Experimental Evaluation of Algorithm-Assisted Human Decision Making: Application to Pretrial Public Safety Assessment

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The Japanese Society for Quantitative Political Science
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Joint work with Zhichao Jiang, D. James Greiner,
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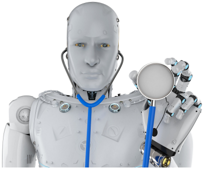

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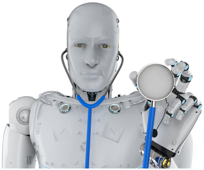

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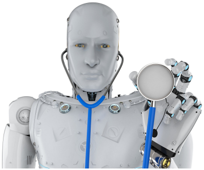

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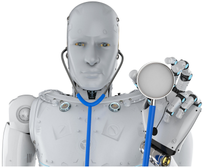

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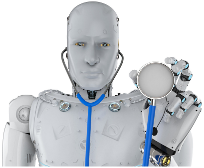

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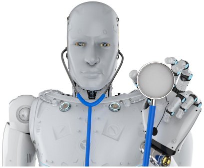


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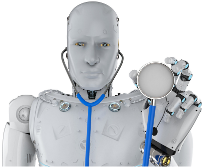

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  - consequential decisions made by judges, doctors, etc.

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  3. first ever field experiment evaluating pretrial public safety assessment

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  - if the first digit of case number is even, PSA is given to the judge
  - mid-2017 – 2019 (randomization), 2-year follow-up for half sample

215 S Hamilton St #1000
Madison, WI 53703
Phone: (608) 266-4311

DANE COUNTY CLERK OF COURTS
Public Safety Assessment – Report

Name: [redacted] **Spillman Name Number:** [redacted]
DOB: [redacted] **Gender:** Male
Arrest Date: 03/25/2017 **PSA Completion Date:** 03/27/2017

New Violent Criminal Activity Flag

No

New Criminal Activity Scale

1	2	3	4	5	6

Failure to Appear Scale

1	2	3	4	5	6

Charge(s):

961.41(1)(D)(1) MFC DELIVER HEROIN <3 GMS F 3

Risk Factors:	**Responses:**
1. Age at Current Arrest	23 or Older
2. Current Violent Offense	No
a. Current Violent Offense & 20 Years Old or Younger	No
3. Pending Charge at the Time of the Offense	No
4. Prior Misdemeanor Conviction	Yes
5. Prior Felony Conviction	Yes
a. Prior Conviction	Yes
6. Prior Violent Conviction	2
7. Prior Failure to Appear Pretrial in Past 2 Years	0
8. Prior Failure to Appear Pretrial Older than 2 Years	Yes
9. Prior Sentence to Incarceration	Yes

Recommendations:

Release Recommendation - Signature bond

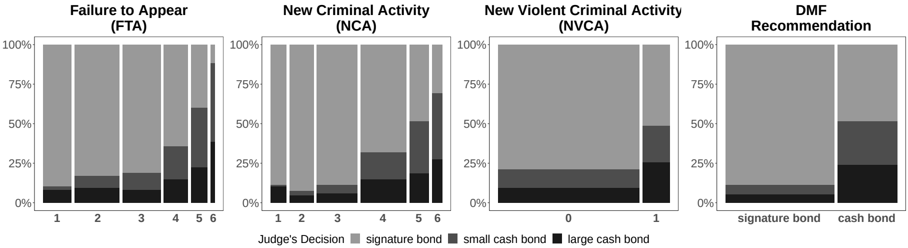
Conditions - Report to and comply with pretrial supervision

PSA Provision, Demographics, and Outcomes

	no PSA			PSA			
	Signature bond	Cash bond *small*	Cash bond *large*	Signature bond	Cash bond *small*	Cash bond *large*	Total (%)
Non-white female	64	11	6	67	6	0	154 (8)
White female	91	17	7	104	17	10	246 (13)
Non-white male	261	56	49	258	53	57	734 (39)
White male	289	48	44	276	54	46	757 (40)
FTA committed	218	42	16	221	45	16	558 (29)
not committed	487	90	90	484	85	97	1333 (71)
NCA committed	211	39	14	202	40	17	523 (28)
not committed	494	93	92	503	90	96	1368 (72)
NVCA committed	36	10	3	44	10	6	109 (6)
not committed	669	122	103	661	120	107	1782 (94)
Total (%)	705 (37)	132 (7)	106 (6)	705 (37)	130 (7)	113 (6)	1891 (100)

