Evaluación de Impacto:
El modelo causal de Rubin

Francesco Bogliacino

Causalidad

- Si pongo unos policía en una cuadra x, reduzco la cantidad de actos criminales;
- Esto es diferente de pensar si hay alguna asociación entre policías y crimen;
- Piénsenlo: si yo fuera a ver que tipo de asociación hay entre policía y crimen seguramente sería positiva.
  - ¿Esto implicaría que los policías causan el crimen?

Causalidad

- El skipper mueve constantemente el timón a la derecha y a la izquierda;
- Y el barco sigue derecho;
- No hay correlación entre el movimiento del timón y la dirección
- ¿Esto implicaría que el timón no causa la dirección?

Fuente: Cunningham (2020)

Outcome alternativo potencial

- Los economistas (o cada vez más los científicos sociales) piensan la causalidad en términos de contrafactual;
- El contrafactual es la hipótesis de defecto (que habría pasado si no hubiéramos …);
- Otro concepto clave es *ceteris paribus:* a paridad de otras condiciones
- En otras palabras:
    - Si comparamos qué pasa a la criminalidad en las cuadras con policías y en las cuadras sin policías podríamos equivocarnos en inferir algo, porque las cuadras sin policías son “diferentes” en muchas dimensiones

Outcome alternativo potencial

- A los experimentalistas nos gusta hablar de “control”
- Hume decía:

  “When we require an action, or blame a person for not performing it.. we esteem it vicious in him to be regardless of it. If we find, upon enquiry, that the virtuous motive was still powerful… tho’ checked in its operation by some circumstances unknown to us, we retract out blame, … (Hume, 1739; 1985, pp. 529–30).”

  - Piensen en la violencia contra los menores y el lockdown. Con el lockdown cayó en número de denuncias…
  - Piensen en las violencia contra las mujeres en Suecia y Arabia Saudí…

Primero una terminología

- Y: LHS, variable dependiente, outcome, variable explicada, variable predecida
- X: RHS, variable independiente, explicativa, control, predictor, regresor

- En casi todo el curso hablaremos de D=1 (tratamiento), D=0 (control)
  - 1 es la cuarentena, el policía en la cuadra, una elección, una institución,… depende del problema que estemos estudiando

Cómo pensar el problema de la causalidad

- El impacto causal sobre cada unidad se define *Teoricamente*
- Pero no lo Podemos medir, porque no Podemos correr la historia dos veces
- *Sliding doors…* vamos al excel un momento

Unidad	Y0	Y1		1=	hace servicio militar
1	0	1		0=	no hace servicio militar
2	1	2		Y	criminal record (número) cinco años después de la edad del servicio
3	0	0			
4	0	0			
5	1	1			
6	1	0			
7	0	2			
8	0	1			
9	1	1			
10	0	0			

$$ATE = \frac{1}{N}\sum_{i=1}^{N} Y_i^1 - Y_i^0 = \frac{1}{N}[\frac{NT}{NT}\sum_{i=1}^{NT} Y_i^1 - Y_i^0 + \frac{N-NT}{N-NT}\sum_{i=1}^{N-NT} Y_i^1 - Y_i^0]$$

= $\frac{1}{N}$[Nt ATT + (N-NT)ATU]=P(D=1)ATT+(1-P(D=1))ATU

$$E[Y1 - Y0|D = 1] = E[Y1|D = 1] - E[Y0|D = 0]$$

El problema de la evaluación

Definimos resultados alternativos potenciales Y_i^0, Y_i^1

Definimos una serie de parámetros teóricos:

ATE	ATT	ATU	En general ATE no es igual a ATT o ATU (heterogeneidad)

Para poder estimar estos parámetros de interés necesitamos poder estimar los contrafactuales

En general Y_i^0 observados sobre D=0 no estima correctamente Y_i^0 sobre D=1 porque D=0 y D=1 son “diferentes” en varias dimensiones

De dónde nace el problema de la evaluación?

- Yo observo
  - Y1 para los que D=1
  - Y0 para los que D=0
- Pero quisiera observar
  - Y0 para los que D=1
  - Y1 para los que D=0

  - Para poder estimar parámetros causales
  - De vuelta al excel

SDO

Piensen en el caso de la educación que predice un incremento en el sueldo, qué pasa si usamos la diferencia en el sueldo para estimar impacto causal?

$$SDO = E[Y_i | D_i = 1] - E[Y_i | D_i = 0] = E\left[Y_i^1 \middle| D_i = 1\right] - E\left[Y_i^0 \middle| D_i = 0\right] =$$

$$E[Y_i|D_i = 1] - E[Y_i|D_i = 0] =$$
$$= E\left[Y_i^1\middle|D_i = 1\right] - E\left[Y_i^0\middle|D_i = 0\right] =$$
$$= E\left[Y_i^1\middle|D_i = 1\right] - E\left[Y_i^0\middle|D_i = 1\right] + E\left[Y_i^0\middle|D_i = 1\right] - E\left[Y_i^0\middle|D_i = 0\right] =$$
$$E\left[Y_i^1 - Y_i^0\middle|D_i = 1\right] + E\left[Y_i^0\middle|D_i = 1\right] - E\left[Y_i^0\middle|D_i = 0\right]$$

$$E[Y_i|D_i = 1] - E[Y_i|D_i = 0] =$$
$$= ATT + SB =$$
$$ATT + E\left[Y_i^1 - Y_i^0\right] - P(D = 1) * ATT - \left(1 - P(D = 1)\right) * ATU + SB=$$
$$ATE + \left(1 - P(D = 1)\right) * ATT - \left(1 - P(D = 1)\right) * ATU + SB =$$
$$\boldsymbol{ATE + \left(1 - P(D = 1)\right)(ATT - ATU) + SB}$$

