Lecture 2: The Quest for Causality

ECON 480 - Econometrics - Fall 2018

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August 29, 2018

The Two Big Problems with Data

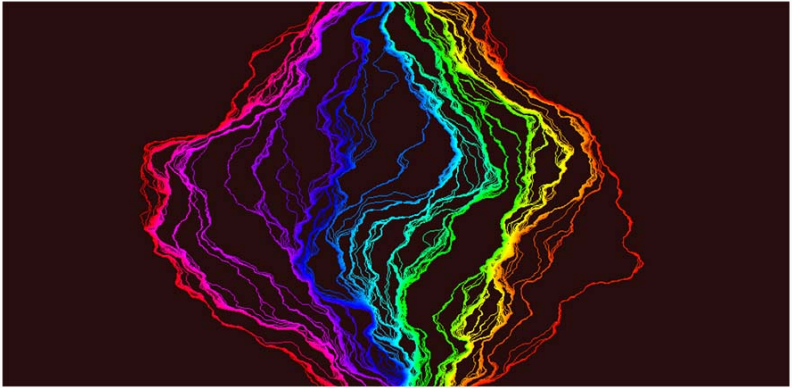
Identifying Causal Effects: Randomized Controlled Trials

Some Theory by Example

Natural Experiments

The Two Big Problems with Data

- We want to use econometrics to **identify** causal relationships and make **inferences** about them



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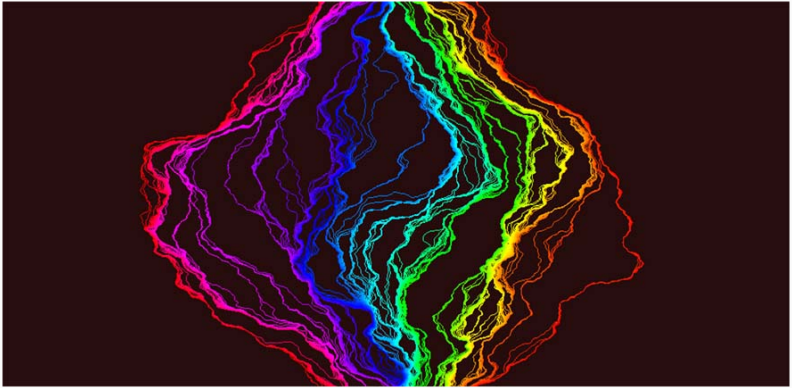
    1. Problem for **identification**: endogeneity



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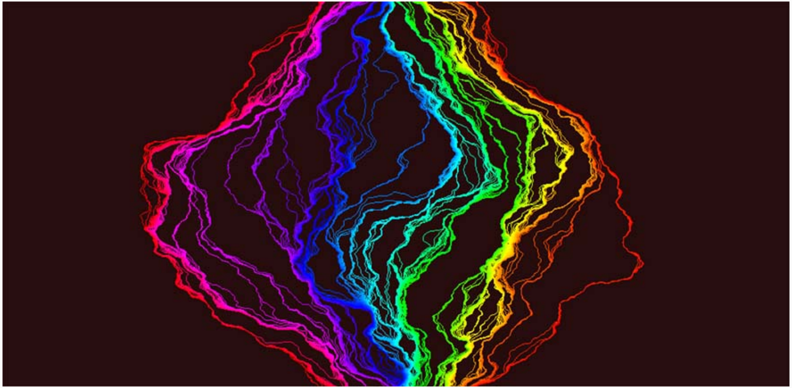
    1. Problem for **identification**: endogeneity
    2. Problem for **inference**: randomness



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Identification Problem: Endogeneity

