

## Part C: Instrumental Variables

### C3: Judge IV Design

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## C3 Outline

Readings:

- Scott Cunningham's "Mixtape" textbook, Ch. 7.8.2
- Goldsmith-Pinkham, Hull, Kolesar (in progress)

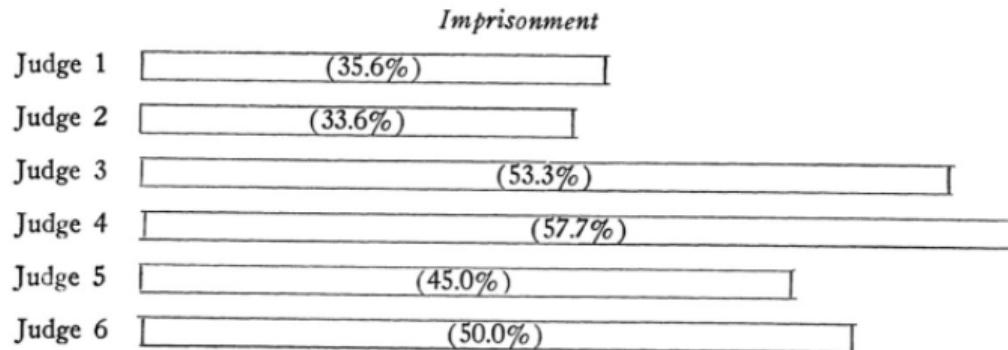
# Setting

- There are many situations where:
  1. the treatment (usually binary) is decided by one of  $K$  “judges” (examiners, caseworkers, ...)
  2. judge’s decision is discretionary
  3. judges are assigned to cases randomly (perhaps within strata, e.g. location-period)
- Examples of treatments:
  - ▶ Incarceration (*Kling 2006, Mueller-Smith 2015*), bail (*Arnold, Dobbie, Yang 2018*)
  - ▶ Patent granting (*Sampat and Williams 2019*)
  - ▶ Credit ratings (*Rieber and Schechinger 2019*)
  - ▶ Psychotherapy treatment (*Blæhr and Søgaard 2021*)
  - ▶ Several types of job training programs for the unemployed (*Humlum, Munch, Rasmussen 2024*)

# Idea

- Judges typically vary by leniency

Percentage of Each Kind of Sentence Given by Each Judge



(Gaudet, Harris and John 1933, reproduced from Scott Cunningham's "Mixtape")

- Can use this heterogeneity to instrument for treatment
  - Leniency is unobserved  $\implies$  what should we do?
  - Under which assumptions is the answer causal?

## Estimated leniency?

- Notation: judge assignment  $Q_i = k \in \{1, \dots, K\}$ ;  $Z_{ki} = \mathbf{1}[Q_i = k]$
- Consider binary treatment. Popular naïve idea:
  - Measure judge leniency as % of lenient decisions:  $\hat{L}_k = \frac{\sum_i Z_{ki} D_i}{\sum_i Z_{ki}}$
  - Then instrument  $D_i$  with  $\hat{L}_{Q_i}$
  - If assignment is random only within strata, control for strata FE
- Problem:  $\hat{L}_k$  is noisy if there are many judges (and not so many cases per judge)
  - $\hat{L}_{Q_i}$  is influenced by  $D_i$ , which correlates with  $\varepsilon_i \implies$  bias
  - Conventional inference doesn't take into account estimation noise

## Correct IV framework

- Note that  $\hat{L}_k = \text{OLS estimates of } L_k \text{ from a first-stage}$

$$D_i = \sum_k L_k Z_{ik} + u_i$$

- $\Rightarrow$  Using fitted values  $\hat{L}_{Q_i}$  as IV  $\iff$  2SLS with  $Z_1, \dots, Z_K$  instruments
- Problem of noisy  $\hat{L}_k$  is the standard many weak IV problem
    - ▶ Without covariates, JIVE is natural: uses leave-out leniency  $\hat{L}_i = \frac{\sum_{j \neq i} \mathbf{1}[Q_j = Q_i] D_j}{\sum_{j \neq i} \mathbf{1}[Q_j = Q_i]}$
    - ▶ With (many) covariates (e.g., strata FEs with few cases per strata), better to use UJIVE (“unbiased JIVE”; Kolesar (2013)): a version of JIVE that is consistent with many controls

## Underlying assumptions

With judge assignment dummies  $Z_{i1}, \dots, Z_{iK}$  as IVs, what about:

- Independence?
- Exclusion?
- Monotonicity?

## Underlying assumptions

With judge assignment dummies  $Z_{i1}, \dots, Z_{iK}$  as IVs, what about:

- Independence?
  - ▶ Guaranteed by random assignment, as long as strata FEs are controlled for
- Exclusion?
  - ▶ Does the judge directly make only one decision  $D_i$ ?
  - ▶ Can the judge indirectly affect others treatments, e.g. by affecting who will be making those decisions?
- Joint monotonicity: very strong (as usual with multiple IVs)
  - ▶ A judge who is more lenient on average should be weakly more lenient on everyone
  - ▶ Violated if judges put different weights on different characteristics of the case

## Tests for monotonicity and exclusion

1. Reject joint monotonicity if the ranking of judges by leniency varies by subgroup of cases based on observables (see Dobbie, Goldin, and Yang (2018))
2. Frandsen, Lefgren, and Leslie (2023):
  - ▶ Under all LATE assumptions, comparing any two judges gives causal effects for some complier population
  - ▶ Causal effects cannot be too large: e.g. bounded by the range of possible outcomes
  - ▶ Reject exclusion or monotonicity if there is a pair of judges with similar  $\mathbb{E}[D_i | Q_i]$  but very different  $\mathbb{E}[Y_i | Q_i]$  (like Sarsons (2015) and Kitagawa (2015))
- Should we panic if monotonicity doesn't hold?
  - ▶ Not with homogeneous effects (or in De Chaisemartin (2017) "Tolerating defiance")
  - ▶ Frandsen et al. (2023): 2SLS identifies a convex average of causal effects under "average monotonicity": for all  $i$ ,  $D_i(k)$  is positively correlated with  $L_k$  across  $k$

## References |

- DE CHAISEMARTIN, C. (2017): “Tolerating defiance? Local average treatment effects without monotonicity: Tolerating defiance?” *Quantitative Economics*, 8, 367–396.
- DOBBIE, W., J. GOLDIN, AND C. S. YANG (2018): “The Effects of Pre-Trial Detention on Conviction, Future Crime, and Employment: Evidence from Randomly Assigned Judges,” *American Economic Review*, 108, 201–240.
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