Instrumental Variables

Understanding IV

MIXTAPE SESSIONS

Roadmap

Where do (Good) Instruments Come From?
- True Lotteries
- Natural Experiments
- Panel Data

2SLS Mechanics
- Just-Identified IV
- Overidentification

Weak and Many Instruments
- Weak IV
- Many IVs

Subtlties of the Validity Condition

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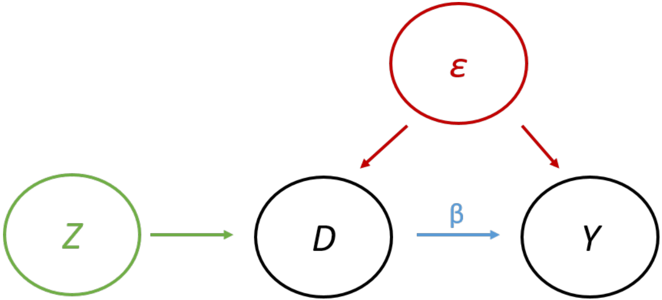
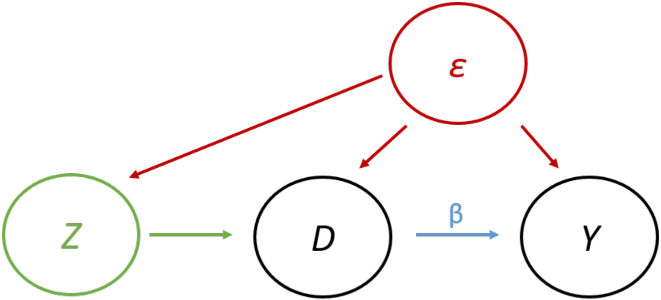
- Confusingly, old-school econometrics texts sometimes refer to $Cov(Z_i, \varepsilon_i) = 0$ as the “exclusion restriction”
  - $\rightarrow$ More modern IV texts take care to distinguish between these two conceptually distinct requirements...

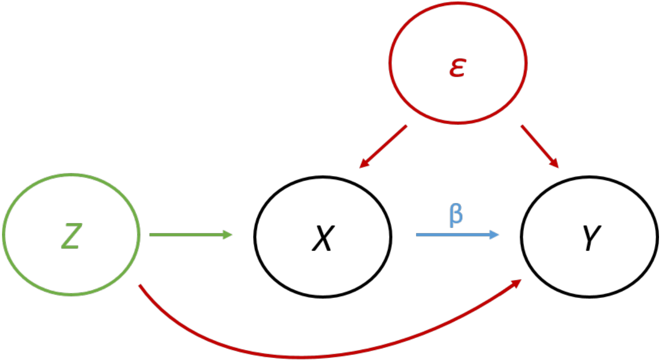
A Valid Instrument



A Violation of As-Good-As-Random Assignment



A Violation of Exclusion



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- "Gold standard" IV: a randomized offer to participate in a program, with X_i recording program participation
  - → Exclusion restriction likely to hold for any Y_i, by construction
  - → Relevance almost guaranteed (provided people want the program!)

Example: Charter School Lotteries

- Abdulkadiroglu et al. (2016) are interested in whether going to a "charter" middle school increases standardized test scores
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- We leverage an institutional feature of charters: *admission lotteries*
  - → When more kids want to enroll than there are seats, admission offers $Z_i \in \{0, 1\}$ are effectively drawn from a hat
  - → Offers plausibly only affect later test scores Y_i by changing charter enrollment $D_i \in \{0, 1\}$, so are plausibly valid instruments
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  - → We need to control for lottery fixed effects ("risk sets") to make Z_i as-good-as-randomly assigned – more on this soon
- We study a particular charter (UP Academy), which is "takeover"
  - → Two offer IVs: "immediate" (on lottery night) and from a waitlist

