Charles Taylor, Sources of the Self, 1989; The Ethics of Authenticity, 1992)

Asian J of Law and Economics 2023

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Stage 1: Predicted Self

- In Stage 1, people use AI as a support tool, speeding up existing processes (for example, by prefilling forms)
  - An AI-based recommender system offers a decision-maker the best prediction of themselves, based on their previous decision-making, from a model using only legally relevant features X.
    - ⋆ assess judges vs. their predicted self
  - (1) Increase consistency across similar cases by offering the relevant reference points and cabining the influence of extraneous factors.
  - (2) Seeing the predicted self leverages self-image motives of pro-social decision-makers (Benabou and Tirole 2011).
  - (3) Deviating from defaults facilitates conscious deliberation.
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Stage 2: Prediction of Error

- A deviation that is more likely to render an error (from a model using all available features X and W) can be accompanied by a nudge to "be more attentive" or spend more time to make a better decision.
  - (1) A nudge, instead of a checklist, might impose less bandwidth.
  - (2) Save time and energy to focus on novel, complex cases.
- self-improvement (nudges)

Stage 3: Explanations

- A decision-maker may want interpretable machine learning **and** request a reason for why the deviation may lead to mistakes.
  - (1) Stage 3 elevates the AI to the role of a more general coach, providing feedback on choices.
  - (2) The more people feel that their autonomy is protected and that they are in control of the conversation—able to choose when feedback is given—the better they respond to it. (West and Thorson 2018)
- self-understanding (why)

Stage 4: Dialogue

- Of course, it is always possible that the AI system's suggestion would not take into account some reliable private information that the decision-maker might have access to.
    - Where this happens, the AI system would be steering the decision-maker off course rather than correcting for their inconsistencies.
    - Therefore, a dialogue, encouraged between the decision-maker and the AI system, allowing for the AI to learn from the user as well.
- self-expression (autonomy)

Stage 5: Community of Experts

- AI brings in other people's decision histories and patterns, serving as a platform for a community of experts.
  - A decision-maker may want to access a community of experts by seeing what the algorithm predicts other to do.
  - This can be accessible as a dropdown menu, to seek advice from a particular decision-maker,
    - or as a statistical distribution to protect privacy.
- community of practice (self vs. others)

Stages 6+

- Stage 6, train novices
  - who tend to make more mistakes
  - experts can input a preferred decision
  - or use prediction if appealed
- Stage 7, open access for citizens
  - for transparency & accountability (Kenya)
  - social image
- Stage 8, use feedback from dialogue stage as recommender system
  - with A|B testing to generate causal inference

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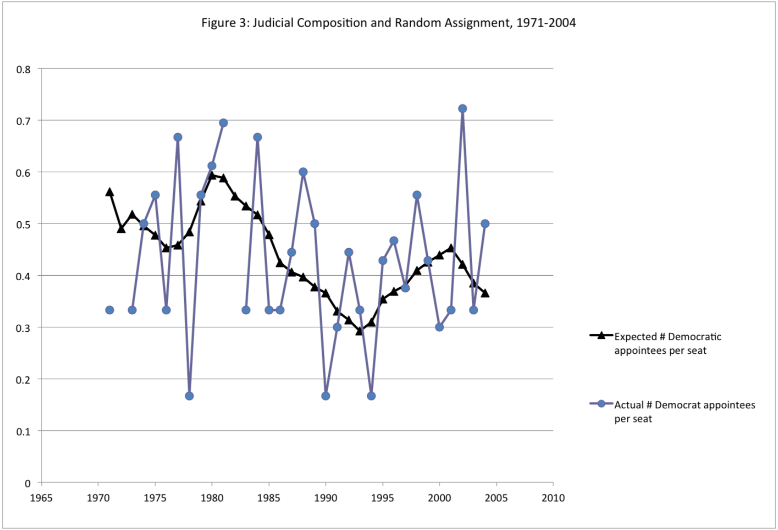
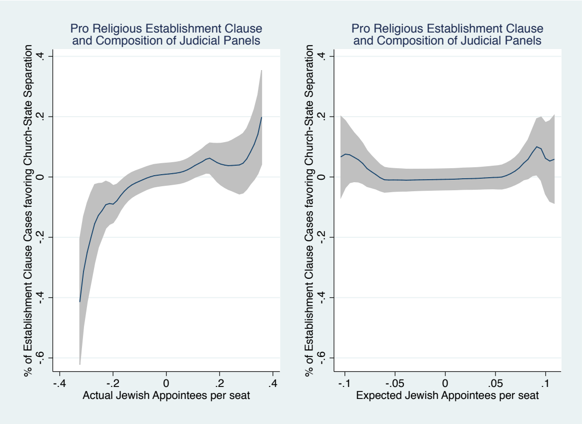
Randomization of cases already yields A|B testing

Decisions are not random, but judges are randomly assigned



Biographies Predict Church-State Separation



Minority religion judges prefer separate church and state

The Political Economy of Beliefs

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

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

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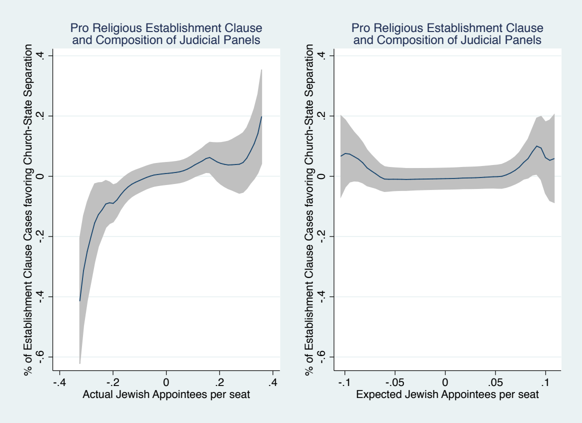

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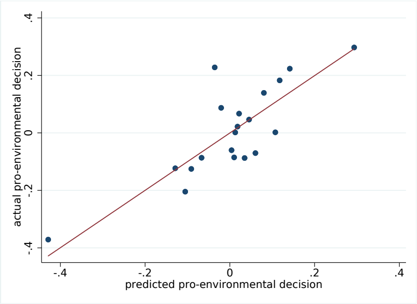
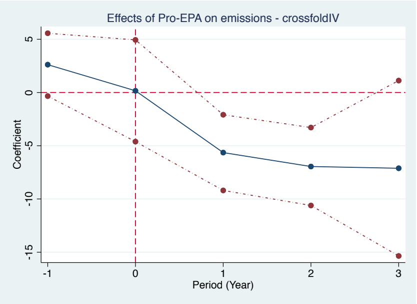
Impact of Environmental Decisions

