MRU Mastering Econometrics **M. Joshway**
Spring 2020

Causality, Experiments, and Potential Outcomes

1 Casual vs Causal Effects

In an argument that's far from casual, Americans debate the causal effects of health insurance. Does health insurance affect health and/or health care costs? The view that insurance is beneficial on both counts motivated the 2010 Affordable Care Act, known also as Obamacare.

The Affordable Care Act imposed tax penalties on the uninsured, but it remains true that some Americans are covered and some aren't (The 2017 Tax Cuts and Jobs Act ended the individual mandate). This brings us to the question at the heart of MM Chapter 1:

> Are the insured healthier than *they* would have been had they not been insured?

Implicit in this question is a "what if" comparison. The answer is not obvious: after all, anyone can go to the emergency department in an hour of need (federal law requires the ED to treat all comers). That might be coverage enough.

The insured are indeed substantially healthier than the uninsured. But perhaps this just tells us something about the people who are lucky enough to have access to cheap health care coverage (like public sector works) or rich enough to pay for it (like MIT faculty). The insured may differ from the uninsured for reasons besides their insurance.

Formal notation for *potential outcomes* makes causal questions precise. For each person, indexed by i, we define two possibilities

- Health of person i when i is insured: Y_{1i}
- Health of person i when i is uninsured: Y_{0i}

The causal effect of insurance on person i is

$$Y_{1i} - Y_{0i}.$$

We never see this individual-level causal effect because, in any given data set and at any point in time, i is either insured or not. Still, we can hope to measure the *average treatment effect* (ATE) of insurance, an *average causal effect*:

$$E[Y_{1i} - Y_{0i}].$$

We might also consider the average causal effect of insurance on the insured:

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

where D_i is a dummy variable equal to 1 for the insured. This parameter is called the *effect of treatment on the treated* (TOT). Parameter ATE tells us whether insurance benefits all in the population of interest, on average, while TOT tells us whether those in the insured population benefit (on average) from their coverage.

1.1 Selection bias

Research on causal effects often starts with TOT. This can be written

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

TOT compares the health of the insured, $E[Y_{1i}|D_i = 1]$, with *their* health when uninsured, $E[Y_{0i}|D_i = 1]$. Now, $E[Y_{1i}|D_i = 1]$ is easy to estimate in a random sample, but $E[Y_{0i}|D_i = 1]$ is *never* seen.

- $E[Y_{0i}|D_i = 1]$ is said to be *counterfactual*

The challenge of measuring counterfactuals emerges clearly in a comparison of health between insured and uninsured, which can be written

$$E[Y_i|D_i = 1] - E[Y_i|D_i = 0]. \tag{2}$$

Note that in (2) the Y_i's have lost 0 and 1 subscripts because we're referencing *observed outcomes* as opposed to *potential outcomes*. Note also that we're ignoring the fact that in practice we make comparisons using sample means and not expectations; for the moment, the distinction between populations and samples is a detail.

Observed and potential outcomes are related. Specifically, we have

$$Y_i = Y_{0i}(1 - D_i) + Y_{1i}D_i \tag{3}$$

In other words, we see Y_{0i} for the uninsured and Y_{1i} for the insured:

$$\begin{aligned} &E[Y_i|D_i = 1] - E[Y_i|D_i = 0] \\ &\quad = E[Y_{1i}|D_i = 1] - E[Y_{0i}|D_i = 0]. \end{aligned} \tag{4}$$

It stands to reason that the difference in average outcomes between insured and uninsured represented by equation (2) tells us something about the average causal effect we're after in equation (1). But not necessarily what we most want to know. Using equation (4), we get

$$\begin{aligned} E[Y_i|D_i = 1] - E[Y_i|D_i = 0] &= E[Y_{1i}|D_i = 1] - E[Y_{0i}|D_i = 0] \\ &= E[Y_{1i}|D_i = 1] - E[Y_{0i}|D_i = 1] + \{E[Y_{0i}|D_i = 1] - E[Y_{0i}|D_i = 0]\} \\ &= E[Y_{1i} - Y_{0i}|D_i = 1] + \{E[Y_{0i}|D_i = 1] - E[Y_{0i}|D_i = 0]\} \end{aligned}$$

- The difference in average health between the insured and uninsured is the causal effect of insurance on the insured (TOT) plus the term in curly brackets. This important term is called *selection bias*.