La teoría detrás

- D=1 es el resultado de una elección [el político, el ciudadano, ….]
- Esta decisión se toma con base cierta información y un criterio decisional. ESTA ES LA TEORÍA ECONÓMICA

La switching regression

$$Y_i = Y_i^1 D_i + (1 - D_i) Y_i^0 =$$

$$= Y_i^0 + (Y_i^1 - Y_i^0) D_i =$$

$$= E[Y_i^0] + \beta D_i + Y_i^0 - E[Y_i^0] =$$

$$\alpha + \beta D_i + \varepsilon_i$$

La switching regression

- La *definición* de outcome alternativo potencial nos lleva a definir el outcome a través de un modelo lineal
- Esto implica que:
  - Necesitamos un estimador que estime correctamente ese Beta;
  - Que si la asignación de ese D es exógena, ese estimador es OLS
- Esto no implica:
  - Que OLS siempre me identifica Beta;
  - Esto no tiene nada que ver con que yo pueda usar OLS (el software lo va a hacer si yo quiero pero depende de como interpreto los datos)

The OLS formula

$$\hat{\beta}_{OLS} = \frac{E[(D_i - \bar{D})(Y_i - \bar{Y})]}{E[(D_i - \bar{D})^2]} = \frac{E[(D_i)(Y_i - \bar{Y})]}{E[(D_i - \bar{D})^2]}$$

$$= \frac{E[(D_i - \bar{D})(Y_i - \bar{Y})]}{P(1-P)} = \frac{E[(D_i)(Y_i - \bar{Y})]}{P(1-P)}$$

$$= \frac{E[(D_i)(Y_i)] - E[(D_i)(\bar{Y})]}{P(1-P)} = \frac{\overline{Y_{D=1}} - \bar{Y}P}{P(1-P)}$$

$$= \frac{P\overline{Y_{D=1}} - P(P\overline{Y_{D=1}} + (1-P)\overline{Y_{D=0}})}{P(1-P)}$$

$$= \frac{P\overline{Y_{D=1}} - P(P\overline{Y_{D=1}} + (1-P)\overline{Y_{D=0}})}{P(1-P)} = \overline{Y_{D=1}} - \overline{Y_{D=0}}$$

Otra manera de verla

$$E[\alpha + \beta D_i + \varepsilon_i | D = 1] - E[\alpha + \beta D_i + \varepsilon_i | \mathrm{D} = 0] =$$

$$\alpha + \beta + E[\varepsilon_i | D = 1] - \alpha + E[\varepsilon_i | D = 0] =$$

$$\beta + E[\varepsilon_i | D = 1] - E[\varepsilon_i | D = 0]$$

En Stata

- clear
- set more off
- prog drop _all

- set obs 200
- gen iid=_n
- gen W1=runiformint(1,6)
- gen W2=runiformint(0,1)
- gen D= .5 -.01 * W1 +.12 * W2 + runiform(-.2, +.2)
- replace D=1 if D>.5
- replace D=0 if D<=.5
- gen y = 600 + 1000 * D - 80* W1 + 300* W2 + runiform(-100, 300)

- tabstat y if D==1, stat(mean)
- tabstat y if D==0, stat(mean)

Randomization

- Aleatorización garantiza EN LA POBLACIÓN que $E\left[Y_i^0 \middle| D_i = 1\right] = E\left[Y_i^0 \middle| D_i = 0\right]$ -> SB desaparece
- Aleatorización garantiza EN LA POBLACIÓN que $E\left[Y_i^1 \middle| D_i = 1\right] = E\left[Y_i^1 \middle| D_i = 0\right] \rightarrow$ $\boldsymbol{ATT} - \boldsymbol{ATU} = E\left[Y_i^1 \middle| D_i = 1\right] - E\left[Y_i^0 \middle| D_i = 1\right] - E\left[Y_i^1 \middle| D_i = 0\right] + E\left[Y_i^0 \middle| D_i = 0\right]$=0
- Aleatorización implica que EN LA POBLACIÓN: SDO=ATE

Esta se llama la hipótesis de independencia

- Se usa esta notación algo inusual $Y^1, Y^0 \perp D$
- Ojo! Esto no implica que $E\left[Y_i^1 \middle| D_i = 1\right] = E\left[Y_i^0 \middle| D_i = 1\right]$, implica solo que la asignación no depende del valor de los outcome alternativos potenciales

Por qué el énfasis en la población?

Porque en general nosotros trabajaremos con un conjunto (una muestra)

De vuelta al excel

Resumen

- Definición de causalidad
- Modelo de Rubin: outcome alternativos potenciales [concepto de contrafactual]
- Los parámetros causales: ATE, ATT, ATU
- En general comparar tratados y no tratados no estima parámetros causales, por el sesgo de selección
- Modelo lineal (por la definición de contrafactual) vs estimador lineal
- La aleatorización elimina el sesgo de selección

SUTVA

- Han notado que nosotros escribimos Y1 o Y0 para la unidad i en general, esto tiene dos implicaciones:
  - La dosis del tratamiento es la misma;
  - Lo que pasa la unidad j no afecta el outcome de la unidad i

  - Hay razones para que esto no ocurra?

SUTVA:

Stable
across all Units
Treatment Value
Assumption

Efectos de spillover:

- vacuna

Efectos de red:

- información

Efectos de equilibrio económico general:

- Escalar una intervención

Si es así, ¿qué hay de nuevo en Eval Impacto?

- La econometría y la economía hacen eso desde siempre:
  - ¿Cuál es el impacto de un impuesto sobre el precio?
  - ¿Cuál es el multiplicador?