Lottery IV Estimates of UP Test Score Effects

TABLE 8—LOTTERY IV ESTIMATES OF UP EFFECTS

				2SLS		
				First stage		
		Comparison group mean (1)	OLS (2)	Immediate offer (3)	Waitlist offer (4)	Enrollment effect (5)
Panel A. All grades						
(Sixth through eighth)	Math (N = 2,202)	0.059	0.301	0.760	0.562	0.270
			(0.022)	(0.063)	(0.067)	(0.056)
	ELA (N = 2,205)	0.103	0.148	0.759	0.562	0.118
			(0.020)	(0.063)	(0.067)	(0.051)

Where do IVs Come From? 2) Natural Experiments

- Without appealing to literal randomization, we may credibly argue Z_i is as-good-as-randomly assigned conditional on some $\mathbf{W}_i$
  - $\rightarrow$ Such "natural experiments" rely on a selection-on-observables argument (for Z_i, instead D_i)
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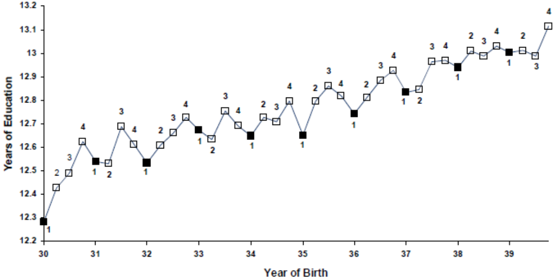
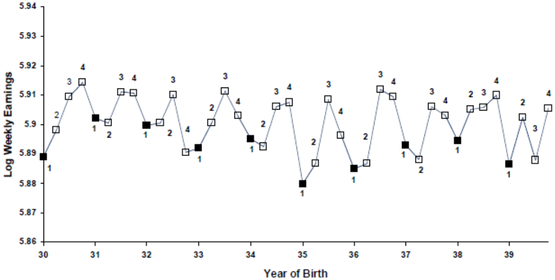
  - $\rightarrow$ Quarter-of-birth seems quasi-randomly assigned — is it excludable? See Buckles and Hungerman (2013)...

The Quarter-of-Birth Natural Experiment: Visualized

A. Average Education by Quarter of Birth (first stage)



B. Average Weekly Wage by Quarter of Birth (reduced form)



Quarter-of-Birth IV Estimates of Returns to Schooling

Table 4.1.1: 2SLS estimates of the economic returns to schooling

	OLS		2SLS			
	(1)	(2)	(3)	(4)	(5)	(6)
Years of education	0.075 (0.0004)	0.072 (0.0004)	0.103 (0.024)	0.112 (0.021)	0.106 (0.026)	0.108 (0.019)
Covariates:						
9 year of birth dummies		✓			✓	✓
50 state of birth dummies		✓			✓	✓
Instruments:			dummy for QOB=1	dummy for QOB=1 or QOB=2	dummy for QOB=1	full set of QOB dummies

Where do IVs Come From? 3) Panel Data

- We might also combine IV + difference-in-difference identification
  - → E.g. instrument with $Z_i \times Post_t$, controlling for Z_i and $Post_t$ FEs
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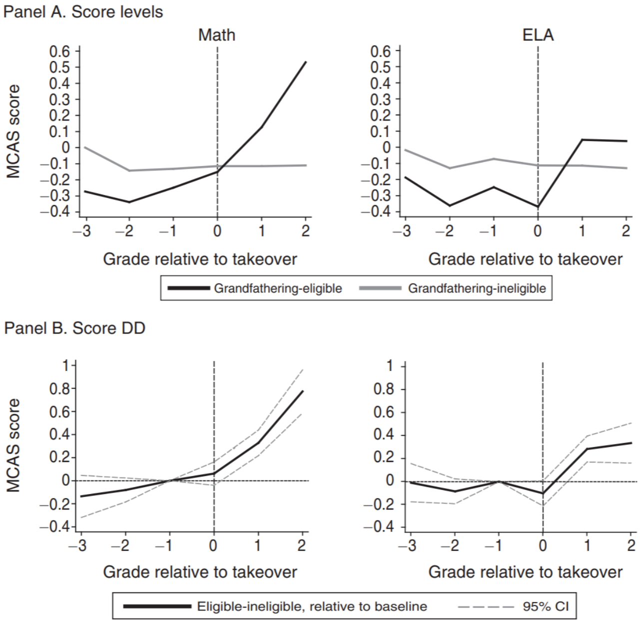
- Abdulkadiroglu et al. (2016) complement their lottery analysis of takeover charters with an instrumented diff-in-diff analysis
  - → Students enrolled in the "legacy" public school were eligible for being "grandfathered" into UP, without having to apply to the charter
  - → We compare their trends in test scores & enrollment to a matched comparison group of observably-similar students at other schools