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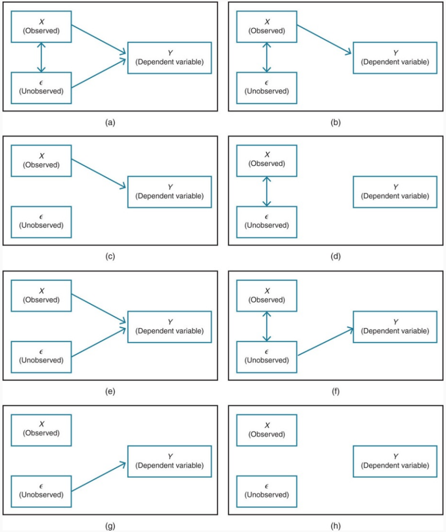
Identification Problem: Endogeneity II



Bailey (2017: 12)

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- Common in statistics, *easy to fix*
- **Inferential Statistics**: making claims about a wider population using sample data
  - We use common tools and techniques to deal with randomness

Identifying Causal Effects: Randomized Controlled Trials

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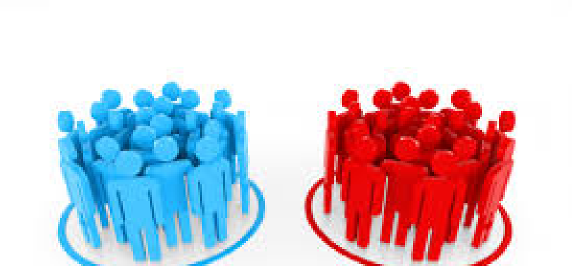

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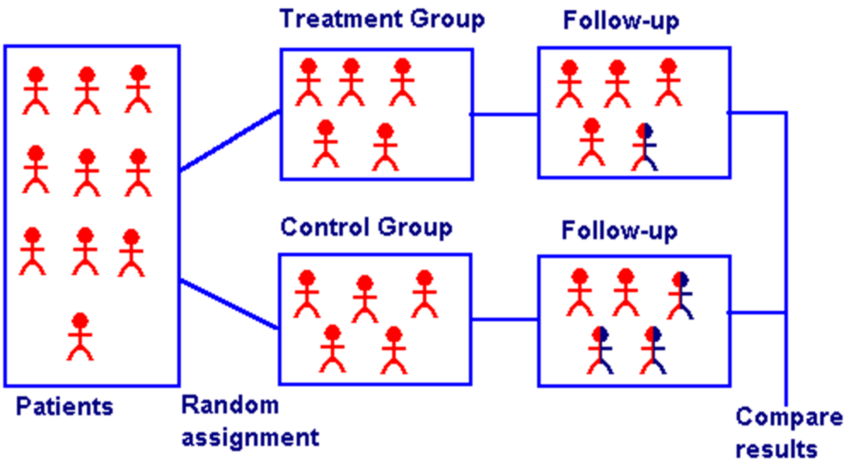
- **We will understand "causality" to mean the ATE from an ideal RCT**



Classic (simplified) procedure of a randomized control trial (RCT) from medicine

- Random assignment to groups ensures that the *only* differences between members of the treatment(s) and control groups is *receiving treatment or not*

Treatment Group

Control Group

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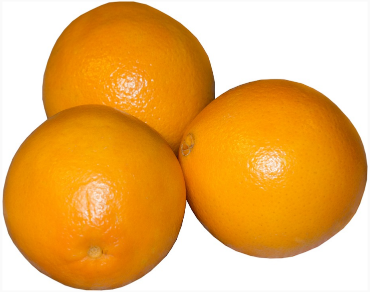
- Selection bias: (pre-existing) differences between members of treatment and control groups *other* than treatment, that affect the outcome

Treatment Group



Control Group

Selection Bias

Some Theory by Example

Example

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Example: The Effect of Having Health Insurance

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  - Treatment (X): Having health insurance (vs. not)

Example: The Effect of Having Health Insurance II

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

Health and demographics of insured and uninsured couples in NHIS (Angrist & Pischke 2015)

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HOOD COLLEGE

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- $(Y_{1,i} - Y_{0,i})$: **causal effect of having insurance for individual i**

Example: A Hypothetical Comparison

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Example: A Hypothetical Comparison II