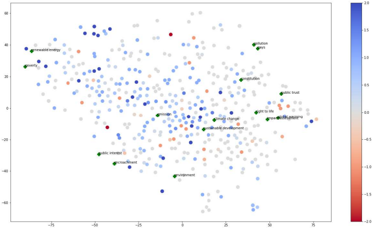


Calibration plot

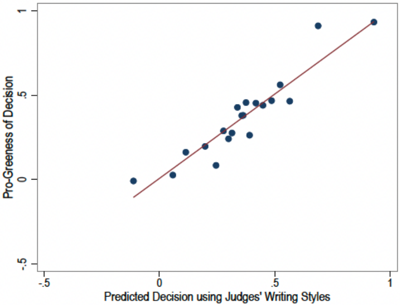


Rulings in favor of EPA regulations reduce air pollution

Impact of Environmental Decisions

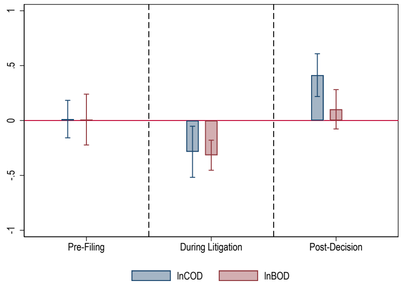


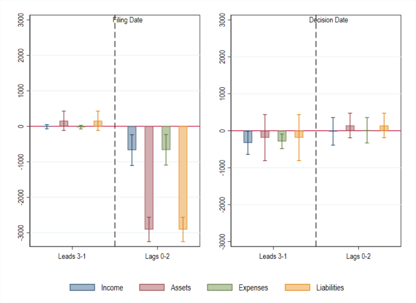
Judges predicted to be Green cluster together



and affect verdicts

Environmental Litigation as Scrutiny





Green judges reduce pollution and firm activity

Automated Impact Analysis?

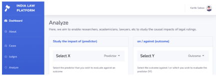
locate the nearest past cases, assignment of judges to those cases, and predict their rulings to identify the consequences of decisions

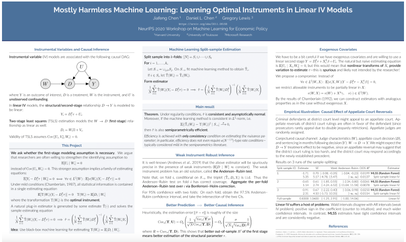
Law Platform

India Law platform is a data discovery and interactive tool for researchers, judges, and policymakers. There are two essential features of this platform.

First, it locates the closest cases to any given case. This allows a user to understand previous rulings and how past decisions were ruled. This can be filtered by jurisdiction, time period, or judge. More broadly, the user can research the details of the cases and what precedents or statutes were cited.

Second, it allows the user to analyse the effects of rulings on downstream outcomes. A dropdown menu offers available outcomes in the platform so that the user can specify the causal outcome of interest. To do this causal analysis, the platform first coalesces the nearby past cases to a given case. Then it uses the identity of the judges assigned in those cases as a historical natural experiment.





Chen, Chen, and Lewis; NeurIPS 2020 (ML for Policy)

Would informing people about impacts of decisions increase intrinsic motivation?

Renewed Attention on Disparities in the Justice System

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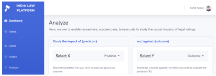

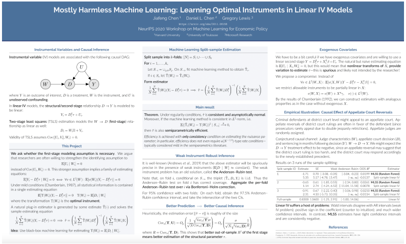

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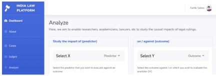

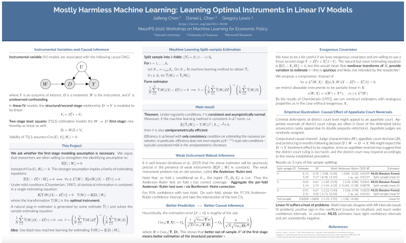

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Renewed Attention on Disparities in the Justice System

How Can We Train Judges to Improve Rule of Law?

- The training of public officials is one of the key dimensions governments use to improve bureaucratic performance
- For example, in 2017 alone, the U.S. allocated approximately 4% of its annual budget for personnel compensation and benefits, or around $10 billion, towards training civil servants (Credibility Engine 2021; USA Spending)
- Despite its significance, there is limited empirical research on effective methods to improve the training of public officials using RCTs
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Prosociality of Civil Servants

Personnel economics of the state (Finan, Olken, and Pande 2017)

selection

incentives

monitoring

attitudes, preferences, beliefs

schools of thought that underlie decision-making (economics)

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Economics trained public servants

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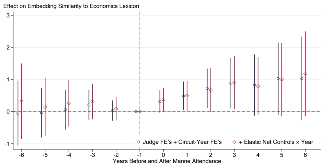
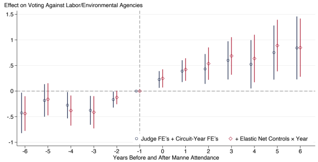
Effect of Manne Program on Economics Language

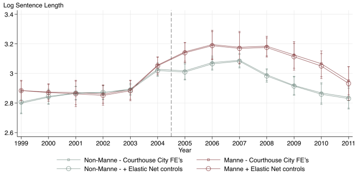


decided against regulations

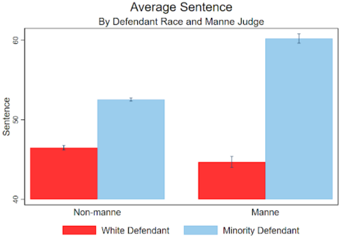
Effect of Manne Program on Ruling Against Labor/Environment Agencies



rendered 20% longer sentences



were harsher to minorities



What about econometrics?