Judge's Decision Is Positively Correlated with PSA

(a) Treatment Group



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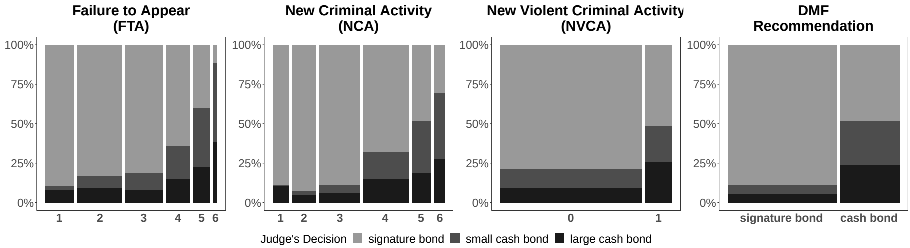
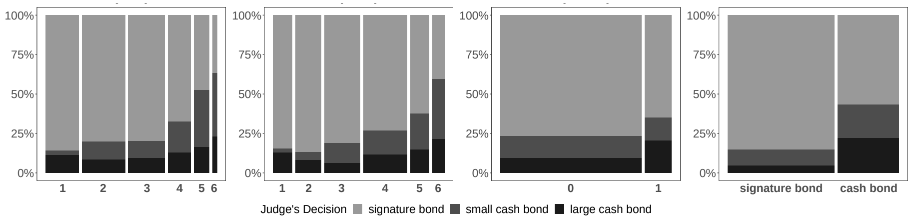
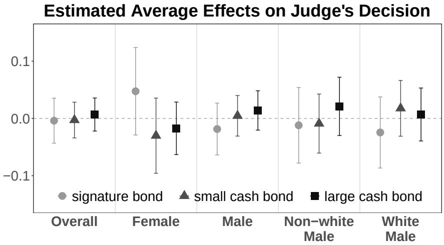


(b) Control Group



Intention-to-Treat Analysis of PSA Provision



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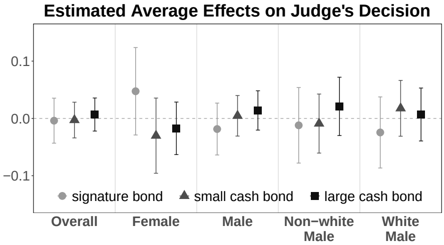

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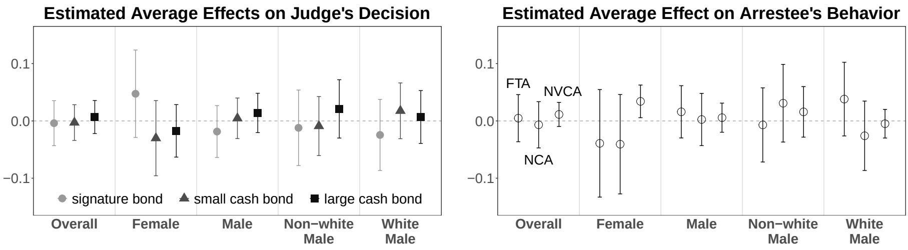

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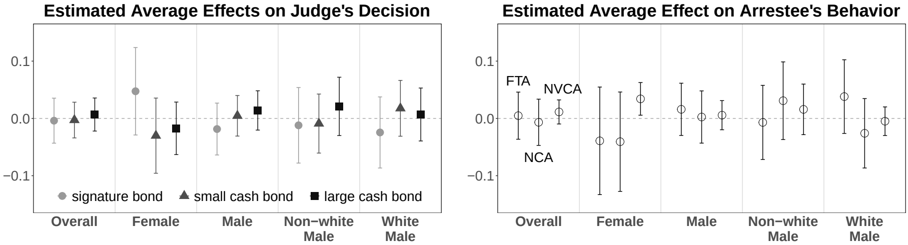

