Lectures 08-09:
Paper overviews

PPHA 34600

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Lecture 08 recap

TL;DR:

1. Instrumental variables are very powerful
2. ...but they require extremely strong assumptions!
3. Hashtag no free lunch

An example: Impacts of parental incarceration on kids

Policy issue:

- Millions of Americans are in jail annually
- This likely impacts not only them, but also their families
- What is the impact of family member incarceration?

Approach:

- (We're not actually evaluating a program here)
- We need a shock to incarceration

→ We don't have randomization, so we use IV

- Instrument of choice: random assignment to strict/harsh judges

→ Do we believe this? Hold that thought...

Treatment effects of parental incarceration on kids

How does parental incarceration affect kids (simplified)?

First stage:

$$\text{Parental incarceration}_i = \alpha + \gamma \text{Judge leniency}_{ij} + \beta X_{ij} + \eta_{ij}$$

where

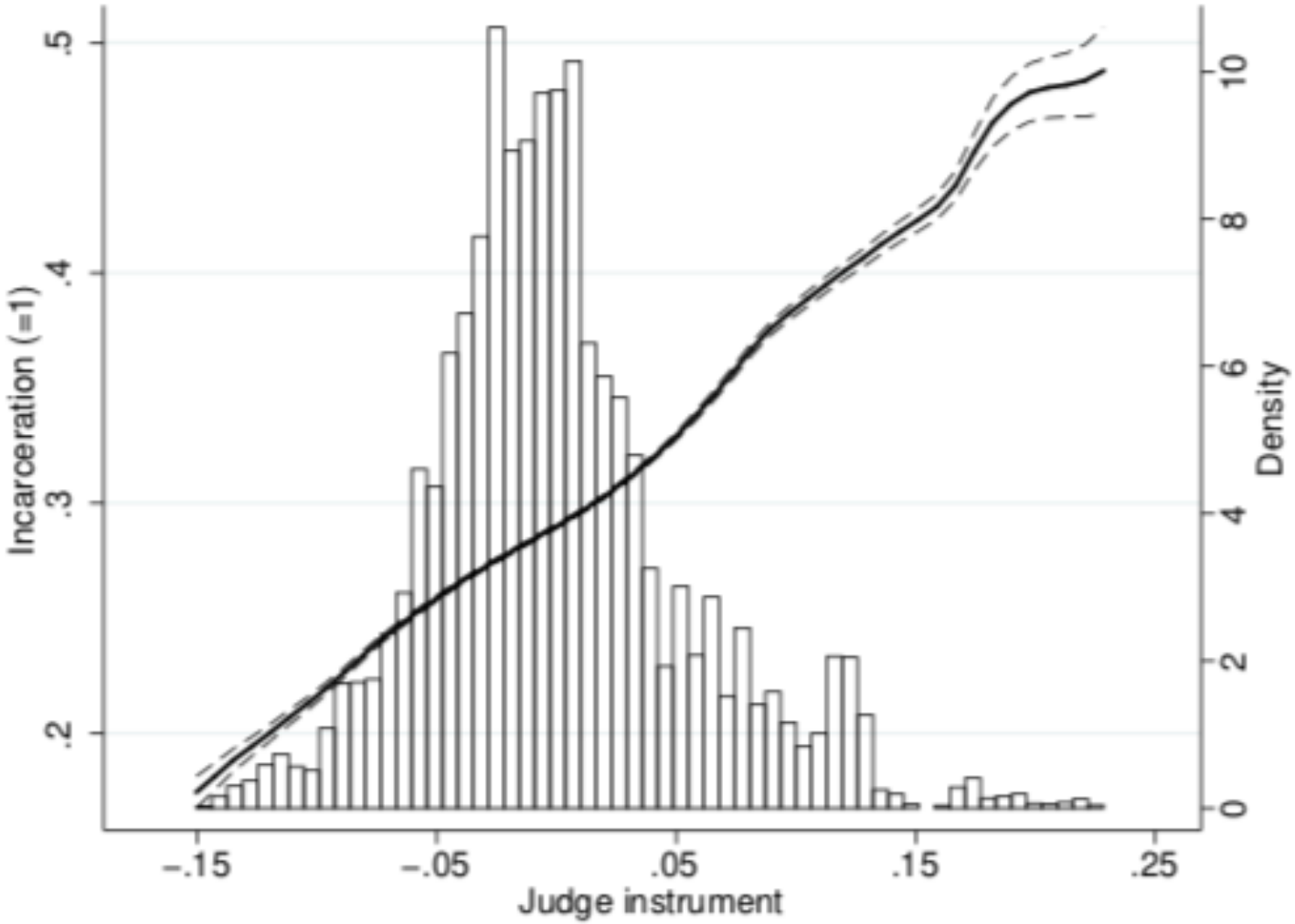
Parental incarceration$_i$ is equal to 1 if i's parent is jailed and 0 otherwise