Grandfathering IV: Visualized



Grandfathering IV Estimates of UP Test Score Effects

TABLE 7—GRANDFATHERING IV ESTIMATES OF UP EFFECTS

		Comparison group mean (1)	OLS (2)	2SLS: First stage (3)	2SLS: Enrollment effect (4)
Panel A. All grades					
(Seventh through eighth)	Math (N = 1,543)	−0.233	0.400	1.051	0.321
			(0.032)	(0.040)	(0.039)
	ELA (N = 1,539)	−0.214	0.296	1.040	0.394
			(0.035)	(0.041)	(0.044)

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where $\mathbf{W}_i$ includes a constant.

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- IV is still "reduced form over first stage": ($\beta = \rho/\pi$)
  - → Can use Frisch-Waugh-Lovell to "partial out" $\mathbf{W}_i$ from Y_i, X_i, D_i, and so get back to an IV regression without controls

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- Overidentification can yield tests of IV validity
  - $\rightarrow$ Intuitively, 2SLS checks whether all the $Z_{i\ell}$ yields the same IV estimate, which is sensible in a constant-effects model...

Putting the "2S" in "2SLS"

- You'll notice I haven't actually defined 2SLS beyond the simple case
  - → Before we had $\beta^{IV} = \frac{Cov(Z_i, Y_i)}{Cov(Z_i, D_i)}$ leading to $\widehat{\beta}^{IV} = \frac{\widehat{Cov}(Z_i, Y_i)}{\widehat{Cov}(Z_i, D_i)}$
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- The proof of this follows from some (simple) linear algebra
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- Although easy, you should never do such "manual 2SLS" yourself!
  - → Your point estimates will be right, but your SEs won't be!

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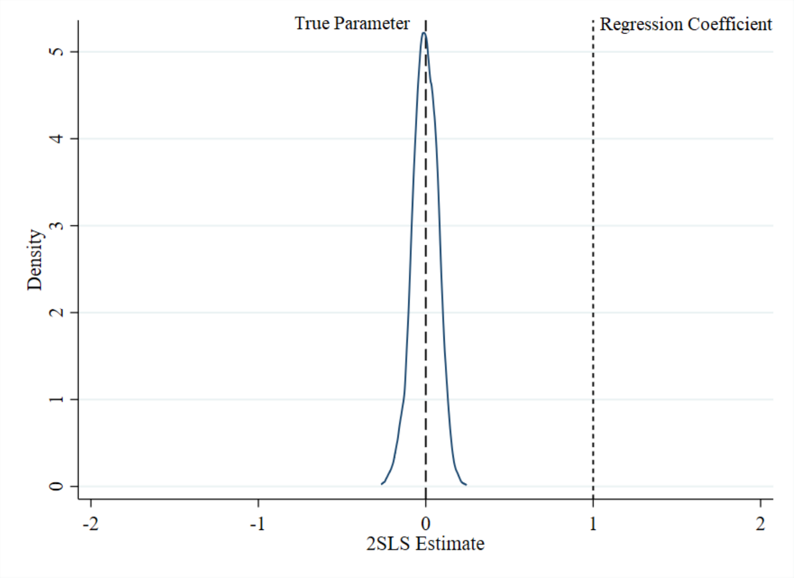
- Much made of this over the years, but Angrist and Kolesár (2022) argue recently that we shouldn't worry too much
  - → The SE increase tends to be large enough to "cover up" the bias
  - → Just-id. 2SLS is "approximately median-unbiased" (as it is LIML)