1.2 Insured and otherwise in the NHIS

- Measuring health on a five point scale, the insured feel a lot better! Check out MM Table 1.1, constructed from the 2009 National Health Interview Survey
- The statistical significance of gaps in health by insurance status is not in doubt
- Statistical inference is easy: with estimates and standard errors you're good to go!
  - What do these differences in means mean?
  - Selection bias lurks in all such causal comparisons

TABLE 1.1
Health and demographic characteristics of insured and uninsured couples in the NHIS

	Husbands			Wives		
	Some HI (1)	No HI (2)	Difference (3)	Some HI (4)	No HI (5)	Difference (6)
A. Health						
Health index	4.01	3.70	.31	4.02	3.62	.39
	[.93]	[1.01]	(.03)	[.92]	[1.01]	(.04)
B. Characteristics						
Nonwhite	.16	.17	−.01	.15	.17	−.02
			(.01)			(.01)
Age	43.98	41.26	2.71	42.24	39.62	2.62
			(.29)			(.30)
Education	14.31	11.56	2.74	14.44	11.80	2.64
			(.10)			(.11)
Family size	3.50	3.98	−.47	3.49	3.93	−.43
			(.05)			(.05)
Employed	.92	.85	.07	.77	.56	.21
			(.01)			(.02)
Family income	106,467	45,656	60,810	106,212	46,385	59,828
			(1,355)			(1,406)
Sample size	8,114	1,281		8,264	1,131	

Notes: This table reports average characteristics for insured and uninsured married couples in the 2009 National Health Interview Survey (NHIS). Columns (1), (2), (4), and (5) show average characteristics of the group of individuals specified by the column heading. Columns (3) and (6) report the difference between the average characteristic for individuals with and without health insurance (HI). Standard deviations are in brackets; standard errors are reported in parentheses.

- Causal effect or selection bias?
- Panel B is cause for worry for those invested in causal claims: when it comes to comparisons by insurance status, *ceteris* is not *paribus*, and the differences here aren't subtle
  - What might this mean for $E[Y_{0i}|D_i = 1] - E[Y_{0i}|D_i = 0]$?

2 Experiments

2.1 Random assignment eliminates selection bias

When insurance coverage is randomly assigned, as in a clinical trial or lottery, selection bias disappears. Suppose that D_i is determined by a coin toss: heads you're covered; tails you're not. By virtue of random assignment, the insured and uninsured in this experiment are similar in every way except their insurance status. Most importantly, when D_i is randomly assigned, the insured and uninsured have the same *potential* outcomes:

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

Consequently,

$$\begin{aligned} E[Y_i|D_i = 1] - E[Y_i|D_i = 0] & \\ &= E[Y_{1i}|D_i = 1] - E[Y_{0i}|D_i = 1] \\ &= E[Y_{1i} - Y_{0i}|D_i = 1] \\ &= E[Y_{1i} - Y_{0i}] \end{aligned}$$

This fact accounts for the centrality of randomized trials in social science and clinical research: random assignment eliminates selection bias.

In a randomized experiment where everyone does what they're assigned to do, the average causal effect on the treated, $E[Y_{1i} - Y_{0i}|D_i = 1]$, is the same as the population average causal effect, $E[Y_{1i} - Y_{0i}]$. This consequence of randomization is important, but it's not as important as the elimination of selection bias. More complicated experiments need not have the feature that ATE=TOT.