Judge leniency$_{ij}$ is the strictness of judge j

X_{jt} are controls

η_{it} is an error term

First stage (graphically)



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Second stage:

$$Y_i = \alpha + \delta \widehat{\text{parental incarceration}}_i + \tau X_{ij} + \eta_i$$

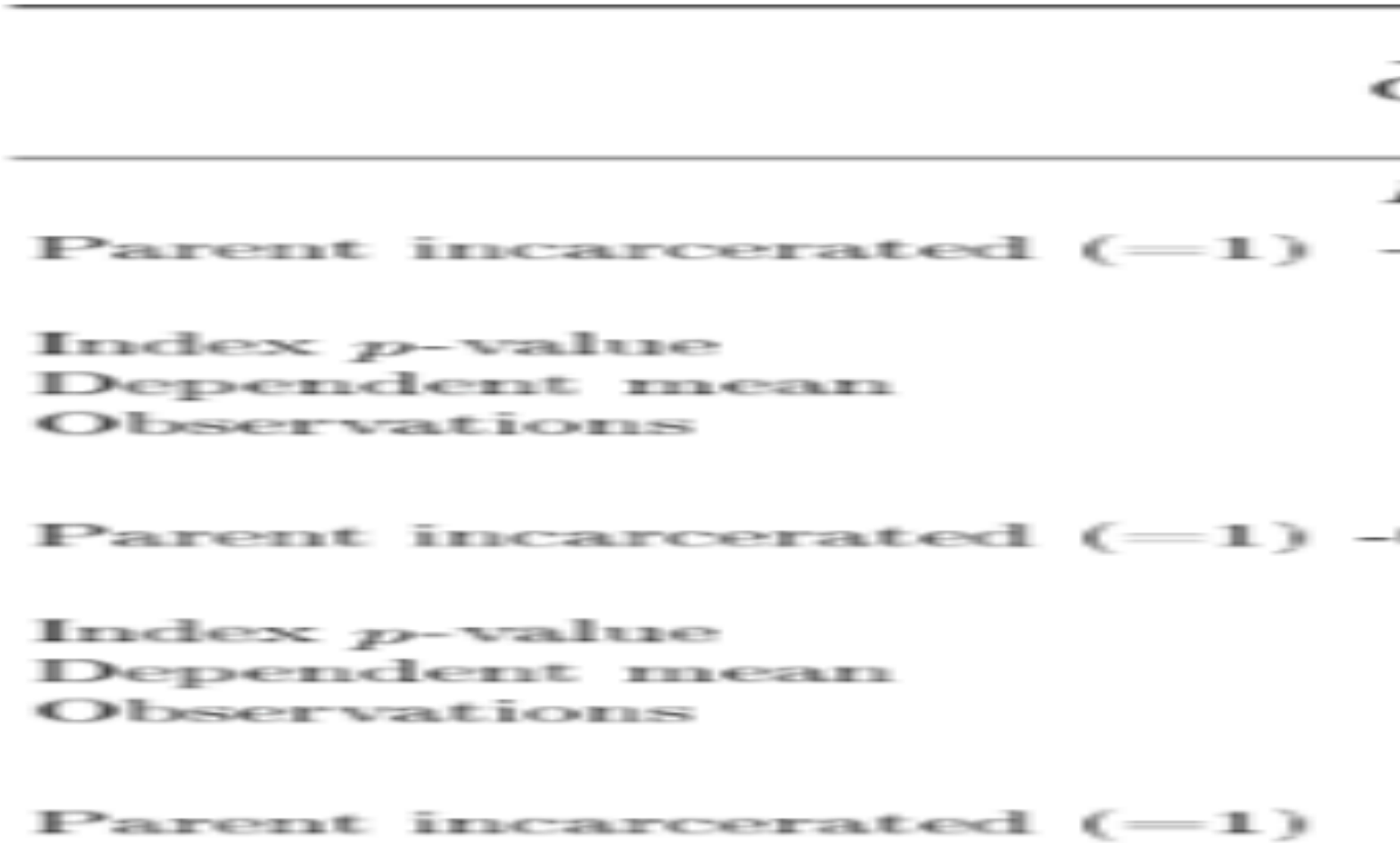
where
Y_i are outcomes for child i $\widehat{\text{parental incarceration}}_i$ is the fitted values from the first stage