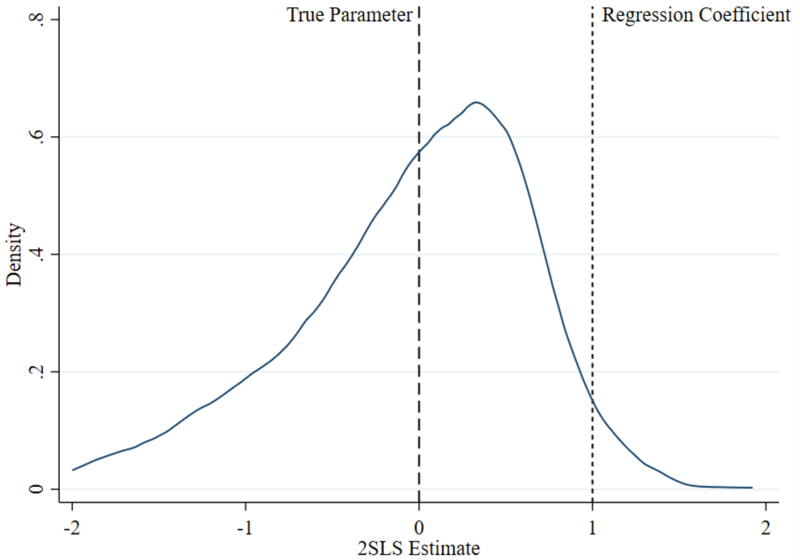
Weak Instruments: Visualized

Monte Carlo: $Y_i = \varepsilon_i$, $D_i = \Pi Z_i + \eta_i$: $\Pi = Var(\varepsilon_i) = Var(\eta_i) = 1$



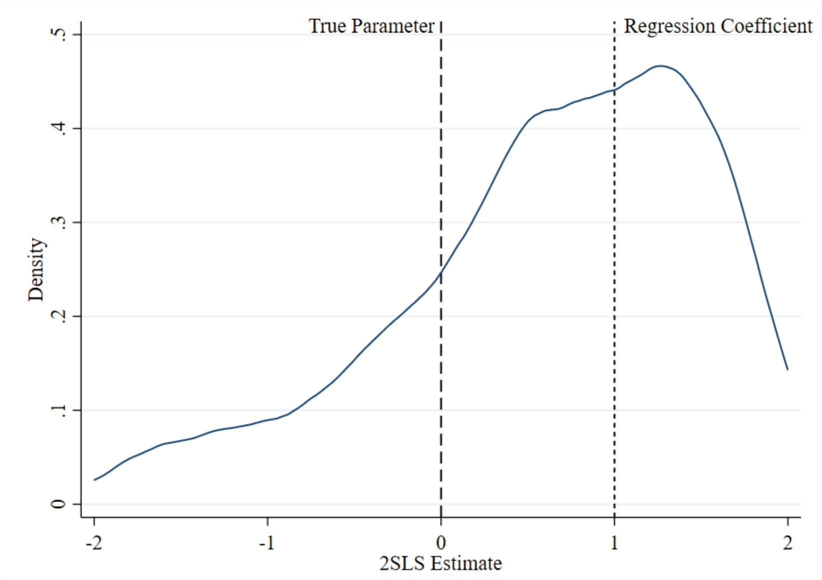
Weak Instruments: Visualized

Monte Carlo: $Y_i = \varepsilon_i$, $D_i = \Pi Z_i + \eta_i$: $\Pi = 0.1$ (Weaker)



Weak Instruments: Visualized

Monte Carlo: $Y_i = \varepsilon_i$, $D_i = \Pi Z_i + \eta_i$: $\Pi = 0.01$ (Very Weak)



