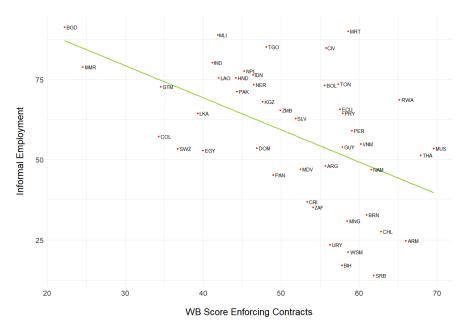
DE JURE (Data and Evidence for Justice Reform)

Innovations in Data with Policy Implications

Daniel L. Chen, Manuel Maqueda, and Sandeep Bhupatiraju

## Economic development & legal institutions are associated



#### **Country Specific Examples of Our Work** CZECH REPUBLIC & CROATIA: · Prisoner survey of perceptions of legitimacy and beliefs on sanctions · Impact of justice on firm outcomes PAKISTAN & BANGLADESH · App-based reporting of and norm interventions on gender based violence BRAZIL: · Impact of legal predictions, what is trustworthy Al Impact of legal rulings and impact of politics on courts · Iudicial training, theory vs. casebased teaching, social-emotional INDIA: · Courts and informality, impact of · Impact of chatbots and search legal rulings on environment algorithms for legal knowledge · Missing cases and gender based violence SENEGAL & KENYA: · Measuring textual slant and the · Behavioral interventions to reduce consequences of it court backlogs · Behavioral interventions in dashboards

· Machine Learning to identify judicial

· Evaluating the impact of procedural

reforms on the speed of justice

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

PERU:

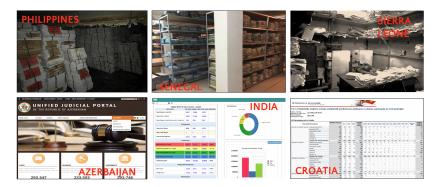
CHILE:

· Mobile justice and e-arbitration

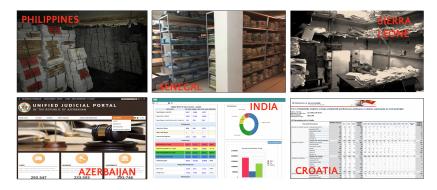
· Impact of COVID-19 on interrupted

· Impact of Electronic Processing Law on efficiency and access to justice

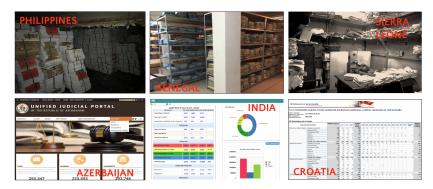
learning interventions



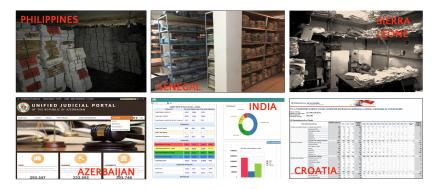
- Recent innovations have opened up new opportunities for delivery of justice
  - Increasingly digitized large-scale datasets
  - ML applications to produce interpretable data from unstructured text
  - Predictive models of decision-making to better understand biases and address them with digital interfaces



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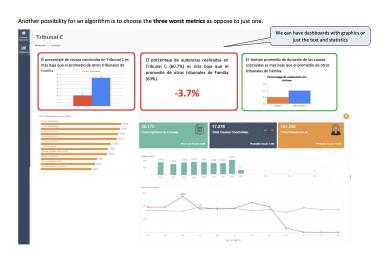
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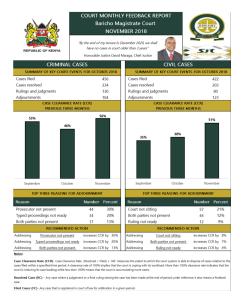
### Personalized Interventions

This kind of data can be used to personalize interfaces for judges.



### Recommending Actions

Lending Agreement with Kenya: Judicial Performance Improvement (P105269)



- 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 (one-pager also sent to Court User Committees)
  - Control: status quo (no information), RCT across all 124 court stations

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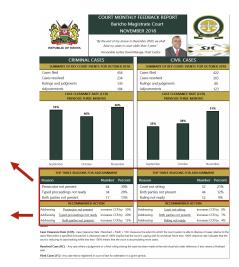
### Data-Driven Recommendations

### **Efficiency in Kenya:**

Can low cost, 'actionable' information improve performance?

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%



.. especially initiated by the judge.

	Adjournment	Internal Adjournment	External Adjournment
OnePager * February 2019	-0.014	-0.017	0.000065
	(0.012)	(0.011)	(0.0043)
OnePager CUC * February 2019	-0.031**	-0.030**	-0.0042
	(0.015)	(0.013)	(0.0043)
OnePager * March 2019	0.0016	0.0028	-0.00028
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OnePager * April 2019	-0.012	-0.0044	-0.0076
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OnePager * Month Before	-0.0089	-0.0030	-0.0069
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OnePager CUC * Month Before	-0.0074	-0.010	-0.0084
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Observations	6162668	6399868	6399868

Starting Oct 2020, will become monthly

Effect size of 3% are large relative to baseline of 18%

ADVICE IS TOP-DOWN BASED ON DATA ALREADY COLLECTED

CAN WE HELP COUNTRIES GENERATE THEIR OWN BETTER POLICIES

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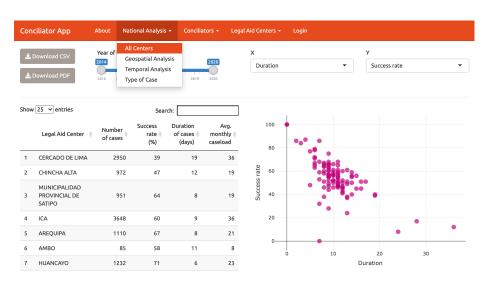
CAN WE HELP COUNTRIES GENERATE THEIR OWN BETTER POLICIES?

### Self Reflection

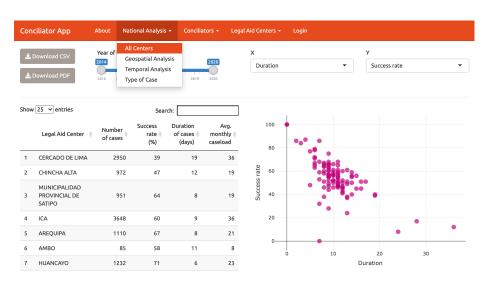
### Social-Emotional Learning Exercises - Advice Giving & Grading



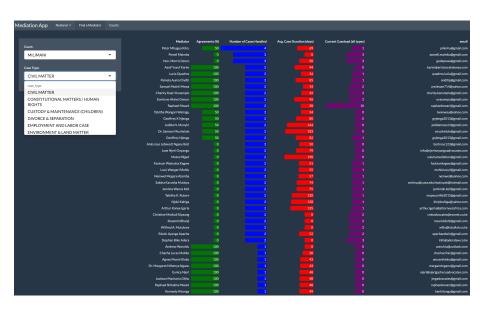
## Recommending Actions to Each Other



## Recommending Actions to Each Other



## Recommending Mediators



### API to create own dashboards



Victim's defense, public defense, psychological support

## Incentivize Case Logs



Record and present correlates of improvement

TRANSFER LEARNING WITHIN AND ACROSS DECISION-MAKERS

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TRANSFER LEARNING WITHIN AND ACROSS DECISION-MAKERS

## Incentivize Case Logs



Record and present correlates of improvement

Transfer learning within and across decision-makers

## Wiki-survey Structured Questions

IEs among lending agreement with Peru

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

Question: Can adaptive learning (advice giving & receiving) improve the performance of court actors and litigant wellbeing?



