Chapter 9: Bonus content — Additional applications

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Overview

- If we've reached these slides, it means I talked slightly faster than planned this semester — so it's time for some bonus content!
- I thought it would be useful to walk through a few different recent applications of the tools we learned in the course
- Focus will be on more recent and more diverse set of authors than earlier (not just papers by Angrist and/or Krueger!)

Juvenile incarceration

- The US incarcerates more people than any country in the world (about 2M people)
- In addition to adult incarceration, a substantial number of juveniles (people under 18) are incarcerated as well (about 70K)
- Anna Aizer (Brown professor!) and Joseph Doyle (2015) studied the impacts of juvenile incarceration
- In particular, they ask how being incarcerated as a juvenile (a) impacts future criminal activity, (b) impacts completion of education

How do you think juvenile incarceration would impact future crime and education?

- Advocates for incarceration would argue that juvenile incarceration (typically pretty short) may help prevent youths on a 'downward spiral' and have a rehabilitative effect. May reduce future crime and increase education completion
- Critics of incarceration argue that juvenile incarcertation may be disruptive to youths and limit their possible employment outcomes $\rightarrow$ less education, more crime as adults

Identifying causal effects

- Hopefully by this point in the course it's clear why we can't just compare youths who are incarcerated to those who aren't. Why not? Confounding variables!
- Do you have any ideas about how we might get a more compelling causal answer to this question?
- Aizer and Doyle exploit the fact that in Chicago, which judge you are assigned to is effectively as good as random. They then use judge leniency as an instrumental variable
- In particular, juvenile defendants are assigned to a "calendar" based on their neighborhood and crime type. Multiple judges are assigned to each "calendar." Which judge you get on the calendar is based on idiosyncratic factors (judges essentially alternate cases).

The judge instrument

- Aizer and Doyle use the leniency of the judge you are assigned to as an instrumental variable.
- Leniency is measured as the fraction of defendants that saw that judge who were incarcerated (excluding the current defendant to avoid overfitting)
- Let Y_i be a defendant outcome – e.g. do they commit a crime as an adult; do they finish HS
- Let D_i be whether a defendant was incarcerated as a juvenile
- Define Z_i to be the average of value of D among other defendants with same judge as i.

Evaluating the assumptions

- **Relevance**: defendants assigned to a stricter judge need to be more likely to be incarcerated. Seems reasonable
- **Independence**: Which judge you are assigned to needs to be independent of other determinants of adult crime and other determinants of incarceration (e.g. crime type, lawyer quality)
  - Conditional on the "calendar", this seems reasonable based on the institutional structure
- **Exclusion**: the stringency of the judge that you get affects future outcomes only through whether you are incarcerated.
  - Reasonable if judge only determines whether you're incarcerated
  - We might worry that judges determine other things — sentence length, probation terms, etc.
- **Monotonicity**: everyone incarcerated with a lenient judge would also be incarcerated with a stricter judge
  - Could be violated if, e.g., judge who is strict on violent crime is lenient on drug crime

Covariate balance

TABLE II

INSTRUMENT VERSUS JUVENILE CHARACTERISTICS

	Z distribution				
	Bottom tercile	Middle tercile	Top tercile	Middle vs. bottom p-value	Top vs. bottom p-value
Z: first judge's leave-out mean incarceration rate in first cases	0.062	0.094	0.147	(.000)	(.000)
Juvenile characteristics					
Male	0.827	0.830	0.833	(.561)	(.311)
African American	0.724	0.737	0.742	(.096)	(.249)
Hispanic	0.189	0.176	0.172	(.061)	(.272)
White	0.078	0.079	0.078	(.833)	(.957)
Other race/ethnicity	0.009	0.008	0.007	(.352)	(.345)
Special education	0.241	0.237	0.252	(.549)	(.130)
U.S. census tract poverty rate	0.264	0.265	0.265	(.572)	(.696)
Age at offense	14.8	14.8	14.8	(.437)	(.434)

Judge leniency is not correlated with defendant characteristics

Specification

- **First stage:** regress incarceration on judge strictness, controlling for "calendar" and defendant characteristics

$$D_i = \pi_1 Z_i + \pi_2' X_i + \delta_{c(i)} + v_i,$$

where X_i is a vector of defendant characteristics, and $\delta_{c(i)}$ is a "calendar" fixed effect.

First stage results

TABLE III
FIRST STAGE

	(1)	(2)	(3)
Dependent variable: juvenile incarcerations		OLS	
First judge's leave-out mean incarceration rate among first cases	1.103	1.082	1.060
	(0.102)	(0.095)	(0.097)
Demographic controls	No	Yes	Yes
Court controls	No	No	Yes
Observations	37,692		
Mean of dependent variable	0.227		

First stage is statistically indistinguishable from 1 $\rightarrow$ a 1 percentage point stricter judge means a 1 percentage point higher chance of incarceration (intuitive!)