2.2 Capturing causal effects without random assignment

Randomized research designs represent a sometimes-unattainable ideal. Masters of 'metrics therefore develop and implement empirical methods that reduce or eliminate selection bias in settings where random assignment is prohibitively expensive, time-consuming, impractical, or unethical. Even so, the experimental ideal disciplines our thinking. The first question to be answered is always thus:

What's the experiment you'd like to do?

3 A Healthy Debate

- Dateline 1974: Kung Fu enters its 3rd season; The RAND Health Insurance Experiment begins
  - In the 1970s, the RAND Corporation randomly assigned about 6,000 people (who agreed to drop their own insurance) to experimental insurance plans that required either no cost-sharing, a modest deductible, or imposed 25%, 50% or 95% coinsurance rates on subscribers, capped at a maximum annual payment of $1000.
- RAND Descriptive statistics and check for balance (we look at four groups requiring different levels and types of cost sharing: the catastrophic coverage plan approximates a no-insurance state; free care is what it sounds like; the deductible and coinsurance plans provided partial coverage)

Table 1.3
Demographic characteristics and baseline health in the RAND HIE

	Means	Differences between plan groups			
	Catastrophic plan (1)	Deductible – catastrophic (2)	Coinsurance – catastrophic (3)	Free – catastrophic (4)	Any insurance – catastrophic (5)
		A. Demographic characteristics			
Female	.560	−.023	−.025	−.038	−.030
		(.016)	(.015)	(.015)	(.013)
Nonwhite	.172	−.019	−.027	−.028	−.025
		(.027)	(.025)	(.025)	(.022)
Age	32.4	.56	.97	.43	.64
	[12.9]	(.68)	(.65)	(.61)	(.54)
Education	12.1	−.16	−.06	−.26	−.17
	[2.9]	(.19)	(.19)	(.18)	(.16)
Family income	31,603	−2,104	970	−976	−654
	[18,148]	(1,384)	(1,389)	(1,345)	(1,181)
Hospitalized last year	.115	.004	−.002	.001	.001
		(.016)	(.015)	(.015)	(.013)
		B. Baseline health variables			
General health index	70.9	−1.44	.21	−1.31	−.93
	[14.9]	(.95)	(.92)	(.87)	(.77)
Cholesterol (mg/dl)	207	−1.42	−1.93	−5.25	−3.19
	[40]	(2.99)	(2.76)	(2.70)	(2.29)
Systolic blood pressure (mm Hg)	122	2.32	.91	1.12	1.39
	[17]	(1.15)	(1.08)	(1.01)	(.90)
Mental health index	73.8	−.12	1.19	.89	.71
	[14.3]	(.82)	(.81)	(.77)	(.68)
Number enrolled	759	881	1,022	1,295	3,198

Notes: This table describes the demographic characteristics and baseline health of subjects in the RAND Health Insurance Experiment (HIE). Column (1) shows the average for the group assigned catastrophic coverage. Columns (2)–(5) compare averages in the deductible, cost-sharing, free care, and any insurance groups with the average in column (1). Standard errors are reported in parentheses in columns (2)–(5); standard deviations are reported in brackets in column (1).

- Impact?

TABLE 1.4
Health expenditure and health outcomes in the RAND HIE

	Means	Differences between plan groups			
	Catastrophic plan (1)	Deductible – catastrophic (2)	Coinsurance – catastrophic (3)	Free – catastrophic (4)	Any insurance – catastrophic (5)
A. Health-care use					
Face-to-face visits	2.78	.19	.48	1.66	.90
	[5.50]	(.25)	(.24)	(.25)	(.20)
Outpatient expenses	248	42	60	169	101
	[488]	(21)	(21)	(20)	(17)
Hospital admissions	.099	.016	.002	.029	.017
	[.379]	(.011)	(.011)	(.010)	(.009)
Inpatient expenses	388	72	93	116	97
	[2,308]	(69)	(73)	(60)	(53)
Total expenses	636	114	152	285	198
	[2,535]	(79)	(85)	(72)	(63)
B. Health outcomes					
General health index	68.5	−.87	.61	−.78	−.36
	[15.9]	(.96)	(.90)	(.87)	(.77)
Cholesterol (mg/dl)	203	.69	−2.31	−1.83	−1.32
	[42]	(2.57)	(2.47)	(2.39)	(2.08)
Systolic blood pressure (mm Hg)	122	1.17	−1.39	−.52	−.36
	[19]	(1.06)	(.99)	(.93)	(.85)
Mental health index	75.5	.45	1.07	.43	.64
	[14.8]	(.91)	(.87)	(.83)	(.75)
Number enrolled	759	881	1,022	1,295	3,198

