

Lectures 08-09:  
Paper overviews

**PPHA 34600**  
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### 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

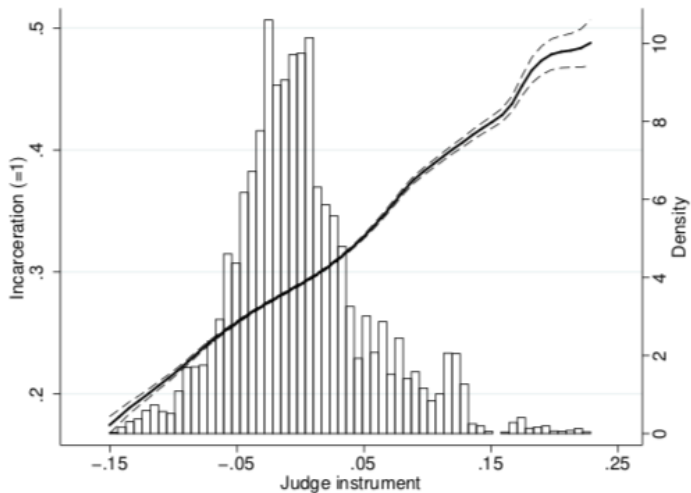
Parental incarceration<sub>*i*</sub> is equal to 1 if *i*'s parent is jailed and 0 otherwise

Judge leniency<sub>*ij*</sub> is the strictness of judge *j*

$X_{jt}$  are controls

$\eta_{it}$  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 (1)	Convicted (2)	Incarcerated (3)	Charged (4)	Convicted (5)	Incarcerated (6)
<i>Panel A: Criminal activity before age 25 (OLS with no controls)</i>						
Parent incarcerated (=1)	0.024*** (0.005)	0.024*** (0.005)	0.015*** (0.004)	0.054*** (0.011)	0.042*** (0.009)	0.030*** (0.007)
Index <i>p</i> -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
<i>Panel B: Criminal activity before age 25 (OLS with controls)</i>						
Parent incarcerated (=1)	-0.004 (0.005)	-0.001 (0.005)	-0.001 (0.003)	-0.009 (0.010)	-0.004 (0.008)	0.000 (0.006)
Index <i>p</i> -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)

	Extensive margin (=1)			Intensive margin (IHS)		
	Charged (1)	Convicted (2)	Incarcerated (3)	Charged (4)	Convicted (5)	Incarcerated (6)
<i>Panel A: Criminal activity before age 25</i>						
Parent incarcerated (=1)	-0.066** (0.030)	-0.055** (0.027)	-0.049** (0.020)	-0.156** (0.061)	-0.097** (0.045)	-0.076** (0.035)
Index <i>p</i> -value			0.011			0.013
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
<i>Panel B: Juvenile criminal activity</i>						
Parent incarcerated (=1)	-0.064*** (0.023)		-0.033*** (0.011)	-0.113*** (0.039)		-0.030** (0.013)
Index <i>p</i> -value			0.001			0.003
Dependent mean	0.202		0.050	0.306		0.052
Observations	64,781		64,781	64,781		64,781
<i>Panel C: Adult criminal activity</i>						
Parent incarcerated (=1)	-0.045 (0.029)	-0.055** (0.027)	-0.033* (0.019)	-0.106* (0.055)	-0.097** (0.045)	-0.055 (0.033)
Index <i>p</i> -value			0.044			0.039



# 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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**Do we believe this? Why or why not?**

## Second stage (IV)

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## 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  $i$

$\varepsilon_i$  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:**  $Z_i = \text{Schooling as reported by twin}_i!$

# 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

## 2SLS estimates

Variable	OLS (i)	GLS (ii)	GLS (iii)	IV <sup>a</sup> (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 <sup>2</sup> :	0.260	0.219	0.219	—	0.092	—