La Revolución de la Credibilidad

Gregg v. Georgia, 428 U.S. 153 (1976)

Opinions Audio & Media

Syllabus **Case**

[Footnote 31]

See, e.g., Peck, The Deterrent Effect of Capital Punishment: Ehrlich and His Critics, 85 Yale L.J. 359 (1976); Baldus & Cole, A Comparison of the Work of Thorsten Sellin and Isaac Ehrlich on the Deterrent Effect of Capital Punishment, 85 Yale L.J. 170 (1975); Bowers & Pierce, The Illusion of Deterrence in Isaac Ehrlich's Research on Capital Punishment, 85 Yale L.J. 187 (1975); Ehrlich, The Deterrent Effect of Capital Punishment: A Question of Life and Death, 65 Am.Econ.Rev. 397 (June 1975); Hook, The Death Sentence, in The Death Penalty in America 146 (H. Bedau ed.1967); T. Sellin, The Death Penalty, A Report for the Model Penal Code Project of the American Law Institute (1959).

Ehrlich 1975

TABLE 2—VARIABLES USED IN THE REGRESSION ANALYSIS, ANNUAL OBSERVATIONS 1933–69

	Variable		Mean (Natural Logarithms)	Standard Deviation (Natural Logarithms)	Arithmetic Mean
y_1	$(Q/N)^0$ =	Crime rate: offenses known per 1,000 civilian population.	−2.857	0.156	0.058
Y_1	P^0a =	Probability of arrest: percent of offenses cleared.	4.997	0.038	89.835
	$P^0c\|a$ =	Conditional probability of conviction: percent of those charged who were convicted of murder.[a]	3.741	0.175	42.733
	$P^0e\|c$ =	Conditional probability of execution; PXQ_1 = the number of executions for murder in the year t+1 as a percent of the total number of convictions in year t.[b]	0.176	1.749	2.590
X_1	L =	Labor force participation: fraction of the civilian population in the labor force.	−0.546	0.030	0.579
	U =	Unemployment rate: percent of the civilian labor force unemployed.	1.743	0.728	7.532
	A =	Fraction of residential population in the age group 14–24.	−1.740	0.118	0.177
	Y_p =	Friedman's estimate of (real) permanent income per capita in dollars.	6.868	0.338	1012.35
	T =	Chronological time (years): 31–37.	2.685	0.867	19.00
X_2	NW =	Fraction of nonwhites in residential population.	−2.212	0.063	0.110
	N =	Civilian population in 1,000s.	11.944	0.161	155,853
	$XGOV$ =	Per capita (real) expenditures (excluding national defense) of all governments in million dollars.	−7.661	0.501	.000532
	$XPOL_{-1}$ =	Per capita (real) expenditures on police in dollars lagged one one year.[a]	2.114	0.306	8.638

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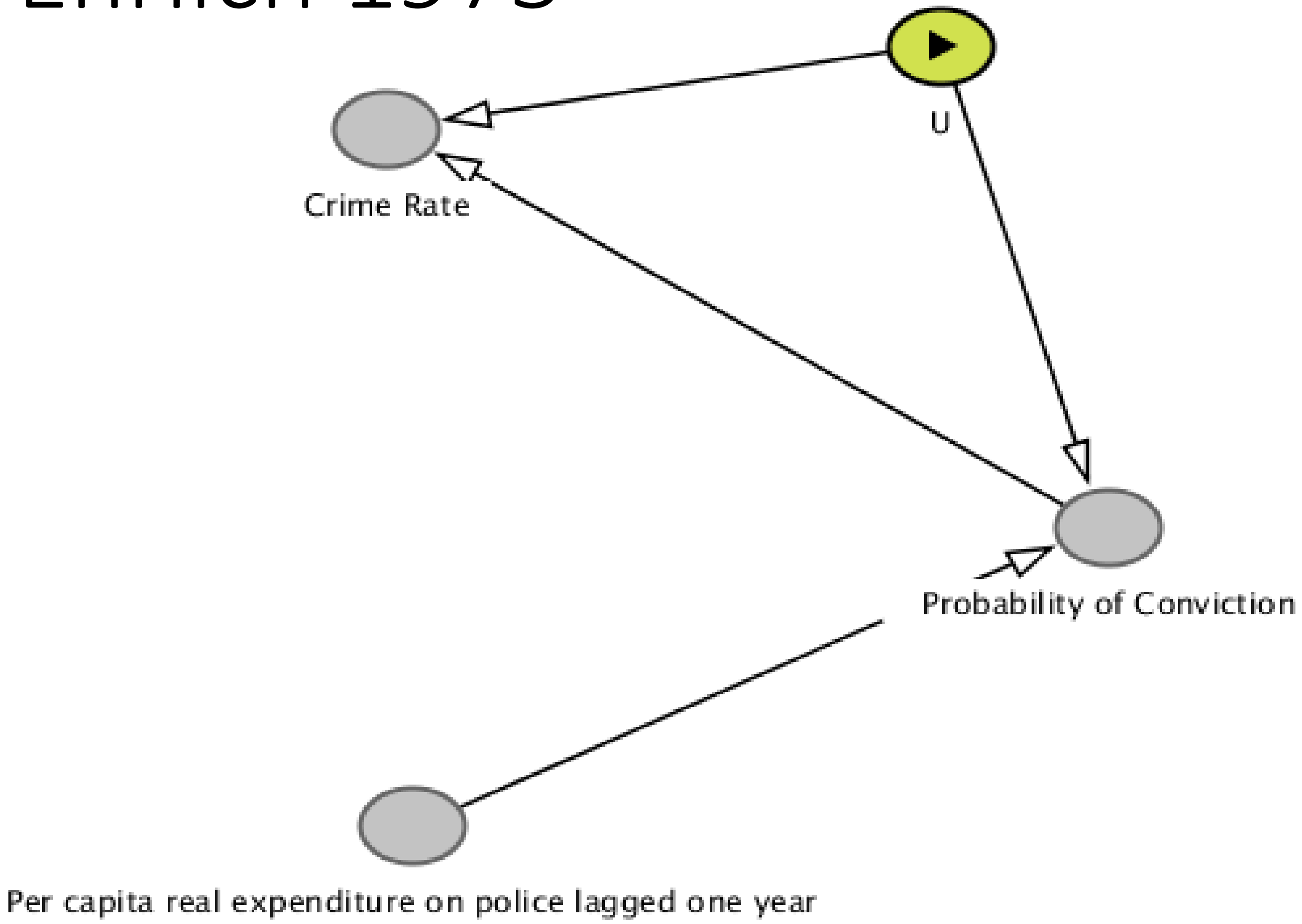