#### Intervention:

- Formalize advice-giving to dynamically generate an automated policy causal inference machine
  - Social-emotional learning exercises have been documented to improve intrinsic motivations, increase empathy and social identity with occupation
- Ask top performers to give advice to others
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  - Analyze impacts on decisions and disparities

#### IE design and timeline:

- Multi-arm Bandit Impact Evaluation
- **2**020-

Key Feature: Lending agreement with Peru includes 3 impact evaluations (legal aid, judicial training, and electronic processing)

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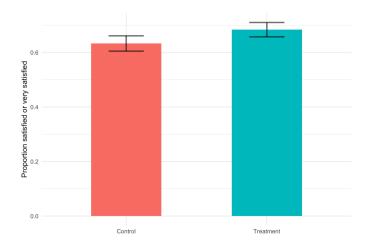
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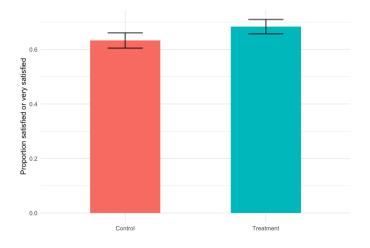
## Online Class Monitoring Improves Student Satisfaction

IE first requested by Peru: what is the effect of monitoring & feedback?



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IE first requested by Peru: what is the effect of monitoring & feedback?



Monitoring + Debrief = "Community of practice" (Etienne Wenger)

## What is the Impact of E-Justice?

IE first requested by Chile: what is the effect of electronic filing?

# **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-**

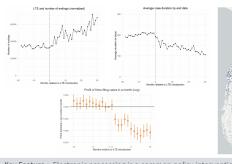
Key Feature: Electronic processing is a common policy intervention; covid accelerates development of e-justice solutions

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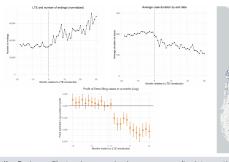
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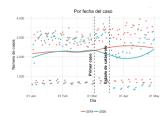
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#### .. like many other countries, Chile experienced

# Decline in reported criminal cases amid COVID



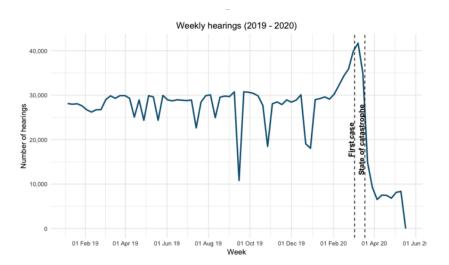
- Most common crimes fell during March and April relative to 2019.
- Theft experienced the largest decline.
- Rebound appears

 There was a significant reduction in crimes reported after the state of catastrophe took place.

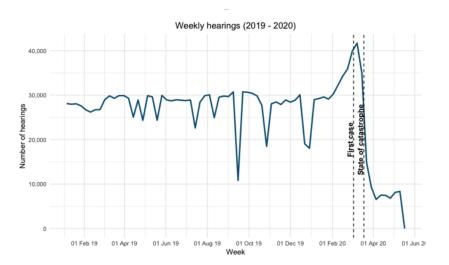
Cambio porcentual en el número de casos (2020 vs. 2019) - Delitos más comunes		
Grupo de delito	Marzo	Abril
HURTOS.	-36.90	-50.37
DELITOS CONTRA LA FE PÚBLICA.	-21.80	-23.33
FALTAS	-19.91	-32.75
DELITOS CONTRA LA LIBERTAD E INTIMIDAD DE LAS PERSONAS.	-13.45	-20.48
DELITOS LEY DE TRÁNSITO	-12.02	-31.02
ROBOS NO VIOLENTOS.	-10.99	-21.60
OTROS DELITOS CONTRA LA PROPIEDAD.	-9.95	-31.21
LESIONES.	-5.39	-16.93
DELITOS ECONÓMICOS.	-1.88	-12.90
DELITOS DE DROGAS.	4.69	-14.11



#### .. and decrease in court activity

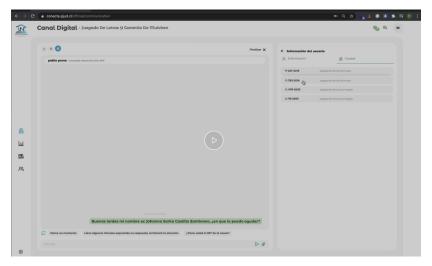


#### .. and decrease in court activity



#### How to facilitate justice amid covid?

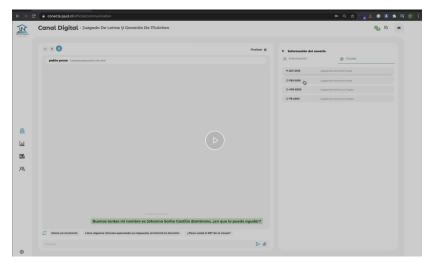
# E-Justice during covid: Whatsapp



for Q&A with courts

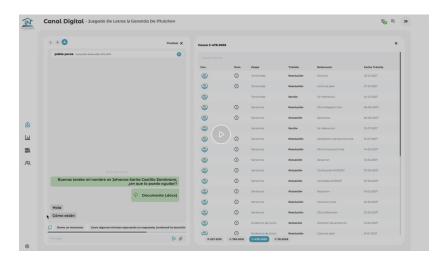
video and audio also enabled

## E-Justice during covid: Whatsapp



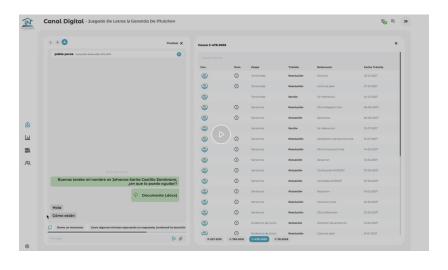
for Q&A with courts video and audio also enabled

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



documents are linked

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documents are linked

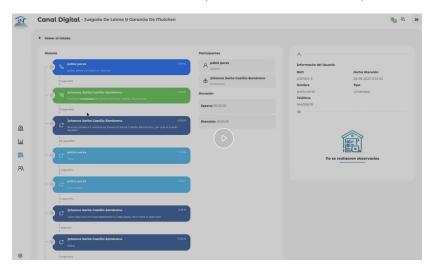
#### Cases are linked across calls

.. and into the courts (DIGITAL INTEROPERABILITY)



#### Cases are linked across calls

.. and into the courts (DIGITAL INTEROPERABILITY)



FACILITATING DOWNSTREAM ANALYSIS ON CONSEQUENCES

# 40% of inquiries have been related to alimony

Pilot being rolled out nationally (and advertised on Facebook)



to improve speed of justice

What do we know about the impact of speed of justice?

## 40% of inquiries have been related to alimony

Pilot being rolled out nationally (and advertised on Facebook)



to improve speed of justice

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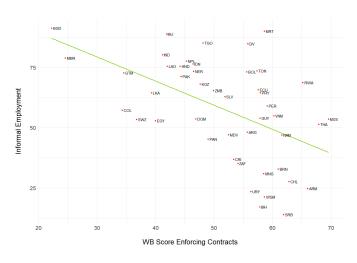
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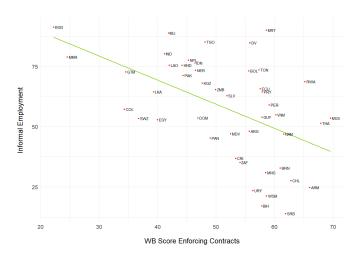
# Economic development & legal institutions are associated

#### MACRO EVIDENCE, E.G.:



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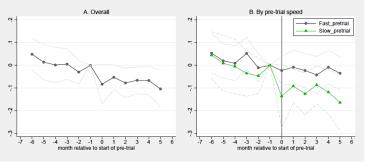


What about the micro evidence?