Second stage (OLS)

Table A4: Effect of parental incarceration on child criminal activity, OLS comparison

	Extensive margin (=1)			Intensive margin (IHS)		
	Charged	Convicted	Incarcerated	Charged	Convicted	Incarcerated
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Criminal activity before age 25 (OLS with no controls)						
Parent incarcerated (=1)	0.024***	0.024***	0.015***	0.054***	0.042***	0.030***
	(0.005)	(0.005)	(0.004)	(0.011)	(0.009)	(0.007)
Index p-value			0.000			0.000
Dependent mean	0.325	0.247	0.124	0.568	0.375	0.205
Observations	83,532	83,532	83,532	83,532	83,532	83,532
Panel B: Criminal activity before age 25 (OLS with controls)						
Parent incarcerated (=1)	-0.004	-0.001	-0.001	-0.009	-0.004	0.000
	(0.005)	(0.005)	(0.003)	(0.010)	(0.008)	(0.006)
Index p-value			0.645			0.645
Dependent mean	0.325	0.247	0.124	0.568	0.375	0.205
Observations	83,532	83,532	83,532	83,532	83,532	83,532

Second stage (IV)



Estimating the reduced form

How does judge leniency affect child outcomes (simplified)?

Reduced form:

$$Y_i = \alpha + \theta \text{Judge leniency}_{ij} + \pi X_{ij} + \eta_i$$

Reduced form

The exclusion restriction is the key to any IV

You should always ask:
What is the exclusion restriction in this analysis saying?

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You should always ask:
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Do we believe this? Why or why not?

Second stage (IV)

Parent incarcerated (=1)

Index p-value
Dependent mean
Observations

Parent incarcerated (=1)

Index p-value
Dependent mean
Observations

Parent incarcerated (=1)

Lecture 09 recap

TL;DR:

1. Instrumental variables are very powerful
2. With the right assumptions...
3. ...we can handle OVB and ME (and simultaneity)

An example: Returns to schooling

Policy issue:

- How much is a year of school worth?
- This is really important for deciding how much school to invest in
- What role does measurement error play in our estimates?

Approach:

- (We're not actually evaluating a program here)
- We want to estimate the effect of schooling on wages
- **Measurement of years of schooling is poor**
- Instrument of choice: sibling $j \neq i$-reported schooling

Estimating the effects of schooling on wages

The authors will run a (simplified) version of:

$$Wages_i = \tau Schooling_i + \varepsilon_i$$

Where:

$Wages_i$ is a measure of wages

$Schooling_i$ is years of schooling for child i

ε_i is an error term

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A big concern

- $Schooling_i$ is measured with error
- We are likely to understate the true effect
- **Solution:** Z_i = Schooling as reported by twin$_i$!

First stage estimates (sort of)

A. *Identical Twins*

Variable	Y_1	Y_2	S_1^1	S_1^2	S_2^2	S_2^1	E_F^1	E_F^2	E_M^1	E_M^2
Y_1	1.000									
Y_2	0.563	1.000								
S_1^1	0.382	0.168	1.000							
S_1^2	0.375	0.140	0.920	1.000						
S_2^2	0.267	0.272	0.658	0.697	1.000					
S_2^1	0.248	0.247	0.700	0.643	0.877	1.000				
Father's education (E_F^1)	0.155	0.088	0.345	0.266	0.361	0.416	1.000			
Father's education (E_F^2)	0.159	0.091	0.357	0.278	0.320	0.389	0.857	1.000		
Mother's education (E_M^1)	0.102	0.088	0.348	0.343	0.392	0.410	0.614	0.644	1.000	
Mother's education (E_M^2)	0.126	0.087	0.316	0.321	0.322	0.337	0.503	0.579	0.837	1.000

Placebo test estimates

Coefficients (std. errors) in regression of outcome on *child's* birthyear rainfall.