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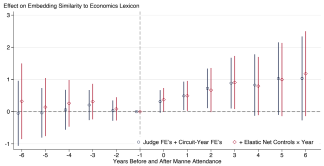

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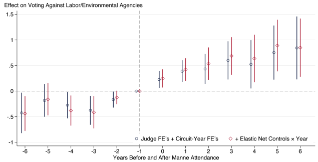

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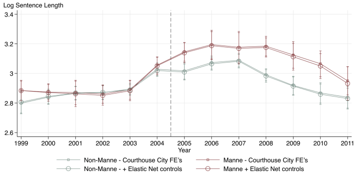

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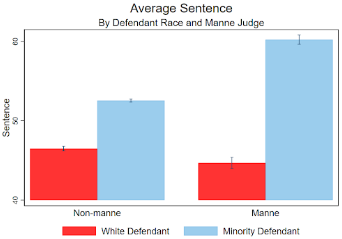
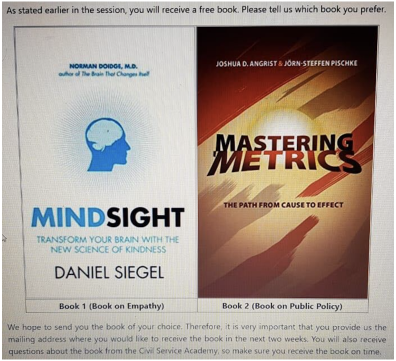


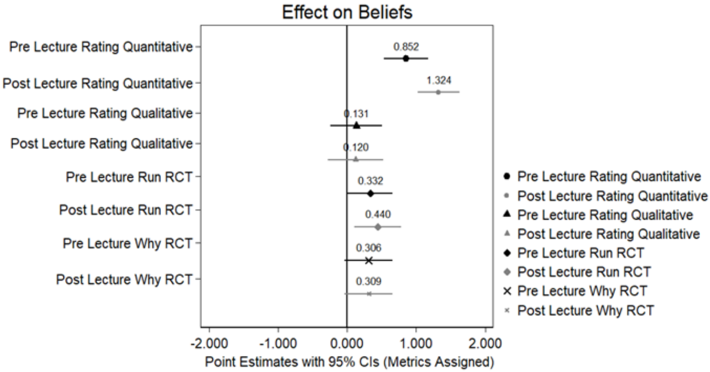
What about econometrics?

Training deputy ministers in school of thought associated with credibility revolution



- Book lottery
- Videos by Authors
- Graded summarization and visualization exercises (SEL)
- Self-persuasion presentation to others

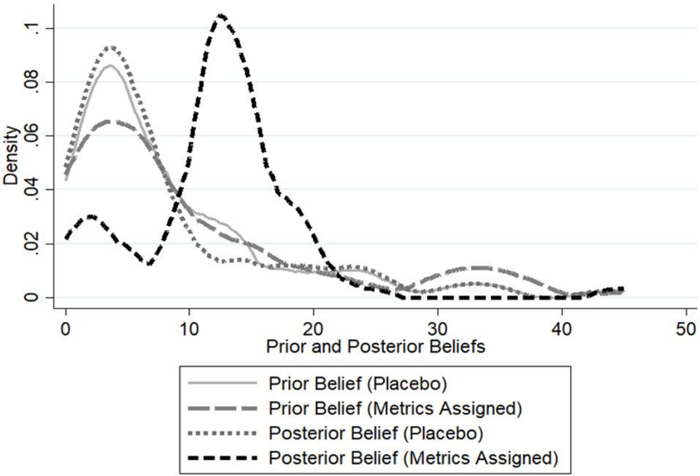
Metrics Training Increased Demand for Causal Evidence



Treated Policymakers Update Posterior Beliefs

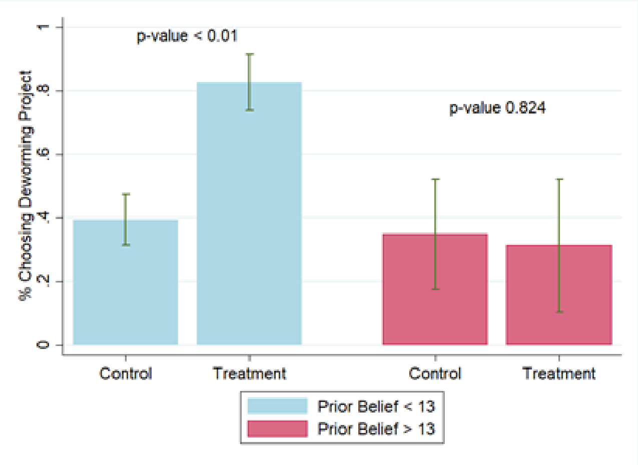
Increased Responsiveness to Causal Evidence

Treated policymakers' performance in national research methods and public policy exams improves and commissioning of RCTs in policy making increases



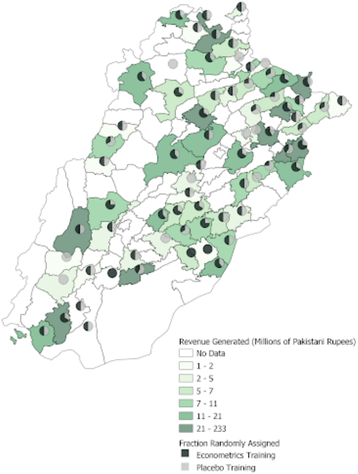
Metrics Training Impacts Deworming Project Choice

In their official duties, twice as likely to choose and triple funding for policies with RCT evidence



Metrics Training Improves Fiscal State Capacity

The results extend to tax officers: Econometrics education led to a 20% increase in the use of tax reminders and 40% increase in tax collection



AEARCTR-0010583, *Training Policymakers in Econometrics II, Management Science R/R*

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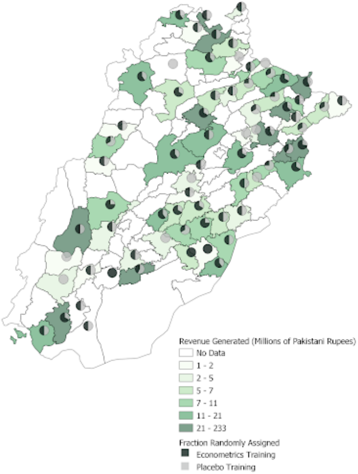

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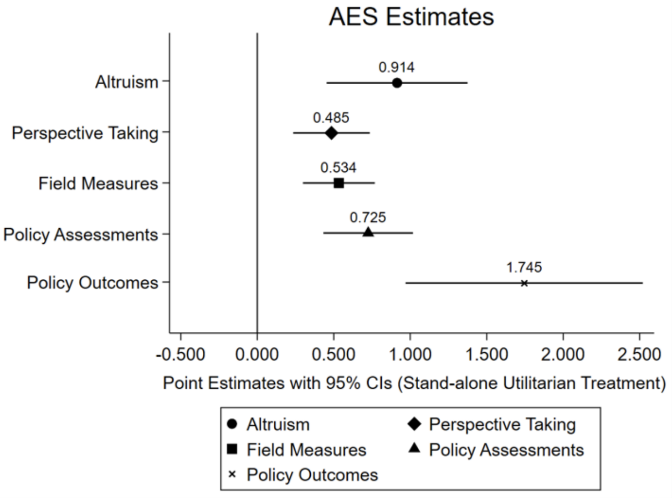
Randomizing schools of thought on cultivating prosociality