#### Senegal: Impact of Procedural Reform (P1222225)

#### Revenue is 8% lower for cases with pre-trial duration $\geq$ 4 months

Figure 1: Case parties' log revenues around the start of the pre-trial



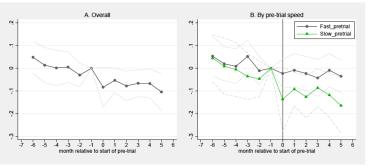
Note: For all x-axes, month is indexed in relation to the case-level pre-trial start month (zero-centered)

=> Staggered roll-out of judicial reform giving judges the duty and powers to conclude pre-trial proceedings in 4 months

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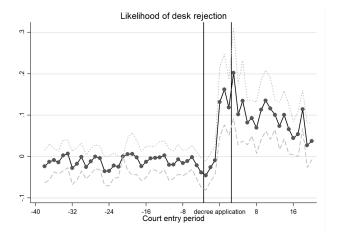
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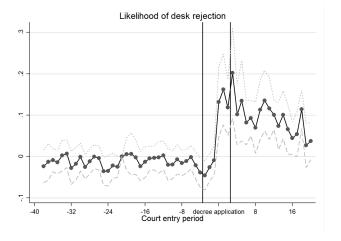
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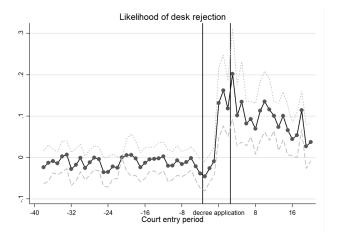
Reform halved the negative impact on revenues & increased firm satisfaction

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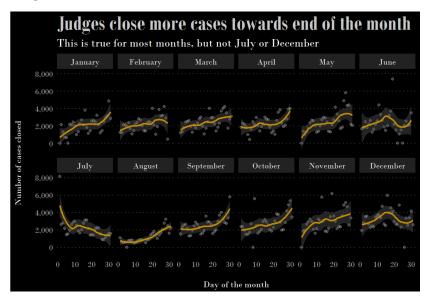
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### Scoring Rules: End-of-Month Quotas



### Firm Assets Associated with Judicial Speed

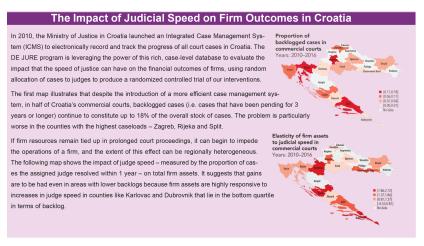
#### .. and more associated, in slower jurisdictions



Justice Sector Support Project (P104749)

### Firm Assets Associated with Judicial Speed

#### .. and more associated, in slower jurisdictions



Justice Sector Support Project (P104749)

IS IT CAUSAL?

### **Empirical Challenges**

#### Medicine, prior to clinical trials

Theories about the effects, but no causal evidence (a century ago)

#### Randomizing judicial decisions

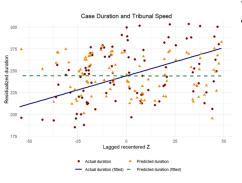
Violates our notion of justice (equal treatment before the law)

#### Randomizing judicial assignment

Generates retrospective "clinical trial" (Kling AER 2006; many since "credibility revolution" in economics)

### What is the Impact of Speed of Justice?

#### Chile cases are randomly assigned to tribunals



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)

#### Preliminary evidence on Summary cases (smaller firms)

	Log Sales		
	t-1	t0	t+1
	(1)	(2)	(3)
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

We are exploring similar research design in Croatia (& anytime infrastructure permits)

knowledge of one's effectiveness as public defender

Instead of leveraging variability

CAN WE REDUCE IT?

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Preliminary evidence on Summary cases (smaller firms)

		Log Sales	5
	t-1	t0	t+1
	(1)	(2)	(3)
Tribunal Speed	-0.008	0.049	0.099***
	(0.025)	(0.034)	(0.034)
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#### Interventions

- Chilean courts are affected by high imbalance of workload and little incentives to perform better.
- Telework aims to improve performance in congested courts by balancing the workload across courts, without incurring the costs of hiring new staff.
- Participants volunteer into an incentives scheme--receive benefits conditional on doing the extra work and on meeting performance targets.

## Research Design

- We use Randomized Controlled Trials (RCT) with treatments:
  - Providing Telework: administrative staffs and judges opt-in the program.
  - Receiving Telework: receive help from another tribunal at no extra cost.
- There are 41 blocks between composed of at least three tribunals of similar competence & jurisdiction.

Stage 1: mechanism to smooth variability across jurisdictions (daily, court-specific incentive)

Stage 2: mechanism to smooth variability across time within jurisdictions ('uber')

UBERIZATION ADDRESS CASES ACTUALLY FILED

WHAT ABOUT CASES THAT NEVER FILE?

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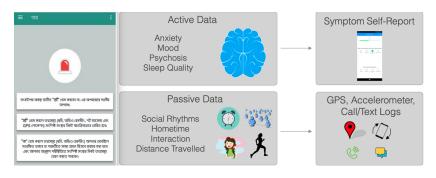
Stage 2: mechanism to smooth variability across time within jurisdictions ('uber')

UBERIZATION ADDRESS CASES ACTUALLY FILED

What about cases that never file?

### Apps for Missing Cases Bangladesh app (nationally advertised on July 2018)

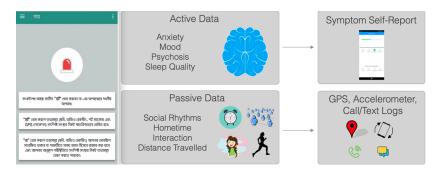
#### smartphone app aiming to address violence against women and children



- Emergency button sends the victim's GPS, picture, and audio recording
- Potentially add passive features for additional revealed preference data

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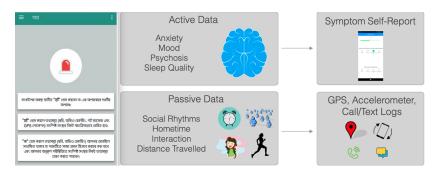
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#### **Country Specific Examples of Our Work** CZECH REPUBLIC & CROATIA: · Prisoner survey of perceptions of legitimacy and beliefs on sanctions · Impact of justice on firm outcomes PAKISTAN & BANGLADESH · App-based reporting of and norm interventions on gender based violence BRAZIL: · Impact of legal predictions, what is trustworthy Al Impact of legal rulings and impact of politics on courts · Iudicial training, theory vs. casebased teaching, social-emotional INDIA: · Courts and informality, impact of · Impact of chatbots and search legal rulings on environment algorithms for legal knowledge · Missing cases and gender based violence SENEGAL & KENYA: · Measuring textual slant and the · Behavioral interventions to reduce consequences of it court backlogs · Behavioral interventions in dashboards

· Machine Learning to identify judicial

· Evaluating the impact of procedural

reforms on the speed of justice

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

PERU:

CHILE:

· Mobile justice and e-arbitration

· Impact of COVID-19 on interrupted

· Impact of Electronic Processing Law on efficiency and access to justice

learning interventions

### India E-courts

	prev. scrape	current scrape	Δ
districts	608	633	+ 04%
courts	6292	7154	+ 14%
# of cases 2015-2018 all states	40.95M	48.9M	+ 19%

year	prev. scrape	new scrape	merged
2000	0.46M	0.53M	calculating
2001	0.71M	0.77M	calculating
2002	0.79M	0.92M	calculating
2003	0.97M	1.12M	calculating
2004	1.15M	1.31M	calculating
2005	1.49M	1.59M	calculating
2006	1.73M	1.92M	calculating
2007	1.86M	2.1M	calculating
2008	2.23M	2.49M	calculating
2009	2.69M	2.89M	calculating
2010	3.31M	3.47M	calculating
2011	2.22M	4.05M	calculating
2012	3.66M	4.92M	calculating
2013	7.26M	7.32M	calculating
2014	10.37M	10.21M	calculating
2015	8.29M	9.13M	10.74M
2016	10.88M	9.4M	12.03M
2017	10.8M	9.82M	12.83M
2018	10.98M	9.37M	13.3M
2019	OM	8.59M	8.59M

#### India

- Impacts of law
  - linkages to litigant (firm or individual)
  - economic data, pollution, land disputes
- Impacts on law
  - inconsistencies, elections, rotations, networks
- Improving rule of law
  - court reforms, decision-support, transparency
- https://explore-ecourts.herokuapp.com/

HIGHLIGHT THREE STUDIES

#### India

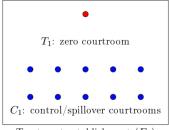
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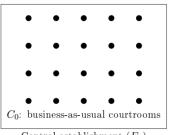
# (1) Impact of "Zero" Courts

Delhi High Court - 11 subordinate courts with no backlog were chosen as 'pilot courts'