Ehrlich (1975)

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TABLE 4—MODIFIED FIRST DIFFERENCES OF MURDER RATES (IN NATURAL LOGARITHMS) REGRESSED AGAINST CORRESPONDING MODIFIED FIRST DIFFERENCES OF SELECTED VARIABLES SET II: ALTERNATIVE TIME PERIODS AND OTHER TESTS

($\hat{\beta}/S_{\hat{\beta}}$ in parentheses)

Effective Period	$\beta(CORC)$				$\Delta^* P^o c \mid c$						War Years	
D.W. Statistic	$\hat{\rho}_e$	*C* (Constant)	$\Delta^* \hat{P}^o a$	$\Delta^* \hat{P}^o c \mid a$	$\Delta^* PXQ_{1-1}$	$\Delta^* TXQ_1$	$\Delta^* L$	$\Delta^* A$	$\Delta^* Y_p$	$\Delta^* U$	Dummy (1942–45)	$\Delta^* T$
1. 1935–69[a]	0.059	−4.060	−1.247	−0.345	−0.066		−1.314	0.450	1.318	0.068		−0.046
1.80	0.044	(−1.00)	(−1.56)	(−3.07)	(−3.33)		(−1.49)	(2.20)	(4.81)	(2.60)		(−6.54)
2. 1937–69[a]	0.287	−2.568	−1.435	−0.474		−0.049	−1.388	0.526	1.289	0.063		−0.044
1.99	0.046	(−0.61)	(−1.87)	(−3.22)		(−2.31)	(−1.57)	(1.94)	(3.91)	(2.10)		(−4.96)
3. 1936–69[b]	—	−3.608	−1.385	−0.345		−0.064	−1.218	0.482	1.348	0.068		−0.047
1.49	0.046	(−1.03)	(−2.12)	(−3.25)		(−3.52)	(−1.40)	(2.13)	(4.94)	(2.59)		(−6.69)
4. 1935–69	0.061	−4.882	−1.172	−0.383	−0.069		−1.487	0.477	1.393	0.077	0.018	−0.048
1.84	0.046	(−1.32)	(−1.73)	(−3.20)	(−3.22)		(−1.61)	(1.89)	(4.30)	(1.95)	(0.31)	(−5.76)
5. 1937–69	0.250	−2.086	−1.634	−0.508		−0.055	−1.444	0.406	1.334	0.077	0.035	−0.045
2.08	0.048	(−0.51)	(−2.16)	(−2.83)		(−2.36)	(−1.51)	(1.23)	(3.73)	(1.80)	(0.50)	(−4.72)
6. 1941–69	−0.164	3.025	−1.744	−0.714	−0.074		−1.008	0.141	0.734	0.028		−0.036
2.21	0.048	(0.57)	(−2.21)	(−3.70)	(−3.70)		(−1.04)	(0.56)	(2.06)	(0.91)		(−4.40)
7. 1941–69	−0.029	3.752	−1.947	−0.723		−0.066	−0.962	0.152	0.771	0.0311		−0.036
2.13	0.048	(0.68)	(−2.38)	(−3.69)		(−3.34)	(−0.99)	(0.55)	(2.00)	(0.96)		(−4.13)
8. 1933–66	−0.001	−5.678	−0.564	−0.265	0.055		−2.111	0.283	0.922	0.036		−0.036
1.90	0.033	(−2.21)	(−1.10)	(−3.49)	(−3.72)		(−3.18)	(1.65)	(4.16)	(1.74)		(−6.30)
9. 1939–66	0.016	−2.601	−0.946	−0.360		−0.051	−1.766	0.212	0.780	0.027		−0.033
1.96	0.037	(−0.598)	(−1.38)	(−1.984)		(−3.23)	(−2.254)	(1.03)	(2.920)	(1.11)		(−4.99)

Note: same references as in Table 3 but the reduced form used to compute $\Delta^* \hat{P}^o a$ and $\Delta^* \hat{P}^o c \mid a$ does not include N.

[a] Same as equations 3 and 4 in Table 3 with the missing data pertaining to $XPOL_{-1}$ interpolated via a smoothing procedure.

[b] Same as equation 4 in Table 3 with $\hat{\rho}$ assumed to be zero (level regression).