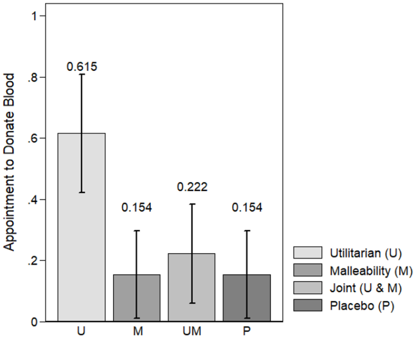
Training effective altruism via the utilitarian value of empathy renders greater altruism

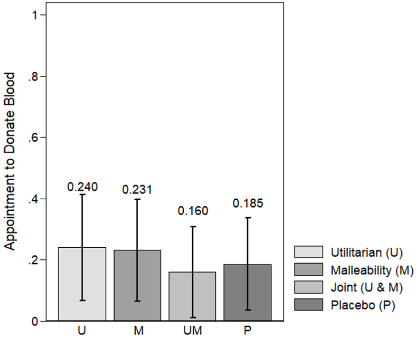


Blood Donations

Training effective altruism increased mentalizing on consequences of decisions

Blood donations doubled only for matching blood type





Perspective-taking in strategic dilemmas improved

Altruism in Action

Orphanage visits and volunteering increased. Amid official duties, ministers were more likely to choose social policies and recommended 4-fold funding for them

Table 6: Impact of Treatments on Policy

	Orphanage Renovation Policy		*School Renovation Policy*	
	Letter Sent	Funds Recommended (PKR)	Letter Sent	Funds Recommended (PKR)
	(1)	(2)	(3)	(4)
U	0.306***	72,708**	0.386***	78,101**
	(0.0754)	(30,867)	(0.0892)	(30,181)
M	0.0599	19,007	-0.0381	17,764
	(0.0562)	(25,173)	(0.0768)	(13,888)
UM	0.0939	17,448	-0.0451	25,848
	(0.0597)	(24,144)	(0.0755)	(18,399)
Individual Controls	Yes	Yes	Yes	Yes
Observations	201	201	201	201
R-squared	0.197	0.125	0.253	0.147
Mean of dep. var. (placebo)	0.041	18367.35	0.163	8367.35

The book lottery illustrates the mechanism

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Demand for Learning Drives Long-Term Impacts

POLICIES ARE INFLUENCED BY TREATMENT ONLY WHEN THE BOOK IS ASSIGNED

Table 9: Causal Mediation Analysis – Mechanism

	Orphanage Renovation Policy		*School Renovation Policy*	
	Letter Sent	Funds Recommended (PKR)	Letter Sent	Funds Recommended (PKR)
	(1)	(2)	(3)	(4)
U	-0.0703	-31,895	-0.250*	-3,443
	(0.0610)	(20,961)	(0.136)	(20,214)
M	0.208*	71,262	-0.0659	41,749
	(0.108)	(44,827)	(0.151)	(30,768)
UM	0.0284	24,604	-0.0430	60,145
	(0.109)	(51,114)	(0.168)	(45,833)
Empathy Book Assigned	0.0169	22,815	-0.317	-1,291
	(0.0534)	(21,408)	(0.203)	(34,365)
UX Empathy Book Assigned	0.458***	56,736	1.124***	119,067**
	(0.138)	(40,251)	(0.229)	(51,932)
MX Empathy Book Assigned	-0.318**	-115,090**	0.0983	-16,161
	(0.134)	(47,621)	(0.254)	(45,536)
UMX Empathy Book Assigned	-0.133	-68,845	0.213	-21,556
	(0.119)	(45,727)	(0.233)	(44,478)
Individual Controls	Yes	Yes	Yes	Yes
Observations	201	201	201	201
R-squared	0.328	0.204	0.429	0.196
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AEARCTR-0006655, *Mehmood, Naseer, and Chen, J Development Econ 2024*

What about AI training?

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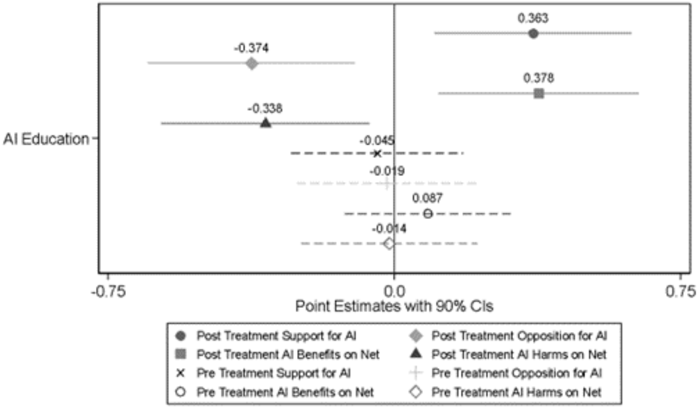
What about AI training?

AI Training and AI Fairness Activism

AI Training/Activism Impacts AI Attitudes of Ministers and their Subordinates



AI Fairness Activism: Weapons of Math Destruction (O'Neill 2016)

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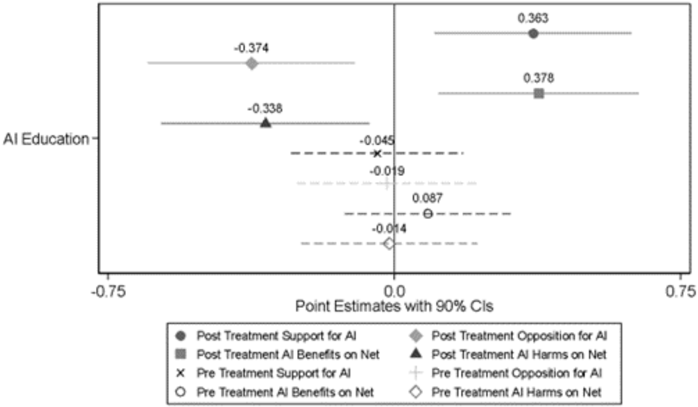

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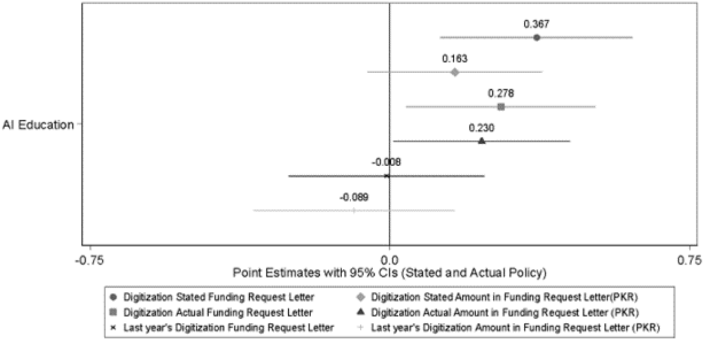
AMID LAND RECORD DIGITIZATION EFFORTS..

