Empirical tools (recap):

- Determination of statistical regularities (correlation).
- Determination of causality.
  - Control vs Treatment groups.
  - Differences-in-differences estimates.
- Experimentation and simulation.
- Structural models.
- ….

THE IMPORTANT DISTINCTION BETWEEN CORRELATION AND CAUSATION

- There are many examples where causation and correlation get confused.
- It is critical for government policy to understand the difference; otherwise policy may not have the intended impact.

THE IMPORTANT DISTINCTION BETWEEN CORRELATION AND CAUSATION

- One interesting example is about Russian peasants.
  - There was a cholera epidemic. Government sent doctors to the worst-affected areas to help.
  - Peasants observed that in areas with lots of doctors, there was lots of cholera.
  - Peasants concluded doctors were making things worse.
  - Based on this insight, they murdered the doctors.

THE IMPORTANT DISTINCTION BETWEEN CORRELATION AND CAUSATION

- Another example concerns SAT preparation courses.
  - In 1988, Harvard interviewed its freshmen and found those who took SAT “coaching” courses scored 63 points lower than those who did not.
  - One dean concluded that the SAT courses were unhelpful and “the coaching industry is playing on parental anxiety.”

The Problem

- In both examples, there is a common problem: an attempt to interpret a *correlation* as a *causal relationship*, without sufficient thought to the underlying data generating process.
- For any correlation between two variables A and B, there are three possible explanations for a correlation:
  - A is causing B.
  - B is causing A.
  - Some other factor is causing both.

The Problem

- In the Russian peasant example, the possibilities might be:
  - Doctors cause peasants to die from cholera through incompetent treatment.
  - Higher incidence of illness caused more physicians to be present.
- Peasants thought the first possibility was correct.

The Problem

- In the Harvard SAT example, the possibilities could be:
  - SAT prep courses worsen preparation for the SATs.
  - Those with poorer test taking ability take prep courses to try to catch up.
  - Those who are generally nervous both like to take prep courses and do the worst on standardized exams.
- Harvard dean thought the first possibility was correct.

MEASURING CAUSATION WITH DATA WE'D LIKE TO HAVE: RANDOMIZED TRIALS

- The "gold standard" of causality is a ***randomized trial***.
- The trial proceeds by taking a group of volunteers and *randomly* assigning them to either a ***"treatment" group*** that gets the intervention, or a ***"control" group*** that is denied the intervention.
- With random assignment, the assignment of the intervention is not determined by anything about the subjects.
- As a result, the treatment group is identical to the control group in every facet but one: the treatment group gets the intervention.

Control vs Treatment groups. Randomness vs Biases.

- In the SAT example, the "treatment" group members are those who took the coaching course; the "control" group members are those who did not.
- In the Russian peasant example, the "treatment" group were communities where doctors were assigned, the "control" group were communities where doctors were not assigned.
- Immediate test (key intuition):

  Do the treatment and control groups differ for any reason other than the treatment?

Randomized Trials in the TANF Context

- Imagine a large group (say, 2000) of single mothers were randomly assigned to one of two groups with a coin flip:
  - The "control" group continues to receive a guarantee of $5,000.
  - The "treatment" group now has their TANF benefit cut to $3,000.
- Follow groups for a period of time, and measure the work effort.

Randomized Trials in the TANF Context

- In an experiment like this in California in 1992, the elasticity of employment with respect to welfare benefits was estimated to be -0.67.
- Thus, a 10% decrease in benefits resulted in a 6.7% increase in employment.