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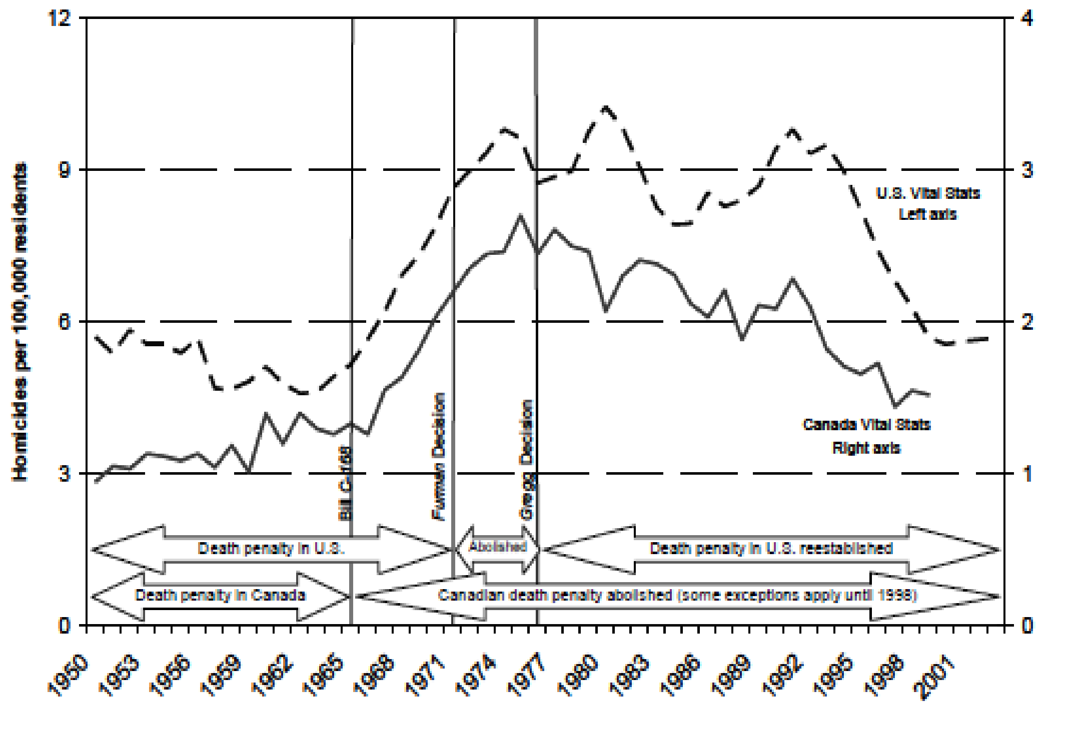
- Use of a comparison group
- "emphasizing the importance of comparing results among those groups or regions receiving the "treatment" of the death penalty with a comparison group that is untreated, but otherwise susceptible to similar influences (a "placebo" or "control group")."

Figure 2. Homicide Rates and the Death Penalty in the United States and Canada



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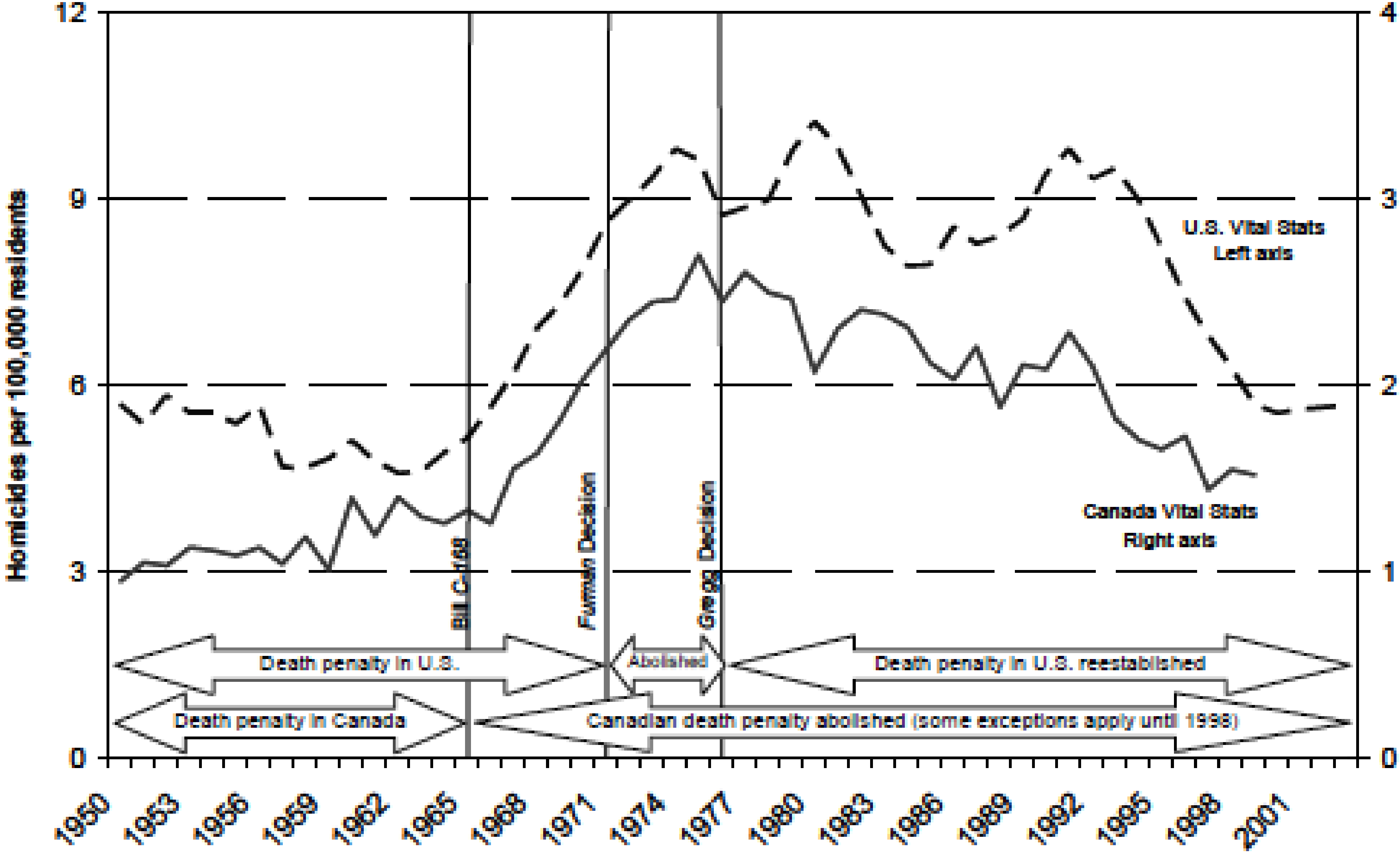

Credibility Revolution

- Mejores y más datos *(recolectar datos según un diseño)*
- Menos distracciones (, robust)
- Diseño de investigación
  - RCT como referente ideal
  - RDD
  - Diferencias in diferencias
  - *Identification strategy*

- What’s your identification strategy?
  More transparency
  Better communication
  More multidisciplinarity
  recovery of RDD and other literature
- A lot of rethorical battle
  Funding
  Macho culture at seminars
- Ethics?
  Theory?
  Non results?