AI Training and AI Fairness Activism

AI Training/Activism Impacts Digitization Funding



AI Training Improves Resolution of Land Disputes

by 33% in resolution time, while AI Fairness Activism worsens resolution of land disputes

Table 9: Impact of AI Education Training and Fairness Activism by Land and Placebo Schools & Road Construction Complaints

	Land and Residential Property Complaints		*Placebo - Schools & Road Construction Complaints*	
	Citizen Rating Average	Resolution Days Average	Citizen Rating Average	Resolution Days Average
	(1)	(2)	(3)	(4)
Panel A: AI Education				
AI Education	0.477**	-22.31**	0.203	-12.49
	(0.185)	(8.746)	(0.270)	(9.157)
Controls	Yes	Yes	Yes	Yes
Observations	95	95	95	95
R-squared	0.155	0.269	0.023	0.192
Mean Dep. Variable	1.703	65.356	2.403	63.723
Panel B: AI Fairness Activism				
AI Fairness Activism	-0.332*	15.85*	-0.373	8.512
	(0.192)	(8.709)	(0.251)	(8.617)
Controls	Yes	Yes	Yes	Yes
Observations	95	95	95	95
R-squared	0.126	0.244	0.041	0.182
Mean Dep. Variable	1.703	65.356	2.403	63.723

AEARCTR-0008431, *AI Education as State Capacity: Experimental Evidence from Pakistan*

Schools of thought have been influential in impacting citizens' lives

WOMEN'S RIGHTS MOVEMENT HAS IMPROVED LIVES OF WOMEN

BUT SLOW PROGRESS IN SOME PLACES SPEAK TO STICKINESS OF NORMS

CAN WE SHIFT THE ATTITUDES OF FRONT LINE CIVIL SERVANTS?

AI Training Improves Resolution of Land Disputes

by 33% in resolution time, while AI Fairness Activism worsens resolution of land disputes

Table 9: Impact of AI Education Training and Fairness Activism by Land and Placebo Schools & Road Construction Complaints

	Land and Residential Property Complaints		*Placebo - Schools & Road Construction Complaints*	
	Citizen Rating Average	Resolution Days Average	Citizen Rating Average	Resolution Days Average
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Panel A: AI Education				
AI Education	0.477**	-22.31**	0.203	-12.49
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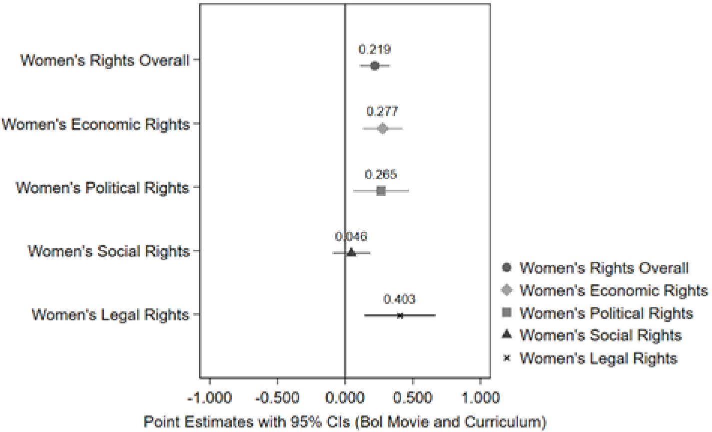
Transmitting Gender Rights Shifts Teacher's Attitudes

Using a visual narrative (best-selling film developed with Johns Hopkins) and 5-page curricular outline, we randomized teachers to conduct structured semester-long class discussions over women's rights.

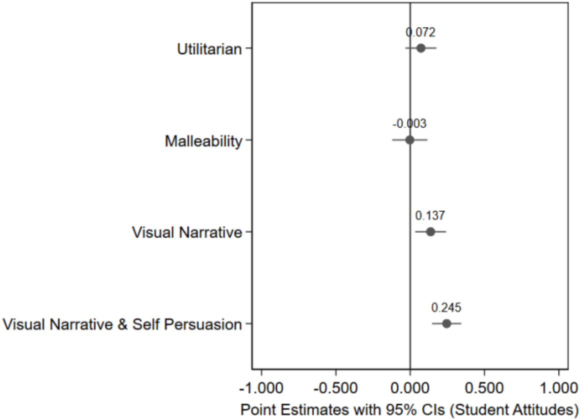


Signing of Petititons and Implicit Attitudes

	(1)	(2)	(3)	(4)
	Gender Recognition Index	*Petition to Criminalize Dowry*	*Petition to Abolish Polygamy*	*Gender IAT Score*
Visual Narrative & Self-Persuasion	0.187***	0.566***	0.512***	0.348**
	[0.0510]	[0.143]	[0.146]	[0.162]
Visual Narrative	0.140***	0.362***	0.349**	0.247*
	[0.0511]	[0.130]	[0.140]	[0.136]
U	0.0607	0.0221	-0.0626	-0.0786
	[0.0445]	[0.104]	[0.0557]	[0.140]
M	0.0897*	0.0595	-0.0191	-0.114
	[0.0531]	[0.109]	[0.0603]	[0.123]
Individual Controls	Yes	Yes	Yes	Yes
School Fixed Effects	Yes	Yes	Yes	Yes
Observations	607	607	607	527
R-squared	0.138	0.140	0.200	0.131

Gender Rights are Oblique Transmitted to Students

Figure 3: Impact on Students' Gender Attitudes



role models may explain oblique transmission of norms

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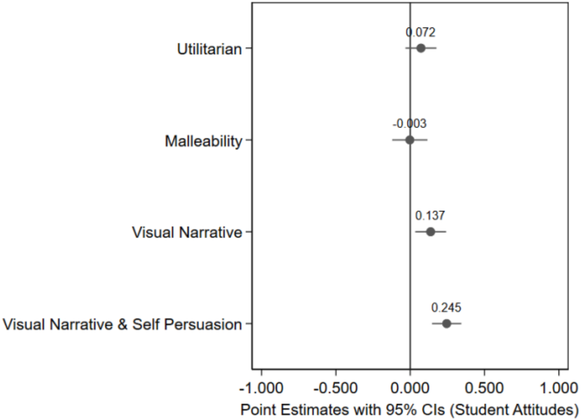