An illustration of two model court establishments:



Treatment establishment  $(E_1)$ 

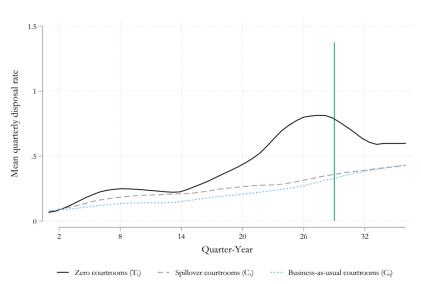


Control establishment  $(E_0)$ 

and their functioning was compared with 11 courts with regular workload

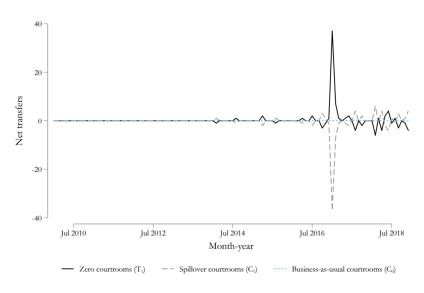
## (1) Selection of "Zero" Courts

Figure 10: Mean quarterly disposal rate



# (1) Impact of "Zero" Courts

Figure 12: Density of transfers by month



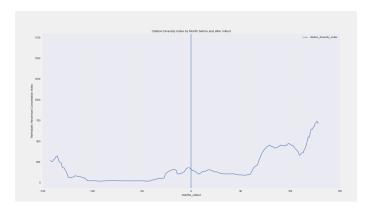
# (1) Impact of Transfers

	Days	Disposed	Number of	Duration of
	in court	within 1 year	Hearings	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	Υ	Υ	Υ	Υ
F-test p-value	.12	.063	.085	.049



- on how cases are decided?
- speed of resolution?
- diversity of citations?
- memes?

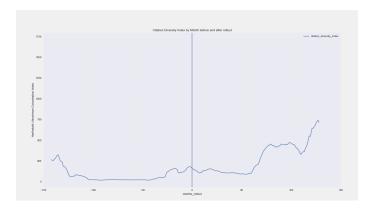
Preliminary evidence that legal search engine increased HHI concentration of citations



The impact of google on wikipedia is hard to know, since wikipedia didn't exist prior to google

here, we can study common law, to see the polarization or democratization of knowledge

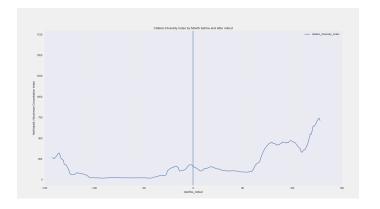
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#### Motivation

- While the proportion of Muslims convicted is close to their share in India's population (14%), only 4% of judges across India's high courts are Muslim. (The Quint, 2016)
- ▶ Women account for 28% of the lower judiciary, and 12% of the High Courts, while they account for 48% of the population.(*India Justice Report, 2019*)
- The importance of substantive representation in the judiciary has been researched extensively in the US (Dobbie et al. 2018, Abrams et al. 2012, Alesina et al. 2014, etc.), but the relevant literature is non-existent in the Indian context.
- This paper is the first to quantitatively study the consequences of a lack of diversity in India's lower judiciary, at scale.

#### Summary of findings

#### Descriptive:

- Muslim defendants are more likely to be charged with theft, crimes against women, property crimes, trespassing, and marriage offenses in the analysis sample.
- Muslim defendants are more likely to be convicted with crimes that endanger public safety and health.

#### Substantive:

- · Random assignment of judges to cases holds in the study sample.
- Female judges are less lenient on male defendants.
- Muslim and Non-muslim judges are indistinguishable.
- On bail cases, marginal evidence that female judges grant bail to female defendants more often than male judges.
- No major difference for crimes against women or property crimes.

#### Data

- ▶ Raw sample: Approximately 8 million cases scraped from e-courts.
- ▶ **Scope:** All metropolitan, district and sessions courts across all states in India.
- ▶ Timeline: 2015-2018
- Variables:
  - (a) For each case, the primary variables are defendant and plaintiff name, dates of various hearings, and final outcome if available.
  - (b) We also scraped judge information data for all the districts in India.
- ▶ Construction:
  - (a) Judge-case data were matched based on state code, district code, court code, and judge designations, provided the date of the case in the case data lies within the start and end date of the judge's tenure provided in the judge dataset.
  - (b) Before the match, we ensured the final judge dataset had no overlaps in tenure at a specific position in a particular court.
- ▶ Final sample: The final analysis dataset has approximately 4 million observations.

#### Classification of names

- The judge and defendant details available on e-court do not include gender and religion details.
- We classified cleaned names as Muslim or not Muslim, and female or male, using a bidirectional Long Short-Term Memory (LSTM) model.
- An LSTM is a specific type of Recurrent Neural Network (RNN) that retains the memory of previous inputs as it handles each new piece of input data.
- Our LSTM model was trained on a database of 1.4 million names of individuals whose religion was recorded when they sat for the National Railway Exam, and on 2,287,973 Delhi voter names for gender classification.

#### Empirical strategy

We exploit random assignment of judges to cases to estimate judicial bias using the following difference-in-difference specification:

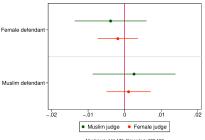
$$Y = \alpha + \beta_1 judge\_female + \beta_2 def\_female + \beta_3 judge\_female*def\_female + \gamma[loc\_month/loc\_year] + \phi acts + \epsilon$$
 (1)

$$Y = \alpha + \beta_1 \text{judge\_muslim} + \beta_2 \text{def\_muslim} + \beta_3 \text{judge\_muslim*} \text{def\_muslim} + \gamma[\text{loc\_month/loc\_year}] + \phi \text{acts} + \epsilon$$
(2)

- ▶ loc\_month: group(state\_code dist\_code court\_no filing\_year filing\_month)
- loc\_year: group(state\_code dist\_code court\_no filing\_year)
- acts: group(act section)
- judge: group(state\_code dist\_code court\_no position tenure\_start tenure\_end)
- ▶ We implement equations (1) & (2) separately for bail and non-bail related cases.

Test using court-month fixed effects: Are defendants more likely to get assigned to a judge with the same identity? No.

$$\textit{judge}\_[\textit{muslim}/\textit{female}] = \alpha + \beta_1 \textit{def}\_[\textit{muslim}/\textit{female}] + \gamma \textit{loc}\_\textit{month} + \phi \textit{acts} + \epsilon$$



N(religion): 141,175 N(gender): 322,150

# Female judges are less lenient

Panel A: Court-month fixed effect				
	(1)	(2)	(3)	(4)
	Female judge on	Female judge on	Interaction	Control mean
	Male def	Female def	effect	
Acquitted	-0.020** ( 0.01)	-0.012 ( 0.011)	0.008 ( 0.008)	.184
Not convicted	-0.016* ( 0.01)	-0.010 ( 0.008)	0.006 ( 0.006)	.903
Positive_0	-0.025** ( 0.01)	-0.008 ( 0.013)	0.017* ( 0.009)	.336
Positive_1	-0.002 ( 0.01)	0.007 ( 0.011)	0.009 ( 0.008)	.714
Observations	157337	157337	157337	157337

Standard errors in parentheses

marginal in-group effect

<sup>\*</sup> p < 0.10, \*\* p < 0.05, \*\*\* p < 0.01

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# Muslim and Non-muslim judges indistinguishable

Panel A: Court-month fixed effect				
	(1)	(2)	(3)	(4)
	Muslim judge on	Muslim judge on	Interaction	Control mean
	non-Muslim def	Muslim def	effect	
Acquitted	0.002 ( 0.011)	0.004 ( 0.016)	0.002 ( 0.012)	.169
Not convicted	-0.008 ( 0.011)	-0.011 ( 0.015)	-0.003 ( 0.007)	.892
Positive_0	0.002 ( 0.015)	0.008 ( 0.019)	0.006 ( 0.013)	.309
Positive_1	0.020 ( 0.021)	0.043 ( 0.033)	0.023 ( 0.016)	.693
Observations	74317	74317	74317	74317

