Part D: Instrumental Variables

D4: Judge IV Design

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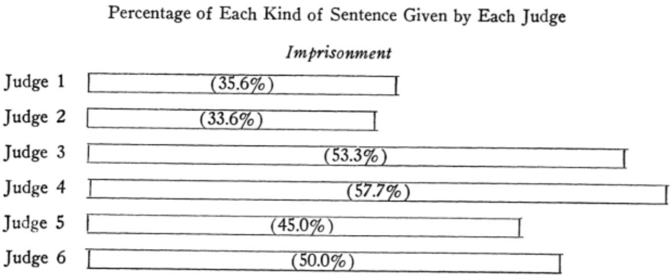
Judge IV / Examiner IV / Leniency designs

- 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 2023)*

Idea

- Judges typically vary by leniency



(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 $Q_i = k \in \{1, \ldots, K\}$; $Z_{ki} = \mathbf{1}[Q_i = k]$
- 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 $\hat{L}_k$ = OLS estimates from a first-stage

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

$\Rightarrow$ Using fitted values $\hat{L}_{Q_i}$ as IV $\Longleftrightarrow$ 2SLS with $Z_1, \ldots, Z_K$ instruments

- Noise problem is the standard many weak IV problem
  - Without covariates, JIVE is intuitive: 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), better to use UJIVE ("unbiased JIVE"; Kolesar 2013): a version of JIVE that is consistent with many controls

Underlying assumptions

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

- Independence?
- Exclusion?
- Monotonicity?

Underlying assumptions

With judge assignment dummies $Z_{i1}, \ldots, Z_{iK}$ 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?
- 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

Partial tests for monotonicity and exclusion

- Reject monotonicity if the ranking of judges by leniency varies by subgroup of cases based on observables (see Dobbie, Goldin, Yang 2018)
- Frandsen, Lefgren, Leslie (2023):
  - Under 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 $\mathbb{E}[D_i \mid Q_i]$ but very different $\mathbb{E}[Y_i \mid Q_i]$
- Should we panic if monotonicity doesn't hold?
  - Not with homogeneous effects (see also de Chaisemartin 2017 "Tolerating defiers")
  - Frandsen et al.: 2SLS identifies a convex average of causal effects under "average monotonicity": for all i, $D_i(k)$ is positively correlated with L_k