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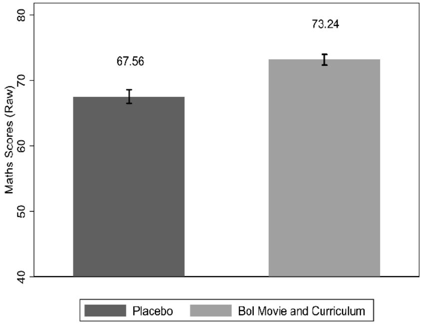
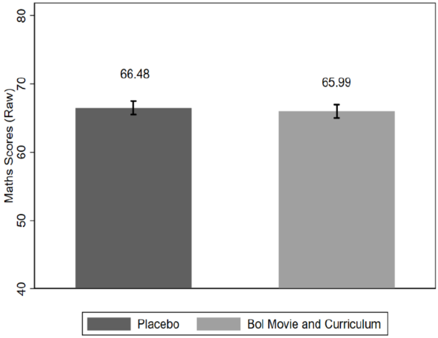
Transmitting Gender Rights Improves Student Achievement

Only for Mixed Gender Study Groups



mixed gender study groups



same gender study groups

Mixed-Gender Study Groups

Increased cooperation and coordination with the opposite gender

Panel A: *Responses when facing opposite gender*

	(1)	(2)	(3)	(4)
	Redistribution	*Competitiveness*	*Cooperation*	*Coordination*
U X Mixed Study Group	-0.0661	-0.0219	-0.00630	-0.0168
	[0.0646]	[0.0666]	[0.0377]	[0.0347]
M X Mixed Study Group	-0.0812	-0.0961	-0.0230	0.0122
	[0.0642]	[0.0669]	[0.0380]	[0.0345]
Movie X Mixed Study Group	-0.0375	-0.0666	0.171***	0.184***
	[0.0705]	[0.0705]	[0.0386]	[0.0481]
Movie-Curriculum X Mixed Study Group	-0.0406	-0.0358	0.299***	0.333***
	[0.0671]	[0.0733]	[0.0349]	[0.0347]
Playing with Opposite Gender	Yes	Yes	Yes	Yes
Individual Controls & School FE	Yes	Yes	Yes	Yes
Observations	9,145	9,145	9,145	9,145
R-squared	0.008	0.013	0.610	0.331

AEARCTR-0007465, *Mehmood, Naseer, and Chen, American Economic J: Policy 2024*

How Can We Train Judges?

are there principles that extend to training judges and apply to human-centric AI?

- SELF-REFLECTION (effective altruism, econometrics, gender rights)
- DEMAND FOR LEARNING (effective altruism, econometrics)
- SOCIAL-EMOTIONAL LEARNING (effective altruism, econometrics, AI)
- COMMUNITY FOR NORM CHANGE (gender rights, mental health)

Civil Servants	**Judges**
Effective Altruism	Simplified Feedback (Stage 1)
Econometrics	**Socratic Method** (Stage 2)
AI Fairness	**Self Reflection (IATs)** (Stage 3)
Gender Rights	Social Emotional Learning (SEL) (Stage 4)
Role Models	Social Comparison (Stage 5)
Moral Bandwagoning	**Community of Practice** (Stage 6)

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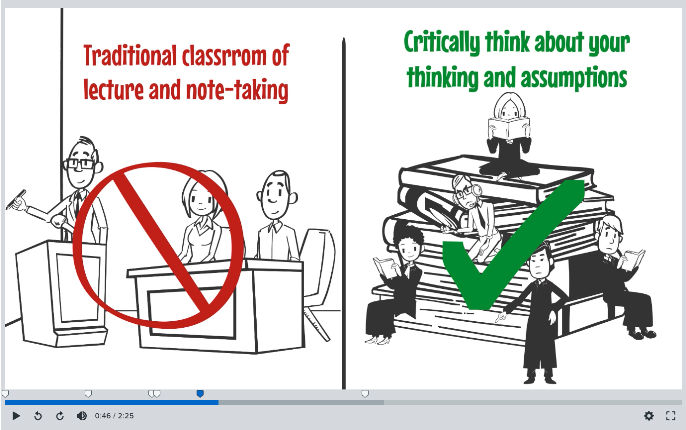
Setting

- Judicial Academy of Peru is working on the transition from theory to case-based teaching, which was already the primary method of teaching in American law schools since the 1970s (Moskovitz 1992).
- In this two-year engagement, we conducted three randomized light-touch interventions.

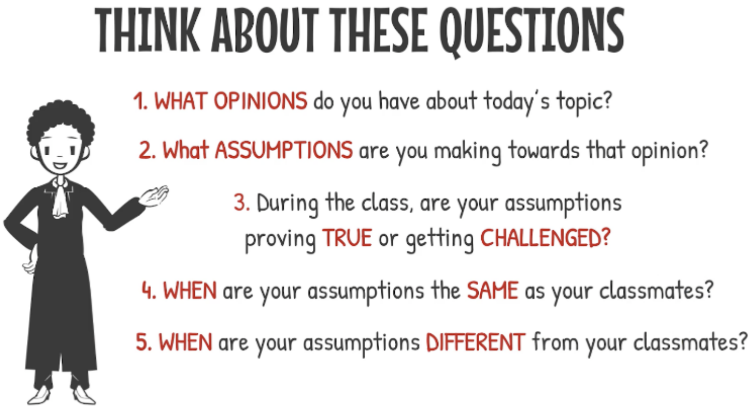
Socratic Method (Study 1)

a pedagogical innovation from antiquity focusing on reflective inquiry



Socratic Treatment

- Socratic treatment encourages student to think critically - challenging their own as well as their teachers and classmates assumptions about the material covered in class.