Standard errors in parentheses

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# Female judges are more lenient in bail

Panel A: Court-month fixed effect				
	(1)	(2)	(3)	(4)
	Female judge on	Female judge on	Interaction	Control mean
	Male def	Female def	effect	
Positive_0	0.056** ( 0.03)	0.090*** ( 0.035)	0.034 ( 0.027)	.39
Positive_1	0.020 ( 0.04)	0.070 ( 0.049)	0.051** ( 0.025)	.739
Observations	14602	14602	14602	14602

Standard errors in parentheses

marginal in-group effect

Empathy is proposed antidote to in-group bias

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Positive_1	0.020 ( 0.04)	0.070 ( 0.049)	0.051** ( 0.025)	.739	
Observations	14602	14602	14602	14602	

Standard errors in parentheses

#### marginal in-group effect

EMPATHY IS PROPOSED ANTIDOTE TO IN-GROUP BIAS

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	(1)	(2)	(3)	(4)
	Female judge on	Female judge on	Interaction	Control mean
	Male def	Female def	effect	
Positive_0	0.056** ( 0.03)	0.090*** ( 0.035)	0.034 ( 0.027)	.39
Positive_1	0.020 ( 0.04)	0.070 ( 0.049)	0.051** ( 0.025)	.739
Observations	14602	14602	14602	14602

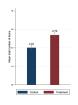
Standard errors in parentheses

marginal in-group effect

EMPATHY IS PROPOSED ANTIDOTE TO IN-GROUP BIAS

<sup>\*</sup> p < 0.10, \*\* p < 0.05, \*\*\* p < 0.01

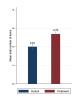
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- Empathy vs. power lectures impacted survey responses (in a list experiment



- Pending analysis of twitter/social media posts and impacts on followers
- Additional rounds administered over zoom
  - ▶ With 1 hour battery of social preference games (other-regarding behavior)
  - ▶ Used for IE of mandatory economics in French high schools (w/ oTree)

LET ME TURN TO MEASUREMENT

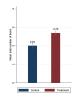
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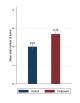
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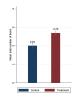
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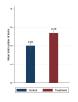
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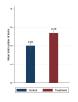
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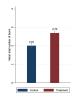
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### Three uses of judicial analytics

- Predictive analytics of judges
  - ► MEASURING PRODUCTIVITY INNOVATIVELY
- Predictive analytics for causal inference
  - ▶ AUTOMATED PROSPECTIVE IMPACT ANALYSIS OF THEIR DECISIONS
- Predictive analytics to increase recognition, dignity
  - DEVELOP INSTITUTIONS TO HELP INDIVIDUALS BE THEIR BEST SELF

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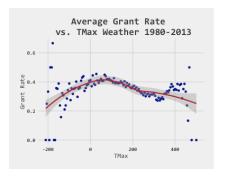
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## Judicial Analytics for Recognition and Dignity

• Cognitive science and psychology suggests that humans have limited and imperfect reasoning capacities (Tversky and Kahneman 1986; Eyster 2019)

#### The weather

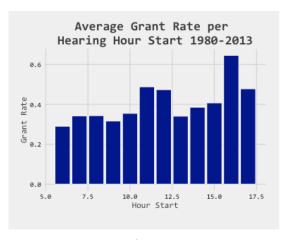
Judges deny refugees asylum when the weather is too hot or too cold



ICAIL 2017

#### Time of Day

They grant asylum more before lunch and less after.

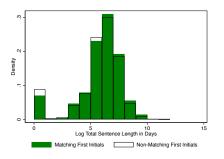


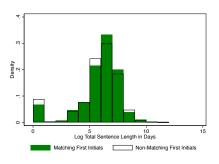
1M decisions

See also Norris 2020, Danziger, Levav, Avnaim-Pesso, PNAS 2011

#### 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

#### The defendant's birthday

When they do the opposite and give the gift of leniency

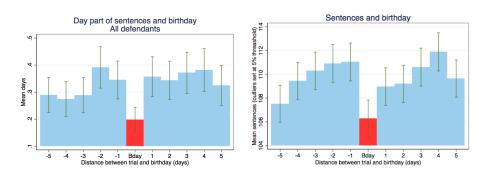
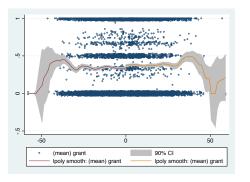


Figure: US and French judicial leniency on defendant birthdays

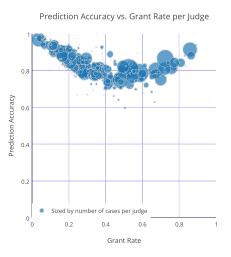
#### NFL Football

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



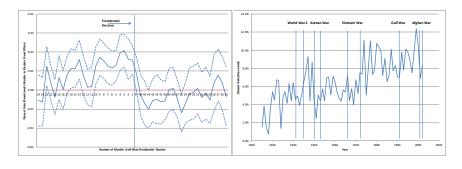
## Snap judgments

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



ICAIL 2017

#### Elections and wartime also affect decisions



JLE 2017

#### Gambler's Fallacy

How people often imagine a sequence of coin flips:

0101001011001010100110100

A real sequence of coin flips:

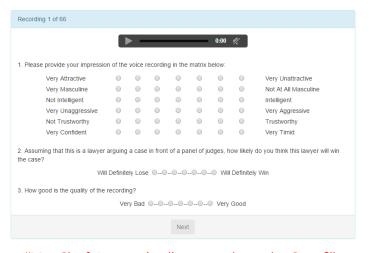
01010111111011000001001101

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



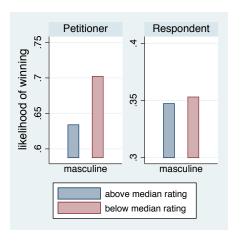
**QJE 2016** 

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



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

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



Plos-ONE 2016

#### Besides voice, there is text



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

#### Besides voice, there is text



- Females: Migraine, hysterical, morbid, obese, terrified, unemancipated, battered
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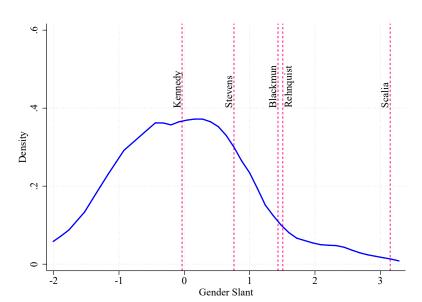
#### Besides voice, there is text

```
pregnant women vawa woman control industrial woman vawa woman deneen breasts spees migraineds spees with born or annest tilbor of propositioned deneen breasts spees migraineds of the speed of the spee
```

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## We can do this judge by judge

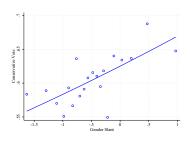
Justice Scalia is an outlier in gender slant

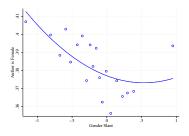


#### In the Circuit Courts, judges with more gender slant...

Vote against women's rights issues

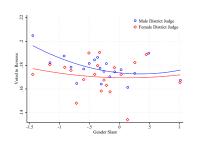
Assign fewer opinions for females to author

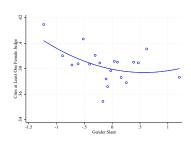




Reverse male judges less often

Cite female judges less often





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



KEY LARGO, Fla., Dec. 18-For three not to relate the theoretical studies

weeks. 19 Federal judges from cases now pending in Federal cow around the country took a grueling, six- "One has to be very cautious in deal ended here vesterday.

sometimes ending at 10 P.M. or later, in economic theory and enable them full semester at the college level.

Nobel laureates in economics, Paul Sam- Federal District Court in the South uelson and Milton Friedman. The courses, District of New York, who is the 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 many lawyers as the most important at Federal judges.

