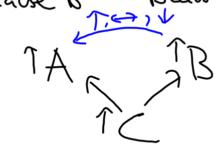
Lecture 3

Correlation versus Causality.

Data on "A" and "B" and They move together.

$A \to B$, $B \to A$,

"A cause B" "B cause A"

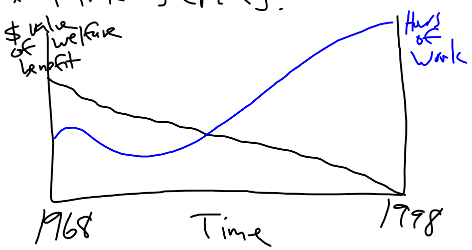


One solution, randomized trials.

$\boxed{\text{Randomly}}$ assign people to treatment and control groups, The only systematic difference between The groups is The treatment itself.

Bias (like C): outside randomized trial, There can be Things correlated with treatment & control. Systematic differences between two groups besides The treatment.

* Time series.



Value of welfare benefit falls, observe more hours of work, by recipients.

Time Series on cost of cigarettes and youth smoking works better.

– Narrower decision

– Sharp movements in prices relatively smaller movements in other factors

-- Little movement in health effects info.

-- Income, employment.

* Cross section data.

Many units, all observed at the same time.

Fit a line.

Double benefit ⇒ ⇓ 110 hours per year.

Was working only 748 hrs./yr.

So 15% reduction.

Problems:

A Third Thing

↓ labor supply   ↑ benefits

↑ C

"C" is unobserved, not measuring it, associated with higher benefits and lower labor supply.

For example, strong taste for leisure.

Regression discontinuity: look at people just above/below thresholds.

Differences-in-differences.

Arkansas: cuts benefits 20%
1996 → 1998,
hours of work ↑ by 200.
"~~First~~ One difference"

Louisiana: no change in benefits.
1996 → 1998,
hours of work ↑ by 50
"Another difference"

Two difference: change in hours of work in each state.

Causal effect of the policy,
200 − 50 = 150 hours.
"Difference-in-difference" estimate.

To do this, need a $\boxed{\text{panel}}$,
Cross section observed over time.

And variation (treatment) hits a subgroup at certain time periods and not others.

Still have to hope that the treatment (policy change) is not caused by something that also affects the outcome (hours of work in this example).

Quasi-experiments ~~are~~ give what we call "reduced form" estimates.

Get the end result, but do not learn about <u>why</u> the result happened, and worry about peculiarities of the units (Louisiana, Arkansas) that may make extrapolation (to the rest of the country) inappropriate.

<u>Structural estimation</u>

-- Leans heavily on theory, estimate the parameters of utility functions, production functions, etc.

-- Reward is, can predict effects of all kinds of policies, including some that have never been tried.