- Control treatment reminded students to focus on the teacher's ideas and take notes

Socratic Training improved Performance

Students assigned to Socratic treatment were 2.6 percentage points more likely to pass

and increased grades by 0.23 standardized units

	ITT		ToT	
	(1)	(2)	(3)	(4)
VARIABLES	grade	pass	grade	pass
Assigned to Socratic	0.311*	0.026*		
	(0.173)	(0.014)		
	[0.088]	[0.088]		
Saw Socratic			0.950*	0.080*
			(0.542)	(0.045)
			[0.080]	[0.080]
Constant	15.633***	0.844***	15.633***	0.844***
	(0.195)	(0.015)	(0.195)	(0.015)
Observations	1,368	1,370	1,368	1,370
R-squared	0.001	0.001		
Individuals	1368	1370	1368	1370

Click data shows larger treatment effects on those who finished the 4-minute video (ToT)

Socratic Training reduced Motivated Reasoning

Students assigned to Socratic treatment were 6.5 percentage points more curious

	ITT			ToT		
	(1)	(2)	(3)	(4)	(5)	(6)
VARIABLES	VDO	SBU	Curiosity	VDO	SBU	Curiosity
Assigned to Socratic	-0.016	0.028	0.065**			
	(0.042)	(0.047)	(0.027)			
	[0.904]	[0.896]	[0.030]			
Saw Socratic				-0.038	0.066	0.122**
				(0.100)	(0.109)	(0.053)
				[0.910]	[0.896]	[0.020]
Constant	0.980***	0.980***	0.874***	0.980***	0.980***	0.874***
	(0.030)	(0.029)	(0.023)	(0.030)	(0.029)	(0.023)
Observations	498	498	300	498	498	300
R-squared	0.000	0.001	0.013		0.004	
Individuals	498	498	300	498	498	300

and requested additional information on the supreme court case vignette

AEARCTR-0007113, *The Impact of Socratic Method*

Community of Practice (Study 2)

- Community of Practice (Wenger 1991) a pedagogical innovation focusing on regular and concrete learning from peers.
  - The peer met the teacher to provide feedback
    - teaching strategies: case method, role play, student participation

Community of Practice increases Grades and Satisfaction

	Grades					Satisfaction	
	(1) Forum grade	(2) Reading grade	(3) Homework grade	(4) Exam grade	(5) Final grade	(6) With teacher	(7) With course
Monitoring	0.0702	0.0818**	0.0794	0.1609	0.1196**	0.0964*	0.0875*
	(0.0759)	(0.0347)	(0.0499)	(0.0956)	(0.0578)	(0.0553)	(0.0504)
Observations	4,968	4,988	5,017	5,000	5,021	10,023	9,967
R^2	0.13221	0.16559	0.12541	0.06765	0.09313	0.02617	0.03810
Dependent variable mean	0.04144	0.01453	0.05110	0.08771	0.07569	0.06086	0.06448
Round fixed effects	✓	✓	✓	✓	✓	✓	✓
Course fixed effects	✓	✓	✓	✓	✓	✓	✓

- 0.12 standard devations (SD) in final grades
- 0.10 and 0.09 SDs in satisfaction

Community of Practice increases Case Clearance Rates

	(1) Ruling favors plaintiff	(2) Appeal of ruling	(3) Reversal of ruling	(4) Clearance rate	(5) Time to disposition	(6) Timely Resolved
Panel A: Post Treatment						
Monitoring	0.0866	-0.1017	-0.0038	0.1683**	-0.2410	0.1799*
	(0.1189)	(0.1384)	(0.0591)	(0.0759)	(0.2485)	(0.1047)
Observations	169	169	169	203	219	219
R Squared	0.102	0.326	0.158	0.101	0.182	0.191
Dependent variable mean	0.8182	0.4915	0.0899	0.3220	-0.0496	0.4622

Note: Standard errors are clustered at the judge level. Time to disposition is standardized with respect to the control group mean. All regressions include strata controls. All regressions include judge pre treatment covariates including age, sex, years of tenure, years in the bar association. They also include case speciality covariates. Panel A shows regression coefficients from a post-treatment specification. Panel B shows coefficients from a DiD specification. $*$ *p* < 0.10, $**$ *p* < 0.05, $***$ *p* < 0.01.

8-month training program

Community of Practice effects are larger for females

Females in treated classes had higher grades and satisfaction

	Grades					Satisfaction	
	(1) Forum grade	(2) Reading grade	(3) Homework grade	(4) Exam grade	(5) Final grade	(6) With teacher	(7) With course
Panel A: Males							
Monitoring	0.0556	0.0467	0.0536	0.1425	0.0829	0.0567	0.0332
	(0.0813)	(0.0470)	(0.0590)	(0.0950)	(0.0663)	(0.0592)	(0.0567)
Observations	3108	3123	3142	3129	3145	6248	6248
R Squared	0.137	0.162	0.119	0.057	0.088	0.035	0.042
Dependent variable mean	0.0371	-0.0076	0.0496	0.0836	0.0644	0.0518	0.0685
Panel B: Females							
Monitoring	0.0971	0.1437***	0.1012*	0.1769	0.1555**	0.1389	0.1794*
	(0.0734)	(0.0511)	(0.0518)	(0.1108)	(0.0672)	(0.0951)	(0.0969)
Observations	1860	1865	1875	1871	1876	3719	3719
R Squared	0.140	0.200	0.169	0.105	0.129	0.050	0.061
Dependent variable mean	0.0487	0.0516	0.0537	0.0945	0.0946	0.0747	0.0576

Community of Practice reduces Gender IAT bias

especially for male judges and prosecutors

	Baseline			Baseline + Controls		
	(1) All	(2) Females	(3) Males	(4) All	(5) Females	(6) Males
Monitoring	0.3580**	0.1451	0.4183**	0.3575**	0.1362	0.4192**
	(0.1469)	(0.2268)	(0.1929)	(0.1498)	(0.2332)	(0.1957)
Lee Lower bound	-0.0065	-0.0571	-0.0057	-0.0065	-0.0571	-0.0057
Lee Upper bound	0.5551	0.2424	0.7446	0.5551	0.2424	0.7446
Observations	292	112	180	291	112	179
R^2	0.02836	0.07132	0.03628	0.03820	0.10496	0.06437
Dependent variable mean	0.15741	0.09413	0.19678	0.15607	0.09413	0.19482

highlights potential for cultivating active participation in mixed groups in

reducing implicit bias in high-stakes decision-makers

AEARCTR-0007113, *Training and Bureaucratic Performance*

WHAT ABOUT DIRECTLY ADDRESSING IMPLICIT BIAS

STEREOTYPED DECISION-MAKING, EARLY PREDICABILITY, AND INATTENTIVENESS

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    - Implicit bias training programs involve compulsory self-reflection
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    - Does the choice to learn about implicit biases reduce implicit bias?
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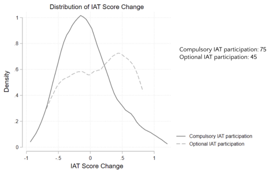

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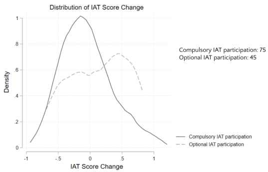

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AEARCTR-0007113, *Impact of Legal Training on Cognitive Reasoning, Biases and Judicial Performance*

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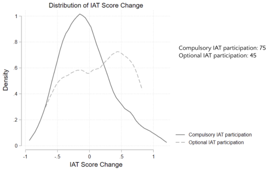