Notes: This table reports means and treatment effects for health expenditure and health outcomes in the RAND Health Insurance Experiment (HIE). Column (1) shows the average for the group assigned catastrophic coverage. Columns (2)–(5) compare averages in the deductible, cost-sharing, free care, and any insurance groups with the average in column (1). Standard errors are reported in parentheses in columns (2)–(5); standard deviations are reported in brackets in column (1).

- Unlike Table 1.1, the comparisons in Table 1.4 carry causal weight, and so the question of their statistical significance is similarly freighted: we see little here to suggest insurance *causes* the insured to be healthier

- Hold your horses: Back on the Oregon Trail
  - In the US, the elderly get publicly provide health insurance through Medicare while many of the poor (families on welfare, some of the disabled, and some poor children and pregnant women) are covered through Medicaid
  - In 2008, Oregon's Medicaid agency offered coverage to about 30,000 otherwise uninsured low-income adults who didn't qualify for Medicaid by the usual rules. These 30,000 were chosen by lottery from about 75,000 applicants.
- This just in from Portlandia ...

TABLE 1.5

OHP effects on insurance coverage and health-care use

	Oregon		Portland area	
Outcome	Control mean (1)	Treatment effect (2)	Control mean (3)	Treatment effect (4)
A. Administrative data				
Ever on Medicaid	.141	.256 (.004)	.151	.247 (.006)
Any hospital admissions	.067	.005 (.002)		
Any emergency department visit			.345	.017 (.006)
Number of emergency department visits			1.02	.101 (.029)
Sample size	74,922		24,646	
B. Survey data				
Outpatient visits (in the past 6 months)	1.91	.314 (.054)		
Any prescriptions?	.637	.025 (.008)		
Sample size	23,741			

Notes: This table reports estimates of the effect of winning the Oregon Health Plan (OHP) lottery on insurance coverage and use of health care. Odd-numbered columns show control group averages. Even-numbered columns report the regression coefficient on a dummy for lottery winners. Standard errors are reported in parentheses.

- Hey, where's my health divided?

TABLE 1.6
OHP effects on health indicators and financial health

	Oregon		Portland area	
Outcome	Control mean (1)	Treatment effect (2)	Control mean (3)	Treatment effect (4)
	A. Health indicators			
Health is good	.548	.039 (.008)		
Physical health index			45.5	.29 (.21)
Mental health index			44.4	.47 (.24)
Cholesterol			204	.53 (.69)
Systolic blood pressure (mm Hg)			119	−.13 (.30)
	B. Financial health			
Medical expenditures >30% of income			.055	−.011 (.005)
Any medical debt?			.568	−.032 (.010)
Sample size	23,741		12,229	

Notes: This table reports estimates of the effect of winning the Oregon Health Plan (OHP) lottery on health indicators and financial health. Odd-numbered columns show control group averages. Even-numbered columns report the regression coefficient on a dummy for lottery winners. Standard errors are reported in parentheses.

- Health insurance makes household *finances* healthier
- As in Table 1.4, the statistical significance of reduced health expenditures in Panel B carries causal weight: that's the miracle of random assignment
- Masters of 'metrics learn well the distinction between random sampling (which supports statistical inference about populations using data from samples) and random assignment (which supports causal inference, i.e., comparisons of potential outcomes free of selection bias)