Specification

- **First stage:** regress incarceration on judge strictness, controlling for "calendar" and defendant characteristics

$$D_i = \pi_1 Z_i + \pi_2' X_i + \delta_{c(i)} + v_i,$$

where X_i is a vector of defendant characteristics, and $\delta_{c(i)}$ is a "calendar" fixed effect.

- **Second stage:** regress outcome of interest (HS grad, future crime) on predictions from the first-stage $\hat{D}$

$$Y_i = \beta_0 + \beta_1 \hat{D}_i + \beta_2' X_i + \beta_{c(i)} + \varepsilon_i$$

TABLE IV

JUVENILE INCARCERATION AND HIGH SCHOOL GRADUATION

	Dependent variable: graduated high school						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Full CPS sample			Juvenile court sample			
	OLS	OLS	Inverse propensity score weighting	OLS	OLS	2SLS	2SLS
Juvenile incarceration	−0.389	−0.292	−0.391	−0.088	−0.073	−0.108	−0.125
	(0.0066)	(0.0065)	(0.0055)	(0.0043)	(0.0041)	(0.044)	(0.043)
Demographic controls	No	Yes	Yes	No	Yes	No	Yes
Court controls	N/A	N/A	N/A	No	Yes	No	Yes
Observations	440,797	440,797	420,033	37,692			
Mean of dependent variable	0.428	0.428	0.433	0.099			

TABLE V

Juvenile Incarceration and Adult Crime

	Dependent variable: entered adult prison by age 25						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Full CPS sample			Juvenile court sample			
	OLS	OLS	Inverse propensity score weighting	OLS	OLS	2SLS	2SLS
Juvenile incarceration	0.407	0.350	0.219	0.200	0.155	0.260	0.234
	(0.0082)	(0.0064)	(0.013)	(0.0072)	(0.0073)	(0.073)	(0.076)
Demographic controls	No	Yes	Yes	No	Yes	No	Yes
Court controls	N/A	N/A	N/A	No	Yes	No	Yes
Observations	440797	440797	420033	37692			
Mean of dependent variable	0.067	0.067	0.057	0.327			

Who is this a treatment effect for?

- Compliers! People who would be incarcerated only if they got a strict judge but not a lenient one
- So this doesn't tell us that we shouldn't incarcerate anyone (maybe it's good for always takers?)
- But on the margin, having the strict judges rule like the lenient ones appears like it would increase HS graduation and reduce adult crime
- Note, though, that this calculation does not consider the deterrence effects — i.e., maybe people commit fewer crimes because they are worried about going to juvie

Does incarceration always cause crime?

- Bhuller et al (2020) use a similar IV using judge stringency in Norway
- This study looks at adults accused of crimes in Norway
- In Norway, it is mandated by law that judges be randomly assigned to defendants

TABLE 4
EFFECTS OF INCARCERATION ON RECIDIVISM (N = 31,428)

	Dependent Variable			
	Pr(Ever Charged)			Number of Charges
	Months 1–24 after Decision (1)	Months 25–60 after Decision (2)	Months 1–60 after Decision (3)	Months 1–60 after Decision (4)
OLS: incarcerated:				
No controls	.130***	.115***	.113***	5.275***
	(.007)	(.007)	(.006)	(.321)
Demographics and type of crime	.126***	.109***	.105***	5.369***
	(.007)	(.007)	(.006)	(.310)
All controls	.068***	.050***	.052***	2.917***
	(.006)	(.007)	(.006)	(.278)
Complier reweighted	.057***	.042***	.049***	1.595***
	(.007)	(.007)	(.006)	(.251)
RF: judge stringency:				
All controls	−.108**	−.111**	−.133***	−5.196**
	(.047)	(.048)	(.045)	(2.452)
IV: incarcerated:				
All controls	−.239**	−.245**	−.293***	−11.482**
	(.113)	(.113)	(.106)	(5.705)
Dependent mean	.57	.57	.70	10.21
Complier mean if not incarcerated	.56	.57	.73	13.62

NOTE.—Shown is the baseline sample of nonconfession criminal cases processed in 2005–9. Controls include all variables listed in table 1. In addition, RF and IV also control for court × court entry year fixed effects. OLS standard errors are clustered at the defendant level, while RF and IV standard errors are two-way clustered at the judge and defen-

Interpreting these results

- One initial thought might be that the reduction in recidivism is the result of incapication — you can't commit a new crime if you're in jail
- But 90% of people incarcerated serve less than 1 year. And the effects persist for 25-60 months
- Clearly, the prisons are doing something to prevent crime even after people leave

What do prisons in Norway do?

of Norwegian Correctional Services. The principle dictates that "life inside will resemble life outside as much as possible" and that "offenders shall be placed in the lowest possible security regime." This means that low-level offenders go directly to open prisons, which have minimal security as well as more freedoms and responsibilities. Physically, these open prisons resemble dormitories rather than rows of cells with bars. More se-