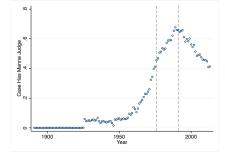
"It was a very enriching experience," said Chief Judge John W. Reynolds of attend the institute to clear any f the Federal District Court in the Eastern questions about a possible conflict of District of Wisconsin, "We were here not terest, to become economists, but to understand the language of economics. Courts are replied that they saw no grounds for only as good as judges and the lawyers conflict of interest in my coming he who appear before us. By and large, our Judge Edelstein said.

training in economics is not really satis- From the beginning, the judges, factory, and yet we are being increasingly of them 60 years old or over, behild called upon to decide economic issues." like students, deferring to their tead The program dealt basically with eco- and reminiscing about undergrad nomic theory, and an effort was made days decades ago.

day-a-week course in economics that with Federal judges," said Henry Man director of the center, "Our goal has be With classes starting at 9 A.M. and to give them the most recent think the judges received the equivalent of a better understand the testimony of exp witnesses and lawvers."

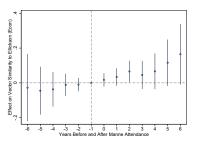
Their teachers were, among others, two | Chief Judge David N. Edelstein 0 in the International Business Mach Corporation antitrust case-regarded trust litigation of the century-inform attorneys in the case of his intention

"All the lawyers were very cordial



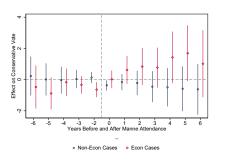
#### The results of these seminars were dramatic

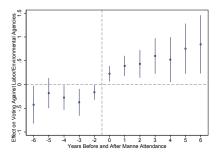
We can see economics language used in academic articles became prevalent in opinions.



#### The results of these seminars were dramatic

We can see economics trained judges changing how they decided





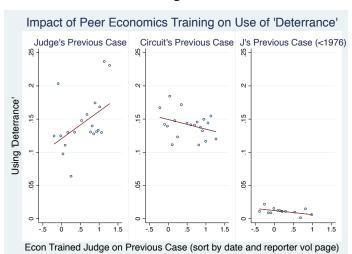
Econ vs Non-Economics Cases

on Labor/Environmental Cases

See also Hjort, Moreira, Rao, and Santini, AER R&R

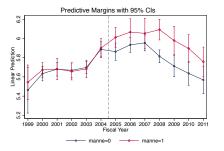
#### Impacting their peers

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



#### When judges were given discretion in sentencing

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



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

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

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

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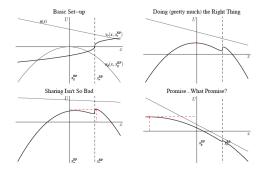
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#### Machine Learning and Rule of Law Computational Analysis of Law 2018

- 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

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

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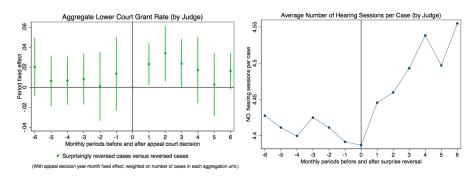
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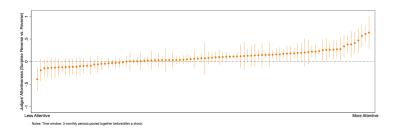
# After "Surprise" Reversals, Judges Grant More Asylum and Hold More Hearing Sessions



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

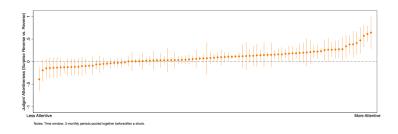
See also Posner, HUP 2010

## Judges Vary in Responsiveness to Reversal



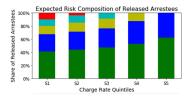
Do less attentive judges have implicit risk rankings closer to random?

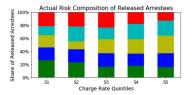
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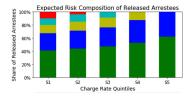


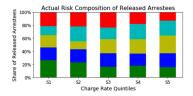




- If defendants released based
- Distribution of risk scores for
- Are the lenient asylum judges, only denying the 'riskiest' applicants
  - ▶ i.e., seeing the lowest reversal rates (of their asylum denials)?

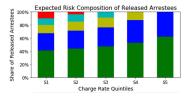




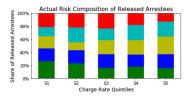


- If defendants released based only on risk score, the harshest prosecutors would only be releasing low-risk defendants.
- Distribution of risk scores for released defendants is similar for most lenient and least lenient prosecutors.
- Are the lenient asylum judges, only denying the 'riskiest' applicants
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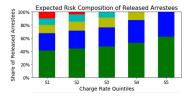


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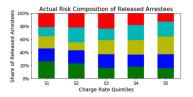


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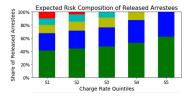


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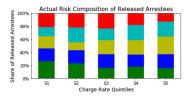


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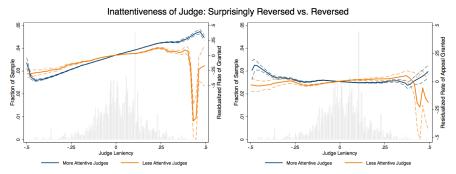
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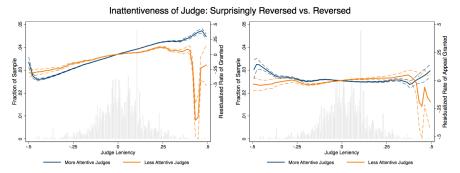
## Left Figure: Judges have strong habits

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



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

# Right Figure: Assess implicit risk ranking

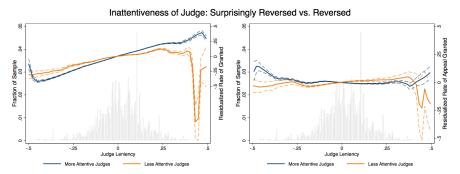


(Time window: 3 monthly periods pooled together before/after shock. More attentiveness: the coefficient of interaction of surprisingly reversed dummy and time-period dummy is bigger)

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

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

### .. but not less attentive judges

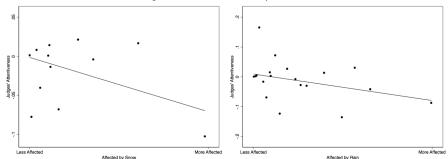


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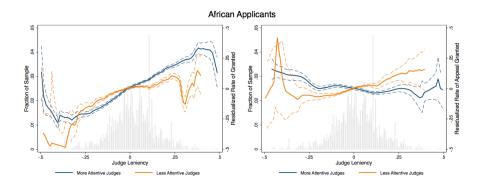
.. who may be more prone to other extraneous factors

#### .. such as weather





# Difference in Indifference for asylees from the Global South



- 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 that shows decision-makers their predicted self and then uses predictions of error to nudge

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- Consider instead an incremental approach that shows decision-makers their predicted self and then uses predictions of error to nudge

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- Gambler's fallacy, mood, time of day, order, ...
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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 Al-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 QJE 2011).
  - ▶ (3) Deviating from defaults facilitates conscious deliberation.
- self-image (predicted self)

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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 Al system, allowing for the Al to learn from the user as well.
- self-expression (autonomy)

# Stage 5: Community of Experts

- Al 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, experts advised it helps train novices
  - who tend to make more mistakes
  - experts can input a preferred decision
  - or use prediction if appealed
- Stage 7, WebMD for litigants, increasing access to justice
  - and transparency & accountability
- Stage 8, use feedback from dialogue stage as recommender system
  - with A|B testing to generate personalized causal inference

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- Reduces Bias
  - Assess judges vs. their predicted self
- Increase Autonomy
  - ► Support tool / default
- Enhance Learning
  - ▶ Pointing out when predicted to error + community of practice
- Explainable Transparency
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# Proof of Concept



- Assess effects on trust and perceived indifference of lawmakers
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#### Personalized Assessments

This kind of data can measure inconsistency in judicial decisions.