LaLonde Study

- National Supported Work Demonstration (NSW): sujetos a baja empleabilidad (AFDC: women, ex-drug addicts, ex-criminal offenders, and high school dropouts of both sexes y un similar male program)
- Treatment versus control:
  - T: 9-18 meses de empleo & profesional de apoyo para discutir de problemas y dar sugerencias
  - C: “Good luck with your life”
- Baseline, y datos cada 9 meses, hasta 4 recolecciones ex post pero con attrition

TABLE 2—ANNUAL EARNINGS OF NSW TREATMENTS, CONTROLS, AND EIGHT CANDIDATE COMPARISON GROUPS FROM THE *PSID* AND THE *CPS-SSA*

			Comparison Group[a,b]							
Year	Treat-ments	Controls	*PSID*-1	*PSID*-2	*PSID*-3	*PSID*-4	*CPS-SSA*-1	*CPS-SSA*-2	*CPS-SSA*-3	*CPS-SSA*-4
1975	$895	$877	7,303	2,327	937	6,654	7,788	3,748	4,575	2,049
	(81)	(90)	(317)	(286)	(189)	(428)	(63)	(250)	(135)	(333)
1976	$1,794	$646	7,442	2,697	665	6,770	8,547	4,774	3,800	2,036
	(99)	(63)	(327)	(317)	(157)	(463)	(65)	(302)	(128)	(337)
1977	$6,143	$1,518	7,983	3,219	891	7,213	8,562	4,851	5,277	2,844
	(140)	(112)	(335)	(376)	(229)	(484)	(68)	(317)	(153)	(450)
1978	$4,526	$2,885	8,146	3,636	1,631	7,564	8,518	5,343	5,665	3,700
	(270)	(244)	(339)	(421)	(381)	(480)	(72)	(365)	(166)	(593)
1979	$4,670	$3,819	8,016	3,569	1,602	7,482	8,023	5,343	5,782	3,733
	(226)	(208)	(334)	(381)	(334)	(462)	(73)	(371)	(170)	(543)
Number of Observations	600	585	595	173	118	255	11,132	241	1,594	87

[a] The Comparison Groups are defined as follows: *PSID*-1: All female household heads continuously from 1975 through 1979, who were between 20 and 55-years-old and did not classify themselves as retired in 1975; *PSID*-2: Selects from the *PSID*-1 group all women who received AFDC in 1975; *PSID*-3: Selects from the *PSID*-2 all women who were not working when surveyed in 1976; *PSID*-4: Selects from the *PSID*-1 group all women with children, none of whom are less than 5-years-old; *CPS-SSA* – 1: All females from Westat *CPS-SSA* sample; *CPS-SSA*-2: Selects from *CPS-SSA*-1 all females who received AFDC in 1975; *CPS-SSA*-3: Selects from *CPS-SSA*-1 all females who were not working in the spring of 1976; *CPS-SSA*-4: Selects from *CPS-SSA*-2 all females who were not working in the spring of 1976.

Con Experimental data

- Observen que como uno se esperaría con asignación aleatoria los sueldos al comienzo son muy parecidos;
- Esto nos permite inferir que SDO=ATE;
- Puedo hacer algo más sofisticado
- Puedo usar controles:
  - Si, si son explicativas
  - No si son causalmente afectadas por el treatment

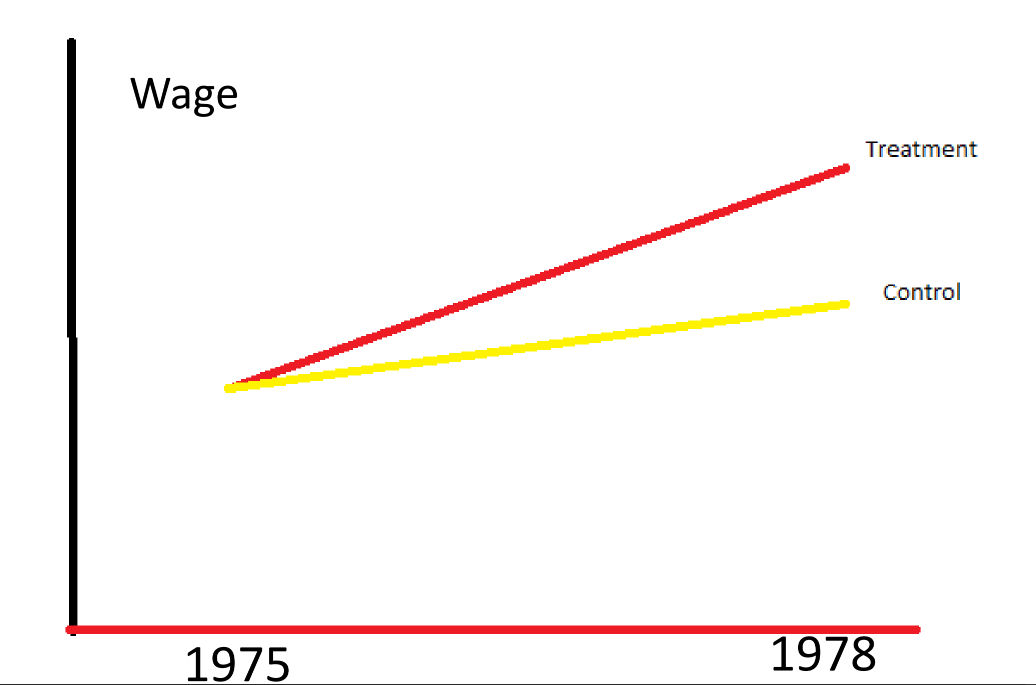

TABLE 4—EARNINGS COMPARISONS AND ESTIMATED TRAINING EFFECTS FOR THE NSW AFDC PARTICIPANTS USING COMPARISON GROUPS FROM THE *PSID* AND THE *CPS-SSA*[a,b]