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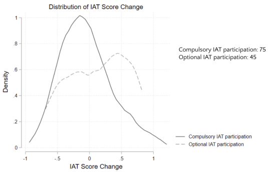

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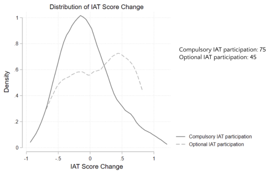

- [0, 0.15]: Low or none bias
-]0.15, 0.35]: Slight bias
-]0.35, 0.65]: Moderate bias
-]0.65, ...]: Strong bias

- Values **greater** than 0: Association between feminine and career

- Values **lower** than 0: Association between feminine and family

AEARCTR-0007113, *Impact of Legal Training on Cognitive Reasoning, Biases and Judicial Performance*

Option to Self-Reflect (Study 3)

- Weak evidence for implicit bias training programs (Paluck, et al. 2021)
  - Implicit bias training programs involve compulsory self-reflection
  - The more people feel that their autonomy is protected and that they are in control of the conversation—able to choose when feedback is given—the better they respond to it (West, et al. 2018)
  - Does the choice to learn about implicit biases reduce implicit bias?
- Judges randomly assigned to
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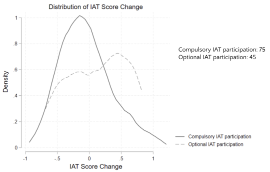

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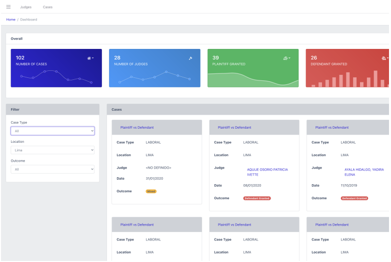
Personalized Case-Based Teaching?

using the tools of machine learning



Leverages history of judge's own written decisions to evaluate how such judge would decide on a case similar to a curricular example (predicted self)

- Bringing case-based teaching to the next level (socratic method)
- Community of practice, Role models (predictions of others)
- Helping create culture of precedent

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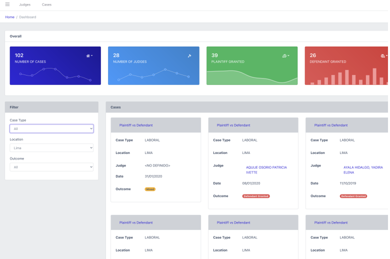

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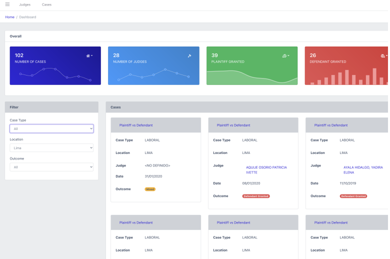

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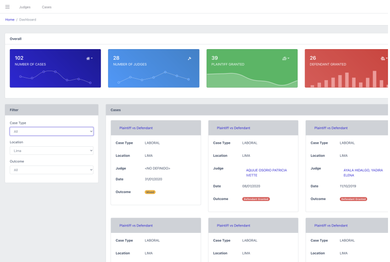

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AI can increase Access, Efficiency, and Fairness of Justice

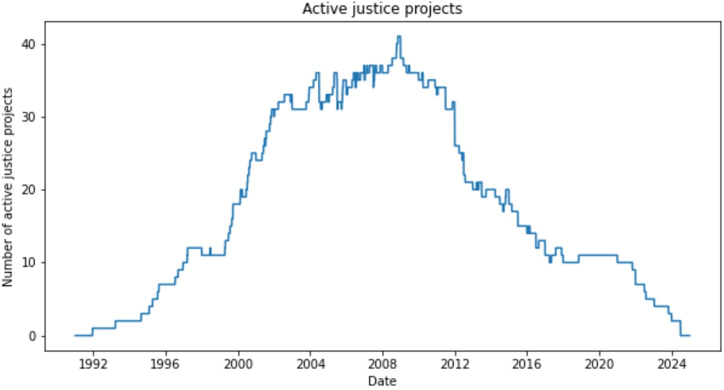
reduce market level constraints to economic development

Judges	Citizens
Static dashboards	Search
Static dashboards with nudges	E-access
Dynamic dashboards	E-resolution
Top-down smart assignments	Chatbots
Bottom-up smart assignments	Decision-Support
Static peer-to-peer exchange	Missing Cases
Dynamic peer-to-peer exchange	Legitimacy
Training attitudes and preferences	Recognition-Respect

Mexico Australia Colombia Taiwan Vietnam China Canada Asylum Brazil Germany

Do multilaterial organizations care about justice?

Decline in Justice Projects at the World Bank

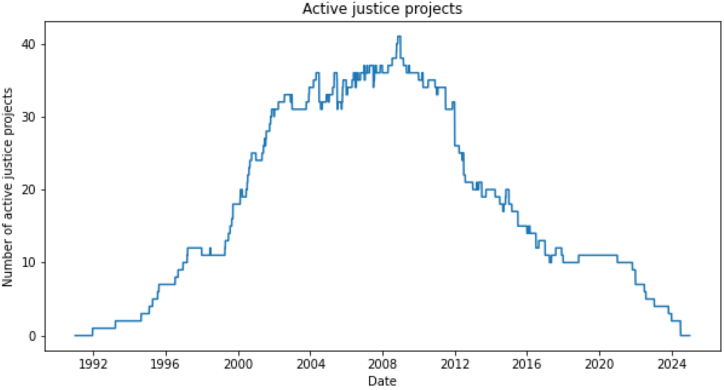


Should we invest more in justice?

What ideas do you have?

Do multilaterial organizations care about justice?

Decline in Justice Projects at the World Bank



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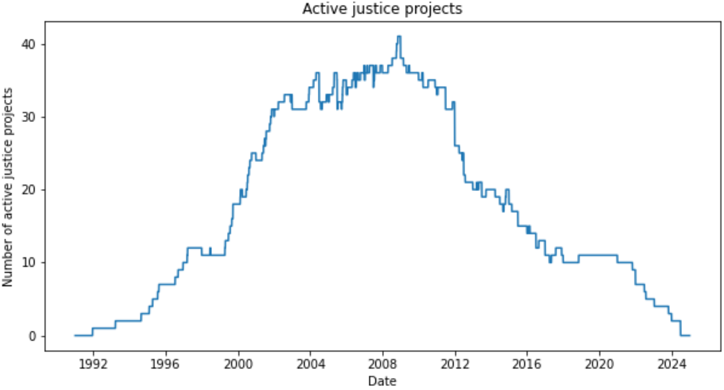

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