To help with rehabilitation, all prisons offer education, mental health, and training programs. In 2014, 38% and 33% of inmates in open and closed prisons, respectively, participated in some type of educational or training program. The most common programs are for high school and

TABLE 7

Effect of Incarceration on Participation in Job Training Programs and Classroom Training Programs (Months 1–24 after Decision)

	Subsample			
	Previously Employed ($N = 16{,}547$)		Previously Nonemployed ($N = 14{,}881$)	
	(1)	(2)	(3)	(4)
Dependent variable	Pr(participated in job training programs)	Pr(participated in classroom training programs)	Pr(participated in job training programs)	Pr(participated in classroom training programs)
RF: judge stringency, all controls	.056	.073	.147**	.054
	(.063)	(.065)	(.063)	(.067)
IV: incarcerated, all controls	.106	.138	.348**	.127
	(.118)	(.122)	(.168)	(.164)
Dependent mean	.17	.19	.22	.17
Complier mean if not incarcerated	.16	.18	.00	.04

Note.—Shown is the baseline sample of nonconfession criminal cases processed in 2005–9. Control variables include all variables listed in table 1 plus controls for court × court entry year fixed effects. Standard errors are two-way clustered at the judge and defendant level.

** $p < .05$.

TABLE 5
EFFECT OF INCARCERATION ON RECIDIVISM BY PREVIOUS LABOR MARKET ATTACHMENT

	Subsample			
	Previously Employed (N = 16,547)		Previously Nonemployed (N = 14,881)	
	(1)	(2)	(3)	(4)
	A. Dependent Variable: Pr(Ever Charged)			
Months 1–60 after decision	Baseline	Reweighted	Baseline	Reweighted
RF: judge stringency, all controls	−.062	−.079	−.183***	−.157***
	(.063)	(.068)	(.060)	(.069)
IV: incarcerated, all controls	−.117	−.146	−.433**	−.365*
	(.119)	(.126)	(.177)	(.192)
Dependent mean	.62	.58	.79	.76
Complier mean if not incarcerated	.55	.60	.96	.86

To summarize

- Prisons in Norway (in contrast to US) focus heavily on rehabilitiation and training
- This appears to have a positive effect on labor market outcomes for those who were not employed at baseline
- For those who were employed at baseline, the disruption effect may dominate the effect of additional training

Examiner designs

- Similar research designs have been used in other contexts where there is an "examiner" who reviews a case and makes a decision of interest
- Here are a few other examples

Debt Relief and Debtor Outcomes: Measuring the Effects of Consumer Bankruptcy Protection†

By Will Dobbie and Jae Song*

Consumer bankruptcy is one of the largest social insurance programs in the United States, but little is known about its impact on debtors. We use 500,000 bankruptcy filings matched to administrative tax and foreclosure data to estimate the impact of Chapter 13 bankruptcy protection on subsequent outcomes. Exploiting the random assignment of bankruptcy filings to judges, we find that Chapter 13 protection increases annual earnings by $5,562, decreases five-year mortality by 1.2 percentage points, and decreases five-year foreclosure rates by 19.1 percentage points. These results come primarily from the deterioration of outcomes among dismissed filers, not gains by granted filers. (*JEL* D14, I12, J22, J31, K35)

Child Protection and Adult Crime: Using Investigator Assignment to Estimate Causal Effects of Foster Care

This paper uses the randomization of families to child protection investigators to estimate causal effects of foster care on adult crime. The analysis uses a new data set that links criminal justice data to child protection data in Illinois, and I find that investigators affect foster care placement. Children on the margin of placement are found to be two to three times more likely to enter the criminal justice system as adults if they were placed in foster care. One innovation describes the types of children on the margin of placement, a group that is more likely to include African Americans, girls, and young adolescents.

Eviction and Poverty in American Cities *

Robert Collinson, John Eric Humphries, Nicholas Mader, Davin Reed,

Daniel Tannenbaum & Winnie van Dijk†

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More than two million U.S. households have an eviction case filed against them each year. Policymakers at the federal, state, and local levels are increasingly pursuing policies to reduce the number of evictions, citing harm to tenants and high public expenditures related to homelessness. We study the consequences of eviction for tenants using newly linked administrative data from two large cities. We document that prior to housing court, tenants experience declines in earnings and employment and increases in financial distress and hospital visits. These pre-trends are more pronounced for tenants who are evicted, which poses a challenge for disentangling correlation and causation. To address this problem, we use an instrumental variables approach based on cases randomly assigned to judges of varying leniency. We find that an eviction order increases homelessness, and reduces earnings, durable consumption, and access to credit. Effects on housing and labor market outcomes are driven by impacts for female and Black tenants.