Table: Name Letter Effect in Judicial Sentencing in Chile

	Log of Total Sentence in Days				
First Letter Match	0.0169***	0.0212***			
	(0.00584)	(0.00480)			
First Name Match			0.0314*	0.0401***	
			(0.0189)	(0.0153)	
N	2763242	2762799	2763242	2762799	
Judge FE	X	X	x	X	
Case Type $\times$ Month $\times$ Year FE		X		X	
Letter FE, Week FE, Day of Week FE		X		x	

NAME LETTER EFFECT RELATED TO WHAT PSYCHOLOGISTS CALL "IMPLICIT EGOISM"

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# **Empirical Challenges**

#### Medicine, prior to clinical trials

Theories about the effects, but no causal evidence (a century ago)

#### Randomizing judicial decisions

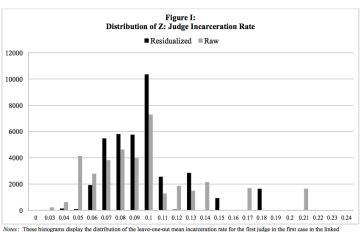
Violates our notion of justice (equal treatment before the law)

#### Randomizing judicial assignment

Generates retrospective "clinical trial" (Kling AER 2006; many since "credibility revolution" in economics)

### Juvenile Incarceration (QJE 2015)

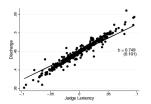
### Reduced human capital formation and increased future imprisonment



Notes: I ness instogration supply the distribution of use leave-one-our mean interacretation frait or the list judge in list scase in the interaction frait of the list judge in list scase in the interaction frait of the list judge in list scase in the interaction frait of the list judge in list scan from the interaction frait of the list judge in list scan frait scan frait in list scan frai

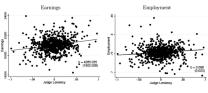
### Debt Relief and Debtor Outcomes (AER 2014)

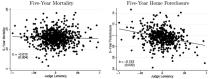
Figure 1 Chapter 13 Judge Leniency and Chapter 13 Bankruptcy Protection



Notes: This figure plots Chapter 13 discharge vs. our leave-one-out measure of judge leniency. The sample consists of all first-time Chapter 13 filers between 1992 and 2005 in the 42 offices that randomly assign filings to judges. Judge leniency is the leave-one-out mean rate of granting Chapter 13 bankruptcy protection for the assigned judge minus binned scatter plot, we first regress an indicator for discharge on office by month-of-filing fixed effects and calculate residuals. We then take the mean residual in each judge by year bin, adding the mean discharge rate to each residual to aid in the interpretation of the plot. The solid line shows the best linear fit estimated on the underlying micro data fixed effects, with standard errors clustered at the office level reported in parentheses.

Figure 3 Chapter 13 Judge Leniency and Labor Supply, Mortality, and Home Foreclosure





Notes: These figures plot earnings, employment, five-year mortality, and five-year foreclosure vs. our leave-one-out measure of judge leniency. The earnings and mortality sample includes all first-time filings between 1992 and 2005 in the 42 offices that randomly assign cases to judges. The foreclosure sample includes the subset of those filings originating in county by year bins with foreclosure data coverage. Judge leniency is the leave-one-out mean rate of granting Chapter 13 bankruptcy protection for the assigned judge minus the leave-one-out mean rate of granting bankruptcy protection for the court in the same filing year. To construct the binned scatter plot, we first regress each outcome on office by month-of-filing fixed effects and calculate residuals. We then take the mean residual in each judge by year bin, adding the mean discharge rate to each residual to aid in the interpretation of the plot. The solid line shows the best linear fit estimated on the underlying micro data estimated using OLS. The coefficients the leave-one-out mean rate of granting bankruptcy protection for the court in the same filing year. To construct the show the estimated slope of the best-fit line including office by month-of-filing fixed effects, with standard errors clustered at the office level reported in parentheses. Farmings are winsorized at the top and bottom one percent Employment is an indicator for non-zero wage earnings on the W-2. All monetary values are expressed in real 2000 dollars. Mortality is an indicator for being deceased in or before the indicated year using information from the Death estimated using OLS. The coefficients show the estimated slope of the best-fit line including office by month-of-filling. Master File. Foreclosure is an indicator for a filer's home receiving a notice of default, receiving a notice of or sale, or being transferred to a REO or a guarantor in or before the indicated year.

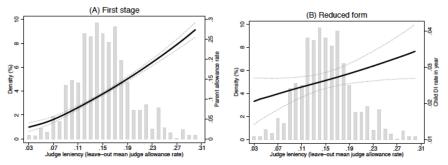
### ↑Earnings, ↑Employment, ↓Mortality, ↓Foreclosure

## Family Welfare Cultures (QJE 2014)

### Is the intergenerational correlation of welfare receipt causal?

Determinants of poverty or health correlated across generations -or- culture of welfare?

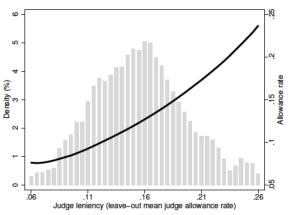
Figure 3: Effect of Judge Leniency on Parents (First Stage) and Children (Reduced Form).



Notes: Baseline sample, consisting of parents who appeal an initially denied DI claim during the period 1989-2005 (see Section 3 for further details). There are 14,722 individual observations and 79 different judges. Panel (A): Solid line is a local linear regression of parental DI allowance on judge leniency. Panel (B): Solid line is a local linear regression of child DI receipt on their parent's judge leniency measure. All regressions include fully interacted year and department dummies. The histogram of judge leniency is shown in the background of both figures (top and bottom 1% excluded from the graph). Dashed lines represent 90 percent confidence intervals.

# Do disability benefits insure? (AER 2019)

Figure 4: Effect of Judge Leniency on DI Allowance

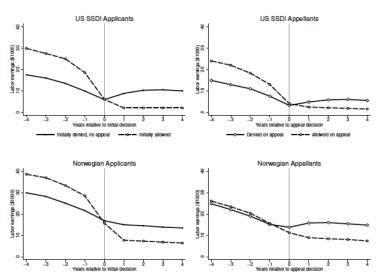


Notes: This figure displays the effect of judge leniency on DI allowance, conditional on fully interacted year and department dummies. Baseline estimation sample consists of individuals who appeal an initially denied DI claim during the period 1994-2005 (see Section 3 for further details). There are 75 unique judges. The solid line plots a local linear regression of allowances on judge leniency. The histogram of judge leniency is shown in the background of both figures (top and bottom 1 percent excluded from the graph).

## DI Applicants' adverse outcomes ameliorated by grant

### measured in employment, earnings, and assets

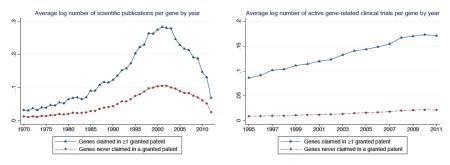
Figure 3: Earnings Trajectories of Allowed and Denied DI Applicants and Appellants



### Patents and Innovation (AER 2019)

### Patented genes are more valuable, but does patenting make them valuable?

Figure 1: Follow-on Innovation on Patented and Non-Patented Human Genes



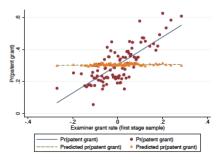
(a) Gene-Level Scientific Publications

(b) Gene-Level Clinical Trials

Notes: This figure plots trends in follow-on innovation by year separately for genes that ever receive a patent and for genes that never receive a patent. The figure is constructed from gene-level data. Panel (a) uses gene-level scientific publications as a measure of follow-on innovation, and plots the average log number of scientific publications by year in each year from 1970 to 2012. Panel (b) uses gene-level clinical trials as a measure of follow-on innovation, and plots the average log number of clinical trials by year in each year from 1995 to 2011.

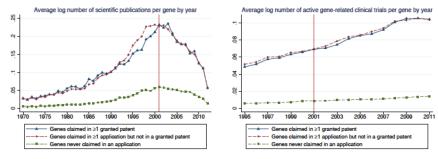
# Patents examiners have strong habits

Figure 3: Probability of Patent Grant by Examiner Leniency



Notes: The figure relates our examiner leniency measure, residualized by Art Unit-by-application year fixed effects, to two variables:
(1) the patent grant rate and (2) the predicted patent grant rate, where we predict patent grant as a function of our two measures of patent value fixed at the time of application (patent family size and claims count). All measures are constructed in our first stage sample (N=14,476).