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  - $Y_{1,J} = 4$
  - $(Y_{1,J} - Y_{0,J}) = 1$
  - Will buy insurance
  - We only observe
    $Y_J = Y_{1,J} = 4$
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  - $Y_{0,M} = 5$
  - $Y_{1,M} = 5$
  - $(Y_{1,M} - Y_{0,M}) = 5$
  - Will *not* buy insurance
  - We only observe
    $Y_M = Y_{0,M} = 5$
- *Observed* difference between John & Maria: $Y_J - Y_M = -1$

HOOD COLLEGE

- Note that what we *actually* see is:

$$Y_J - Y_M = \underbrace{Y_{1,J} - Y_{0,M}}_{=-1}$$

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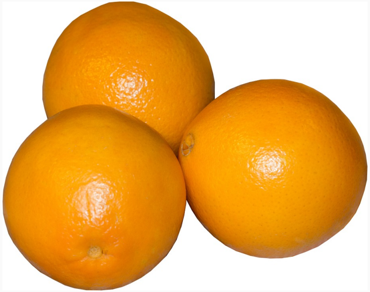
- Causal effect of buying health insurance for John
- Difference between John & Maria before treatment: called **selection bias**

Treatment Group



Control Group

Selection Bias

Ideal (but impossible) data

i	$Y_{1,i}$	$Y_{0,i}$	$(Y_{1,i} - Y_{0,i})$
J	4	3	1
M	5	5	0
	$avg(Y_{1,i})$	$avg(Y_{0,i})$	$avg(Y_{1,i}) - avg(Y_{0,i})$
	4.5	4	0.5

Example: Thinking About the Data

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Actually observed data

i	$Y_{1,i}$	$Y_{0,i}$	$(Y_{1,i} - Y_{0,i})$
J	4	?	?
M	?	5	?
	$avg(Y_{1,i})$	$avg(Y_{0,i})$	$avg(Y_{1,i}) - avg(Y_{0,i})$
	?	?	?

HOOD COLLEGE

- For entire groups (of size n), the average treatment effect (ATE) is:

$$ATE = \frac{1}{n}\sum_{i=1}^{n}[Y_{1,i} - Y_{0,i}]$$

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  - i.e. $Y_{1,J} - Y_{0,J}$ and $Y_{1,M} - Y_{0,M}$

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  - Imagine a world where *nobody* has insurance, who would be healthiest?

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  - Creates *ceterus paribus* conditions in economics: groups are otherwise identical (same education, family size, age, etc...) *on average*

Treatment Group

Control Group

Natural Experiments

- Society is not our laboratory (probably a good thing)

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- We rarely can collect experimental data

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The Quest for Causal Effects II

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- Instead, we often rely on observational data
    - This data is *not random*!
    - Must take extra care in forming an **identification strategy**
- To make good claims about causation in society, we must get clever!

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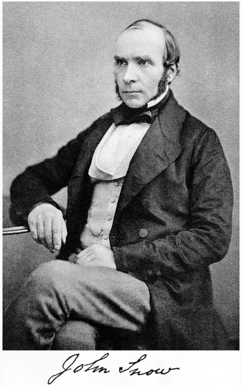
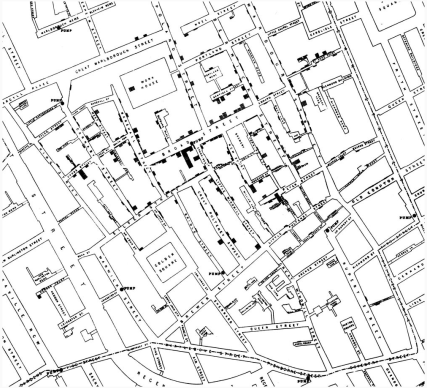
    - e.g. natural disasters, U.S. State laws, military draft

Jon Snow utilized the first famous natural experiment to establish the foundations of epidemiology and the germ theory of disease

The 'First' Natural Experiment II





*John Snow (1855) utilized the first famous natural experiment to establish the foundations of epidemiology and the germ theory of disease: water pumps *downstream* of a sewage dump in the Thames river spread cholera while water pumps *upstream* did not - Read More

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