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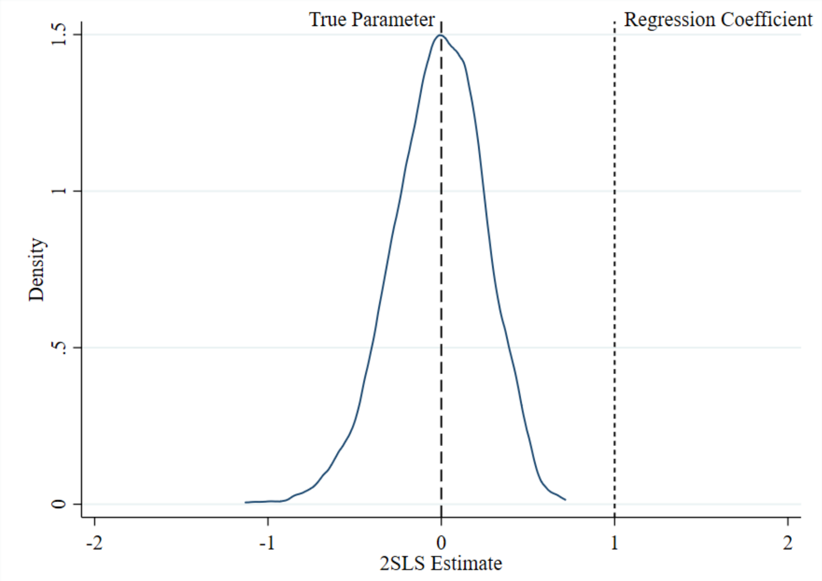
- As we'll see, this bias is especially relevant in judge IV designs
  - $\rightarrow$ Potentially many judge assignment indicators as the instrument
  - $\rightarrow$ Leave-out corrections (e.g. Angrist et al. 1999) have been adapted to this setting in recent years (e.g. Kolesár 2013)

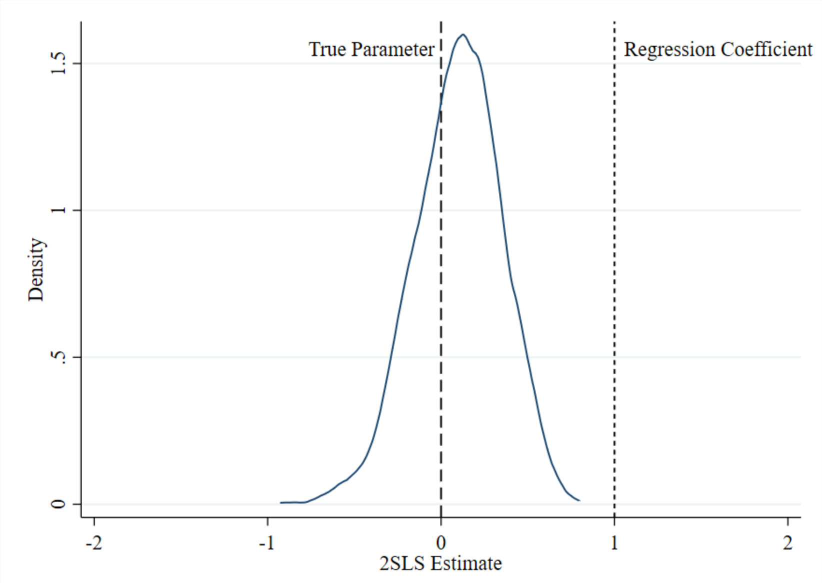
Weak and Many Instruments VIII

Monte Carlo: $Y_i = \varepsilon_i$, $X_i = \Pi Z_{i1} + \eta_i$: IV with one Z_{i1}



Weak and Many Instruments IX

Monte Carlo: $Y_i = \varepsilon_i$, $X_i = \Pi Z_{i1} + \eta_i$: IV with ten Z_{ij}



Weak and Many Instruments X

Monte Carlo: $Y_i = \varepsilon_i$, $X_i = \Pi Z_{i1} + \eta_i$: IV with 100 Z_{ij}