## Genes accepted & rejected for patents are similar



#### (b) Gene-Level Scientific Publications

#### (c) Gene-Level Clinical Trials

Notes: This figure plots trends in patenting and follow-on innovation by year separately for three groups of genes: genes claimed in at least one granted patent; genes claimed in at least one patent application but never in a granted patent; and (in Panels (b) and (c)) genes never claimed in a patent application. The figure is constructed from gene-level data. Panel (a) documents the share of genes receiving a patent grant by year; by construction, this is zero for the circle-denoted red dashed line in all years and reaches one for the triangle-denoted blue line in 2010; the intermediate years simply illustrate the time path of patent grants between 2001 and 2010 for the triangle-denoted blue line. Panel (b) uses gene-level scientific publications as a measure of follow-on innovation and plots the average log number of scientific publications by year in each year from 1970 to 2012. Panel (c) uses gene-level clinical trials as a measure of follow-on innovation and plots the average log number of clinical trials by year in each year from 1975 to 2011. The vertical line in the calendar year 2001 in Panels (b) and (c) denotes that, because this figure focuses on patents that were filed in or after November 2000, all years prior to 2001 can be considered a pre-period and used to estimate the selection of genes into patenting based on pre-patent filing measures of scientific research (publications) and commercialization (clinical trials).

### Random Variation in Precedent



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

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

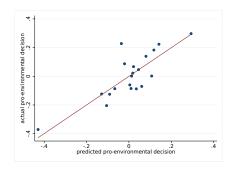
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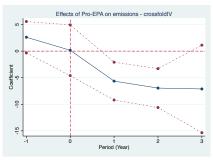


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# Impact of Environmental Decisions





Calibration plot

Rulings in favor of EPA regulations reduce air pollution

### Data

#### U.S. Circuit Courts

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

Can be used to facilitate large scale data collection in other countries

e.g., coding of case categories or direction of verdicts

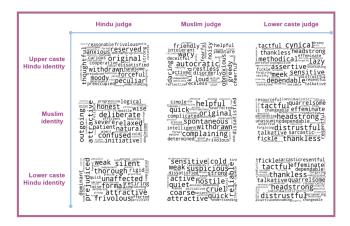
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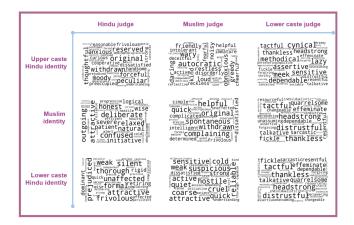
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Preliminary evidence that Hindu judges describe the Hindu identity more positively  $SC/ST \ judges \ describe \ Muslims \ more \ negatively$ 

- Can we measure "missing cases" and access to justice? (if so, how?)
- Can we measure impact of justice on confidence in law? (if so, how?)

CAN WE MOVE BEYOND LIKERT SCALES OF USER SATISFACTION?



Preliminary evidence that Hindu judges describe the Hindu identity more positively  $SC/ST \ judges \ describe \ Muslims \ more \ negatively$ 

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Upper caste Hindu identity	reasonable frivolousents and reasonable frivolousents and reasonable frivolousents and reasonable friends and reas	friendly helpful intolerant to same the same time to same time time time time time time time ti	tactful cynica thankless headstrong headstrong thankless headstrong head
Muslim identity	being a proposative logical be	simple	resourceful individualistic some factful quarrel some changeable effeminate crassistante de la companya de la c
Lower caste Hindu identity	thorough risid	sensitive cold weak suspicious de meak suspicious de meating active fostile; active cruel de corse de meating colore de	ficklesarcasticresentful tactfuleffeminate dependable thankless registre second thankless registre and thankless registre and the second thankless and tha

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Muslim identity	monopositivi logical monoposit	simple similar helpful la disconnection helpfu	resourceful individualistic some it cactfulquarrel some it changeable effeminate established by the care of the ca
Lower caste Hindu identity	weak silent uthorough rigid to button affected up b	sensitive cold weak suspicious de weak suspicious de active nostile de color de la color d	ficklesarcasticresentful tactfuleffeminate dependance thankless and talkative quarrel some talkative quarrel some individualistic and the second some individualistic and the

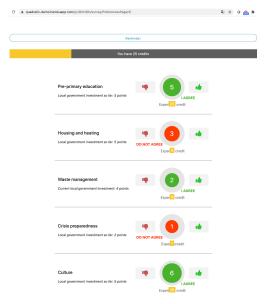
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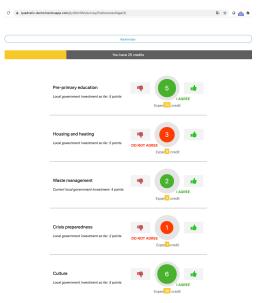
# Quadratic Voting for Surveys

Estonian IE of public-facing dashboard for local government accountability

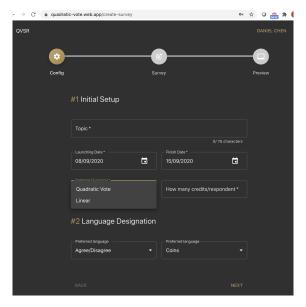


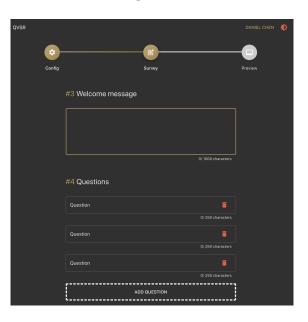
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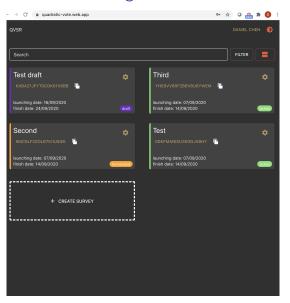
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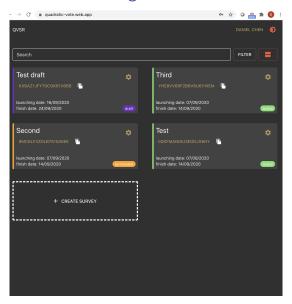
Giving civil servants and citizens the ability to ask questions of each other







Kenya: Propose measuring court satisfaction to better target infrastructure improvements



• Kenya: Propose measuring court satisfaction to better target infrastructure improvements

# Open-source platform for lab, web, and field experiments



- Estonia, Peru, Pakistan, France
  - allowing interactive experiments, socially-distanced
- Czech: Measure trust in the law (through revealed preference questionnaires)
  - Does trust correlate with legal compliance?
  - Do revealed preferences predict recidivism beyond psychometric surveys?

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## Looking Ahead

- Country counterparts have asked
  - e-arbitration
  - Al for scheduling
  - ► AI in civil justice (to manage evidence)
  - blockchain technologies for follow-up of compliance of cases
  - online judicial auction platform (ebay for bankruptcy judges)

## Training

- Theory vs. case-based teaching (diff-in-diff)
  - ▶ vs. personalized case-based teaching using own decisions (digital module RCT)
- Social-emotional learning interventions (15 minute self-reflection writing exercises)
  - ▶ self-affirmation, advice giving (RCT treatment vs. control treatment)
  - ▶ advice displayed to new judges who evaluate two random writings (RCT)
- Monitoring & debrief ≈ "community of practice"
  - of teachers (RCT)
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  - knowledge of one's effectiveness as public defender (RCT)

## **Training**

- Theory vs. case-based teaching (diff-in-diff)
  - vs. personalized case-based teaching using own decisions (digital module RCT)
- Social-emotional learning interventions (15 minute self-reflection writing exercises)
  - ▶ self-affirmation, advice giving (RCT treatment vs. control treatment)
  - advice displayed to new judges who evaluate two random writings (RCT)
- ullet Monitoring & debrief pprox "community of practice"
  - of teachers (RCT)
- Algorithmic search
  - do off-the-shelf search algorithms lead to polarization vs. de-polarization ML (RCT)
- Legal Aid / Mediation
  - knowledge of one's effectiveness as public defender (RCT)

# Strengths of DE JURE Program @ DIME

- Design
- Deploy
- Evaluating effects of justice reforms
- Developing technologies to do so
- Dialogue with country partners
  - Look forward to hearing how this model synergizes with your work