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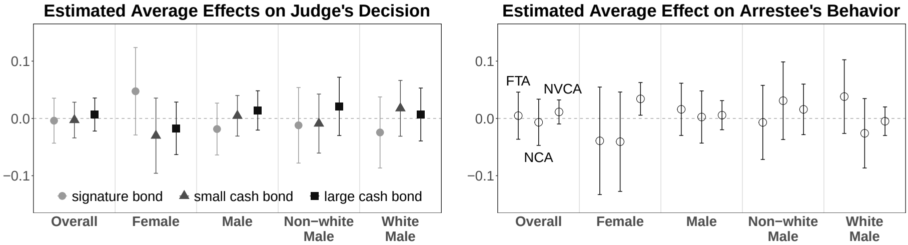

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- Does PSA provision help judges make "better" decisions?
- Need to explore causal heterogeneity based on risk-levels

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- Notation
  - Z_i: PSA provision indicator
  - D_i: detain ($D_i = 1$) or release ($D_i = 0$)
  - Y_i: binary outcome (e.g., NCA)
  - X_i: observed covariates
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- Potential outcomes
  - $D_i(z)$: potential value of the decision when $Z_i = z$
  - $Y_i(z, d)$: potential outcome when $Z_i = z$ and $D_i = d$
  - No interference across cases: first arrests only

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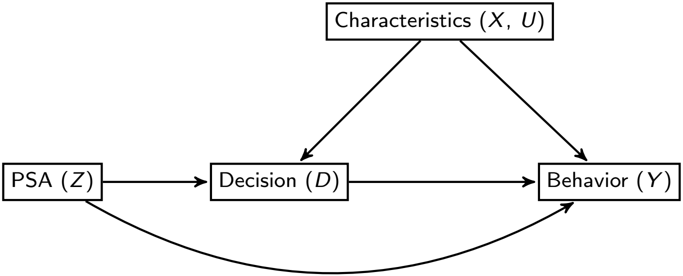

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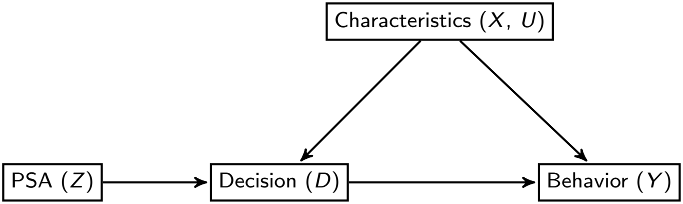

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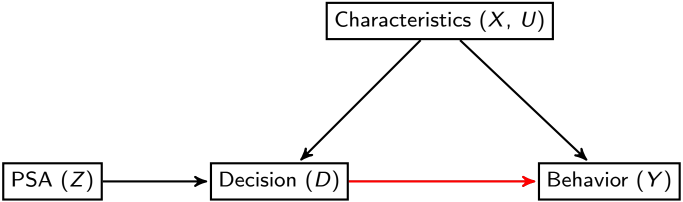
Assumptions



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Causal Quantities of Interest

- Principal stratification (Frangakis and Rubin 2002)
  - $(Y_i(1), Y_i(0)) = (0, 1)$: preventable cases
  - $(Y_i(1), Y_i(0)) = (1, 1)$: risky cases
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\text{APCEp} &= \mathbb{E}\{D_i(1) - D_i(0) \mid Y_i(1) = 0, Y_i(0) = 1\}, \\
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- If PSA is helpful, we should have APCEp > 0 and APCEs < 0.
- The desirable sign of APCEr depends on various factors.