Name of Comparison Group[d]	Comparison Group Earnings Growth 1975–79 (1)	NSW Treatment Earnings Less Comparison Group Earnings: Pre-Training Year, 1975: Unadjusted (2)	NSW Treatment Earnings Less Comparison Group Earnings: Pre-Training Year, 1975: Adjusted[c] (3)	NSW Treatment Earnings Less Comparison Group Earnings: Post-Training Year, 1979: Unadjusted (4)	NSW Treatment Earnings Less Comparison Group Earnings: Post-Training Year, 1979: Adjusted[c] (5)	Difference in Differences: Difference in Earnings Growth 1975–79 Treatments Less Comparisons: Without Age (6)	Difference in Differences: Difference in Earnings Growth 1975–79 Treatments Less Comparisons: With Age (7)	Unrestricted Difference in Differences: Quasi Difference in Earnings Growth 1975–79: Unadjusted (8)	Unrestricted Difference in Differences: Quasi Difference in Earnings Growth 1975–79: Adjusted[c] (9)	Controlling for All Observed Variables and Pre-Training Earnings: Without AFDC (10)	Controlling for All Observed Variables and Pre-Training Earnings: With AFDC (11)
Controls	2,942	−17	−22	851	861	833	883	843	864	854	–
	(220)	(122)	(122)	(307)	(306)	(323)	(323)	(308)	(306)	(312)	
PSID-1	713	−6,443	−4,882	−3,357	−2,143	3,097	2,657	1746	1,354	1664	2,097
	(210)	(326)	(336)	(403)	(425)	(317)	(333)	(357)	(380)	(409)	(491)
PSID-2	1,242	−1,467	−1,515	1,090	870	2,568	2,392	1,764	1,535	1,826	–
	(314)	(216)	(224)	(468)	(484)	(473)	(481)	(472)	(487)	(537)	
PSID-3	665	−77	−100	3,057	2,915	3,145	3,020	3,070	2,930	2,919	–
	(351)	(202)	(208)	(532)	(543)	(557)	(563)	(531)	(543)	(592)	
PSID-4	928	−5,694	−4,976	−2,822	−2,268	2,883	2,655	1,184	950	1,406	2,146
	(311)	(306)	(323)	(460)	(491)	(417)	(434)	(483)	(503)	(542)	(652)
CPS-SSA-1	233	−6,928	−5,813	−3,363	−2,650	3,578	3,501	1,214	1,127	536	1,041
	(64)	(272)	(309)	(320)	(365)	(280)	(282)	(272)	(309)	(349)	(503)
CPS-SSA-2	1,595	−2,888	−2,332	−683	−240	2,215	2,068	447	620	665	–
	(360)	(204)	(256)	(428)	(536)	(438)	(446)	(468)	(554)	(651)	
CPS-SSA-3	1,207	−3,715	−3,150	−1,122	−812	2,603	2,615	814	784	−99	1,246
	(166)	(226)	(325)	(311)	(452)	(307)	(328)	(305)	(429)	(481)	(720)
CPS-SSA-4	1,684	−1,189	−780	926	756	2,126	1,833	1,222	952	827	–
	(524)	(249)	(283)	(630)	(716)	(654)	(663)	(637)	(717)	(814)	

[a] The columns above present the estimated training effect for each econometric model and comparison group. The dependent variable is earnings in 1979. Based on the experimental data, an unbiased estimate of the impact of training presented in col. 4 is $851. The first three columns present the difference between each comparison group's 1975 and 1979 earnings and the difference between the pre-training earnings of each comparison group and the NSW treatments.

Miremos a STATA

Sin experimental data

- $y_i = \delta D_i + X_i\beta + b_i + n_t + \varepsilon_{it}$
- $\varepsilon_{it} = \rho\varepsilon_{it-1} + v_{it}$
- $D_i = 1 \text{ if } y_{is} + Z_i\gamma + \vartheta_{is} > 0$