	Women	Men
Mother's characteristics		
Completed grades of schooling	0.204	0.132
	(1.136)	(0.947)
	[2,447]	[2,258]
Currently alive (indicator)	0.084	0.029
	(0.083)	(0.108)
	[4,542]	[4,039]
Father's characteristics		
Completed grades of schooling	0.273	0.166
	(1.172)	(1.309)
	[2,810]	[2,621]
Currently alive (indicator)	0.010	-0.093
	(0.080)	(0.169)
	[4,541]	[4,040]

2SLS estimates

Variable	OLS (i)	GLS (ii)	GLS (iii)	IV[a] (iv)	First difference (v)	First difference by IV (vi)
Own education	0.084 (0.014)	0.087 (0.015)	0.088 (0.015)	0.116 (0.030)	0.092 (0.024)	0.167 (0.043)
Sibling's education	—	—	−0.007 (0.015)	−0.037 (0.029)	—	—
Age	0.088 (0.019)	0.090 (0.023)	0.090 (0.023)	0.088 (0.019)	—	—
Age squared (÷100)	−0.087 (0.023)	−0.089 (0.028)	−0.090 (0.029)	−0.087 (0.024)	—	—
Male	0.204 (0.063)	0.204 (0.077)	0.206 (0.077)	0.206 (0.064)	—	—
White	−0.410 (0.127)	−0.417 (0.143)	−0.424 (0.144)	−0.428 (0.128)	—	—
Sample size:	298	298	298	298	149	149
R^2:	0.260	0.219	0.219	—	0.092	—

2SLS estimates

TABLE 2—EFFECT OF BIRTH YEAR RAINFALL ON ADULT OUTCOMES: WOMEN AND MEN BORN 1953–1974
(Instrumental variables estimates. Coefficients (standard errors) in regression of outcome on rainfall in individual's birth year and birth district. Instrumental variables for birth year/birth district rainfall are rainfall measured at second- through fifth-closest rainfall stations to respondent's birth district.)

	Women	Men
Self-reported health status very good (indicator)	0.101	−0.029
	(0.058)*	(0.072)
	[4,613]	[4,270]
Self-reported health status poor/very poor (indicator)	−0.192	−0.100
	(0.082)**	(0.098)
	[4,613]	[4,270]
Ln (lung capacity)	−0.044	−0.073
	(0.049)	(0.062)
	[4,454]	[3,907]
Height (centimeters)	2.832	0.998
	(0.821)***	(1.795)
	[4,495]	[3,924]
Days absent due to illness (last four weeks)	−1.175	0.515
	(0.831)	(0.779)
	[4,611]	[4,267]
Completed grades of schooling	1.086	−0.474
	(0.453)**	(1.490)
	[4,598]	[4,259]
Ln (expenditures per capita in household)	0.095	−0.274
	(0.204)	(0.301)
	[4,615]	[4,277]
Asset index	0.876	−0.279
	(0.324)**	(0.507)
	[4,613]	[4,276]
Ln (annual earnings)	0.065	−0.202
	(0.988)	(0.350)
	[2,332]	[3,963]

2SLS estimates

TABLE 3—EFFECT OF RAINFALL IN YEARS BEFORE AND AFTER BIRTH: WOMEN BORN 1953–1974
(Instrumental variables estimates. Rainfall in individual's birth year and birth district instrumented with rainfall measured at second- through fifth-closest rainfall stations to respondent's birth district.)

Dependent variable	Self-reported health status very good (indicator)	Self-reported health status poor/very poor (indicator)	Height (centimeters)	Completed grades of schooling	Asset index
Coefficient on rainfall in:					
Year −3	0.025	−0.114	1.505	−0.065	0.003
	(0.084)	(0.120)	(1.572)	(0.992)	(0.424)
Year −2	−0.037	−0.013	0.854	−0.852	−0.426
	(0.103)	(0.075)	(1.813)	(1.670)	(0.721)
Year −1	−0.080	−0.045	3.338	0.104	−0.380
	(0.123)	(0.088)	(2.155)	(1.332)	(0.530)
Year 0	0.090	−0.179	3.833	1.598	0.750
	(0.067)	(0.093)*	(1.420)**	(0.675)**	(0.399)*
Year 1	−0.008	−0.096	0.676	1.083	0.203
	(0.053)	(0.067)	(1.592)	(0.769)	(0.272)
Year 2	−0.041	−0.015	1.666	0.117	−0.229
	(0.043)	(0.068)	(0.984)	(0.840)	(0.452)
Year 3	−0.020	−0.104	1.996	−0.135	0.088
	(0.116)	(0.067)	(1.774)	(0.802)	(0.232)
Observations	4,613	4,613	4,495	4,598	4,613