Partial Identification Results

- The assumptions of randomization, exclusion restriction, and monotonicity imply,

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\text{APCEr} &= \frac{\Pr(D_i = 1, Y_i = 1 \mid Z_i = 1) - \Pr(D_i = 1, Y_i = 1 \mid Z_i = 0)}{\Pr\{Y_i(1) = 1\}} \\
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- The bounds on APCE can be obtained

$$\begin{aligned}
\Pr\{Y_i(d) = 1\} &= \Pr\{Y_i = 1 \mid D_i = d\} \Pr(D_i = d) \\
&\quad + \Pr\{Y_i(d) = 1 \mid D_i = 1 - d\} \Pr(D_i = 1 - d)
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Point Identification

- Unconfoundedness: $Y_i(d) \perp\!\!\!\perp D_i \mid \mathrm{X}_i, Z_i = z$
- Violation of unconfoundedness
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Extension to Ordinal Decision

- Judges decisions are typically ordinal (e.g., bail amount)
  - $D_i = 0, 1, \ldots, k$: a bail of increasing amount
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  - Example with $k = 2$

principal strata	$(Y_i(0), Y_i(1), Y_i(2))$	R_i
risky cases	$(1,1,1)$	3
preventable cases	$(1,1,0)$	2
easily preventable cases	$(1,0,0)$	1
safe cases	$(0,0,0)$	0

APCE for Ordinal Decision

- For people with $R_i = r$
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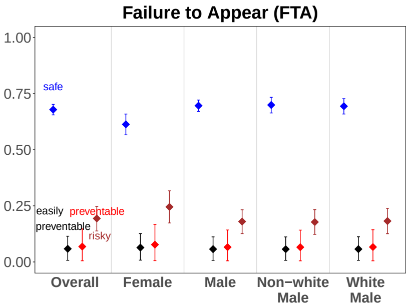
- $\rho = 0 \rightsquigarrow$ unconfoundedness

Estimated Proportions of Principal Strata



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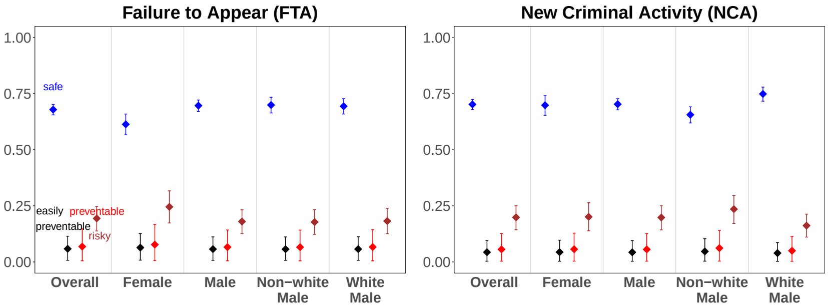

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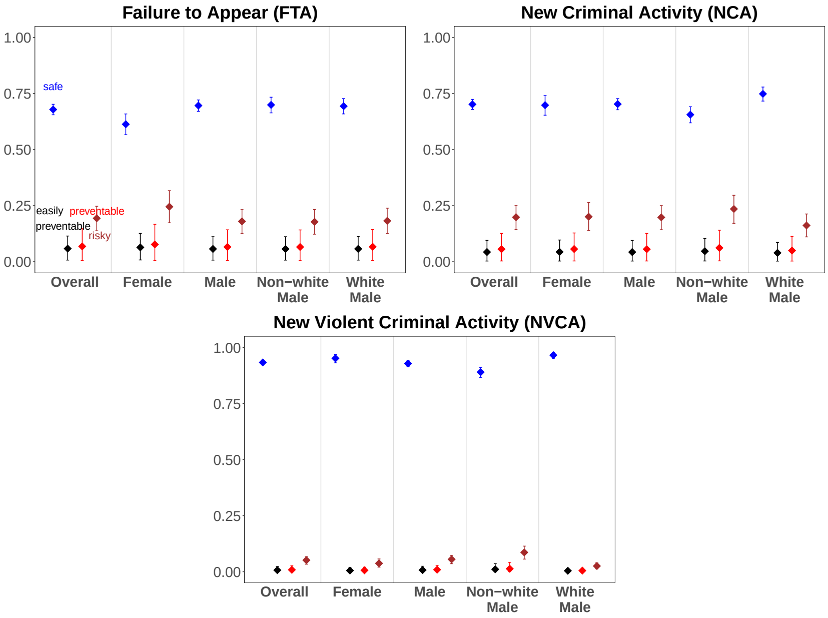