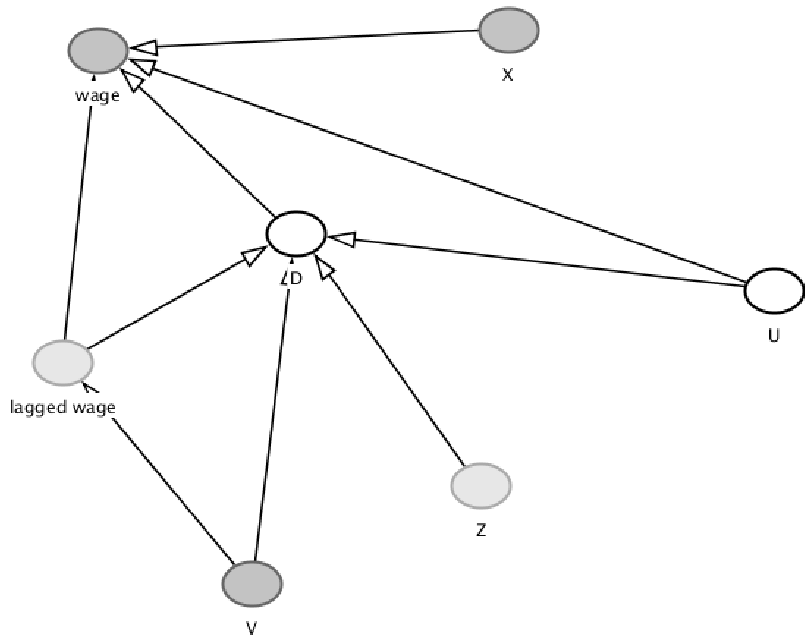

TABLE 4—EARNINGS COMPARISONS AND ESTIMATED TRAINING EFFECTS FOR THE NSW AFDC PARTICIPANTS USING COMPARISON GROUPS FROM THE *PSID* AND THE *CPS-SSA*[a,b]

Name of Comparison Group[d]	Comparison Group Earnings Growth 1975–79	NSW Treatment Earnings Less Comparison Group Earnings: Pre-Training Year, 1975		NSW Treatment Earnings Less Comparison Group Earnings: Post-Training Year, 1979		Difference in Differences: Difference in Earnings Growth 1975–79 Treatments Less Comparisons		Unrestricted Difference in Differences: Quasi Difference in Earnings Growth 1975–79		Controlling for All Observed Variables and Pre-Training Earnings	
		Unadjusted	Adjusted[c]	Unadjusted	Adjusted[c]	Without Age	With Age	Unadjusted	Adjusted[c]	Without AFDC	With AFDC
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
Controls	2,942	−17	−22	851	861	833	883	843	864	854	–
	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	
PSID-1	713	−6,443	−4,882	−3,357	−2,143	3,097	2,657	1746	1,354	1664	2,097
	(210)	(326)	(336)	(403)	(425)	(317)	(333)	(357)	(380)	(409)	(491)
PSID-2	1,242	−1,467	−1,515	1,090	870	2,568	2,392	1,764	1,535	1,826	–
	(314)	(216)	(224)	(468)	(484)	(473)	(481)	(472)	(487)	(537)	
PSID-3	665	−77	−100	3,057	2,915	3,145	3,020	3,070	2,930	2,919	–
	(351)	(202)	(208)	(532)	(543)	(557)	(563)	(531)	(543)	(592)	
PSID-4	928	−5,694	−4,976	−2,822	−2,268	2,883	2,655	1,184	950	1,406	2,146
	(311)	(306)	(323)	(460)	(491)	(417)	(434)	(483)	(503)	(542)	(652)
CPS-SSA-1	233	−6,928	−5,813	−3,363	−2,650	3,578	3,501	1,214	1,127	536	1,041
	(64)	(272)	(309)	(320)	(365)	(280)	(282)	(272)	(309)	(349)	(503)
CPS-SSA-2	1,595	−2,888	−2,332	−683	−240	2,215	2,068	447	620	665	–
	(360)	(204)	(256)	(428)	(536)	(438)	(446)	(468)	(554)	(651)	
CPS-SSA-3	1,207	−3,715	−3,150	−1,122	−812	2,603	2,615	814	784	−99	1,246
	(166)	(226)	(325)	(311)	(452)	(307)	(328)	(305)	(429)	(481)	(720)
CPS-SSA-4	1,684	−1,189	−780	926	756	2,126	1,833	1,222	952	827	–
	(524)	(249)	(283)	(630)	(716)	(654)	(663)	(637)	(717)	(814)	

[a] The columns above present the estimated training effect for each econometric model and comparison group. The dependent variable is earnings in 1979. Based on the experimental data, an unbiased estimate of the impact of training presented in col. 4 is $851. The first three columns present the difference between each comparison group's 1975 and 1979 earnings and the difference between the pre-training earnings of each comparison group and the NSW treatments.

Con modelos de selección

TABLE 6—ESTIMATED TRAINING EFFECTS USING TWO-STAGE ESTIMATOR

Variables Excluded from the Earnings Equation, but Included in the Participation Equation	Comparison Group	NSW AFDC Females: Training Dummy	NSW AFDC Females: Estimate of Expectation	NSW Males: Training Dummy	NSW Males: Estimate of Expectation
		Heckman Correction for Program Participation Bias, Using Estimate of Conditional Expectation of Earnings Error as Regressor in Earnings Equation — Estimate of Coefficient for			
Marital Status, Residency in an SMSA, Employment Status in 1976, AFDC Status in 1975, Number of Children	*PSID*-1	1,129	−894	−1,333	−2,357
		(385)	(396)	(820)	(781)
	CPS-SSA-1	1,102	−606	−22	−1,437
		(323)	(480)	(584)	(449)
	NSW Controls	837	−18	899	−835
		(317)	(2376)	(840)	(2601)
Employment Status in 1976, AFDC Status in 1975, Number of Children	*PSID*-1	1,256	−823	–	–
		(405)	(410)		
	CPS-SSA-1	439	−979	–	–
		(333)	(481)		
	NSW Controls	–	–	–	–
Employment Status in 1976, Number of Children	*PSID*-1	1,564	−552	−1,161	−2,655
		(604)	(569)	(864)	(799)
	CPS-SSA-1	552	−902	13	−1,484
		(514)	(551)	(584)	(450)
	NSW Controls	851	147	889	−808
		(318)	(2385)	(841)	(2603)
No Exclusion Restrictions	*PSID*-1	1,747	−526	−667	−2,446
		(620)	(568)	(905)	(806)
	CPS-SSA-1	805	−908	213	−1,364
		(523)	(548)	(588)	(452)
	NSW Controls	861	284	889	−876
		(318)	(2385)	(840)	(2601)