

6) Instrumental Variables (IV) and Local Average Treatment Effect (LATE)

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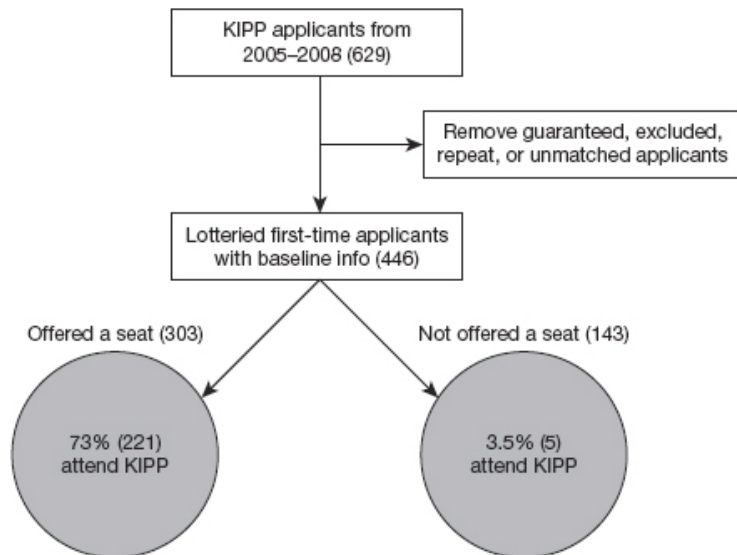
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Tables, Graphics, and Figures from

**Mastering 'Metrics: The Path from Cause
to Effect**

Angrist & Pischke (2014): Chapter 3.1 and 3.2

Knowledge Is Power Program (KIPP)



Analysis of KIPP Lotteries (A)

		KIPP applicants			
	Lynn public fifth graders (1)	KIPP Lynn lottery winners (2)	Winners vs. losers (3)	Attended KIPP (4)	Attended KIPP vs. others (5)
Panel A. Baseline characteristics					
Hispanic	.418	.510	-.058 (.058)	.539	.012 (.054)
Black	.173	.257	.026 (.047)	.240	-.001 (.043)
Female	.480	.494	-.008 (.059)	.495	-.009 (.055)
Free/Reduced price lunch	.770	.814	-.032 (.046)	.828	.011 (.042)
Baseline math score	-.307	-.290	.102 (.120)	-.289	.069 (.109)
Baseline verbal score	-.356	-.386	.063 (.125)	-.368	.088 (.114)

Analysis of KIPP Lotteries (B)

		KIPP applicants			
	Lynn public fifth graders (1)	KIPP Lynn lottery winners (2)	Winners vs. losers (3)	Attended KIPP (4)	Attended KIPP vs. others (5)
Panel B. Outcomes					
Attended KIPP	.000	.787	.741 (.037)	1.000	1.000 —
Math score	-.363	-.003	.355 (.115)	.095	.467 (.103)
Verbal score	-.417	-.262	.113 (.122)	-.211	.211 (.109)
Sample size	3,964	253	371	204	371

Effect of offers on scores

$$=(\text{Effect of offers on attendance}) \times (\text{Effect of attendance on scores})$$

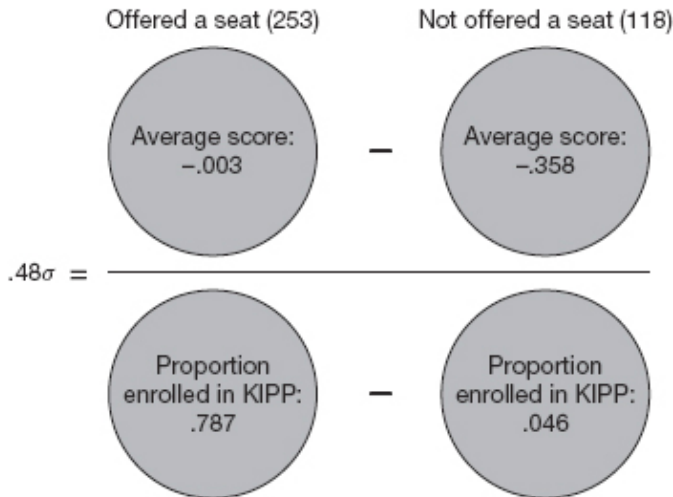
Effect of attendance on scores

$$= (\text{Effect of offers on scores}) / (\text{Effect of offers on attendance})$$

Local Average Treatment Effect (LATE)

$$\lambda = \frac{\rho}{\phi} = \frac{E[Y_i|Z_i=1] - E[Y_i|Z_i=0]}{E[D_i|Z_i=1] - E[D_i|Z_i=0]}$$

IV in School: Effect of KIPP Attendance on Math Scores



The Four Types of Children

		Lottery losers $Z_i = 0$	
		Doesn't attend KIPP $D_i = 0$	Attends KIPP $D_i = 1$
Lottery winners $Z_i = 1$	Doesn't attend KIPP $D_i = 0$	Never-takers (<i>Normando</i>)	Defiers
	Attends KIPP $D_i = 1$	Compliers (<i>Camila</i>)	Always-takers (<i>Alvaro</i>)

$$\lambda = \frac{\rho}{\phi} = E[Y_{1i} - Y_{0i} | C_i = 1]$$

$$TOT = E[Y_{1i} - Y_{0i} | D_i = 1]$$

The Minneapolis Domestic Violence Experiment (MDVE)

Assigned treatment	Delivered treatment			Total
	Arrest	Coddled		
		Advise	Separate	
Arrest	98.9 (91)	0.0 (0)	1.1 (1)	29.3 (92)
Advise	17.6 (19)	77.8 (84)	4.6 (5)	34.4 (108)
Separate	22.8 (26)	4.4 (5)	72.8 (83)	36.3 (114)
Total	43.4 (136)	28.3 (89)	28.3 (89)	100.0 (314)

$$P(\text{Coddled} | \text{Assig. Coddled}) = .797 \left(\frac{84+5+5+83}{108+114} \right)$$

$$P(\text{Coddled} | \text{Not. Assig. Coddled}) = .011 \left(\frac{1}{92} \right)$$

- Police were called for a second domestic violence intervention at 18% of the addresses in the MDVE sample

Y_i : at least one post-treatment episode of suspected abuse

D_i : incidents where coddling was delivered

Z_i : assignment to coddling

Intention-to-Treat (ITT) Effects

$$E[Y_i|Z_i = 1] - E[Y_i|Z_i = 0] = .211 - .097 = .114$$

- Captures the causal effect of being assigned to treatment
- But, ITT effect does not take the noncompliance into account
- ITT as IV for treatment delivered eliminates the selection bias

$$E[Y_i|D_i = 1] - E[Y_i|D_i = 0] = .216 - .129 = .087$$

$$E[Y_i|Z_i = 1] - E[Y_i|Z_i = 0] = .211 - .097 = .114$$

$$E[D_i|Z_i = 1] - E[D_i|Z_i = 0] = .797 - .011 = .786$$

$$\lambda = \frac{.114}{.786} = .145$$

- Almost no always-takers in the MDVE
- Always-takers are suspected batterers who were coddled without regard to treatment assigned

$$E[Y_{1i} - Y_{0i} | C_i = 1] = E[Y_{1i} - Y_{0i} | D_i = 1]$$