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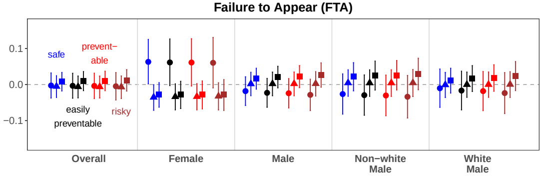

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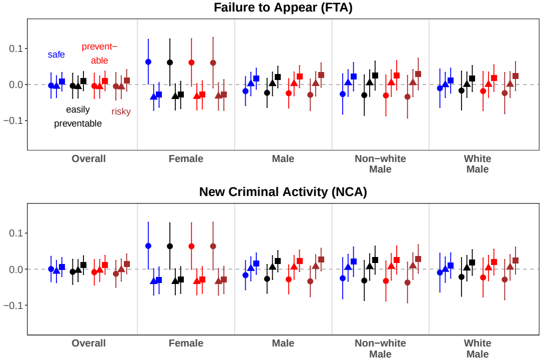

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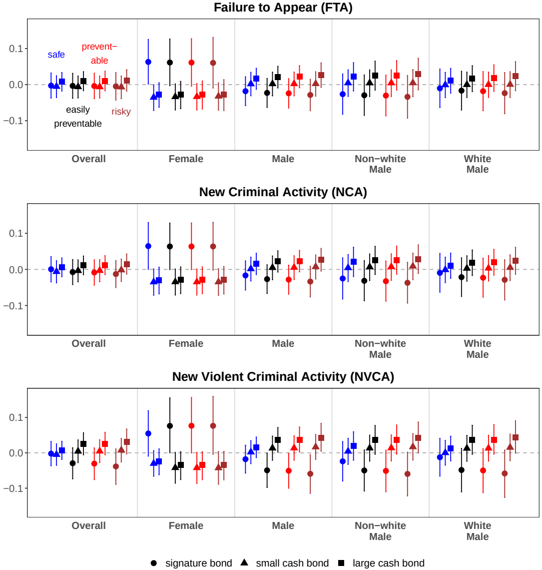

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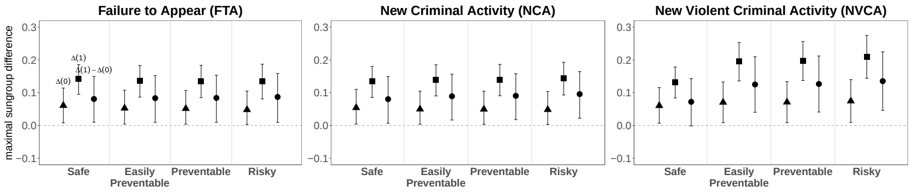
$$\Delta_r(1) - \Delta_r(0)$$

Gender and Racial Fairness



(a) Gender fairness

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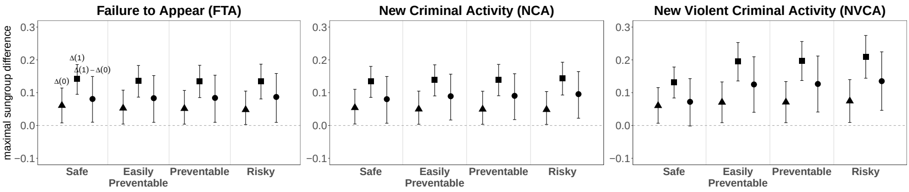

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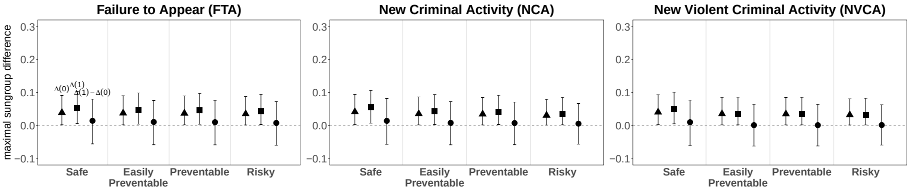

(b) Racial fairness

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