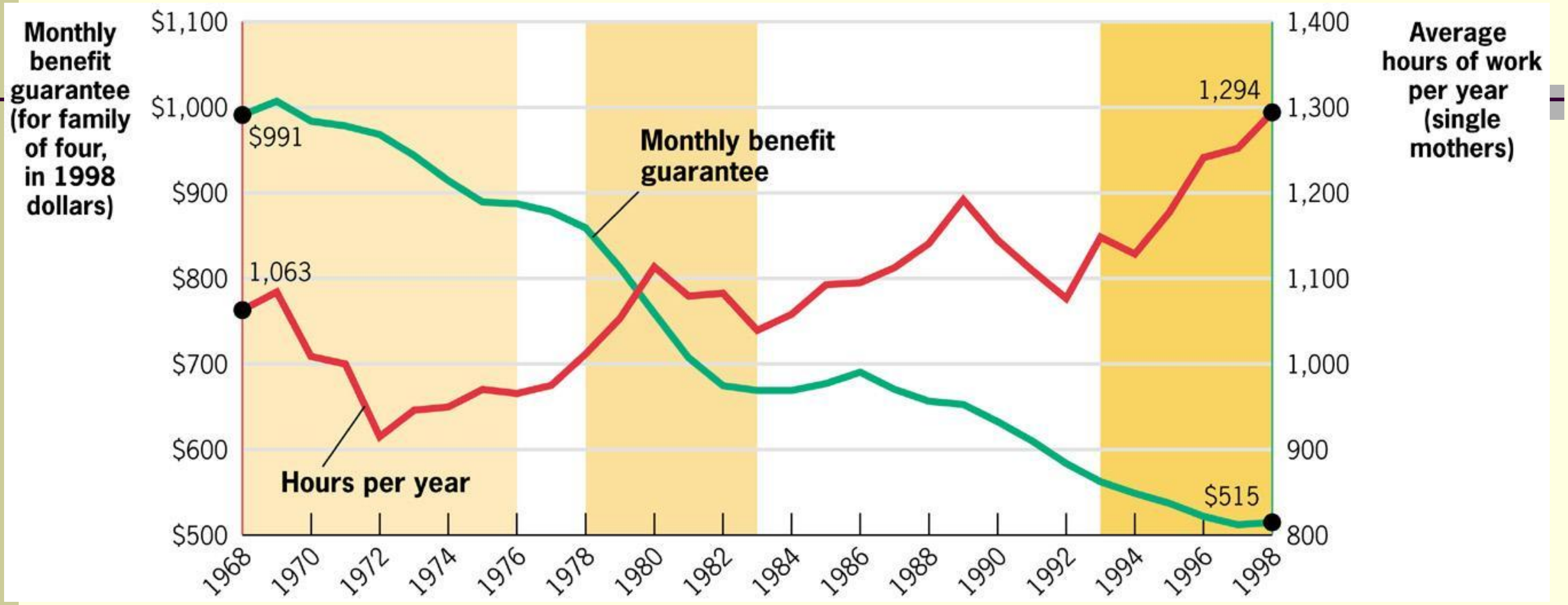
Why We Need to Go Beyond Randomized Trials

- Randomized trials present some problems:
  - They can be expensive.
  - They can take a long time to complete.
  - They may raise ethical issues (especially in the context of medical treatments).
    - Parkinson's disease treatment.
  - The inferences from them may not generalize to the population as a whole.
  - Subjects may drop out of the experiment for non-random reasons, a problem known as *attrition*.
- For these reasons (especially the first one about randomized trials being expensive), economists often take different approaches to try to assess causal relationships in empirical research.

ESTIMATING CAUSATION WITH THE DATA WE ACTUALLY GET: OBSERVATIONAL DATA

- There are four main approaches:
  - Time series analysis
  - Cross-sectional regression analysis
  - Quasi-experiments
  - Structural modeling

Figure 1



Monthly benefit guarantee (for family of four, in 1998 dollars)
$1,100
$1,000
$900
$800
$700
$600
$500
Average hours of work per year (single mothers)
1,400
1,300
1,200
1,100
1,000
900
800
$991
1,063
1,294
$515
Monthly benefit guarantee
Hours per year
1968
1970
1972
1974
1976
1978
1980
1982
1984
1986
1988
1990
1992
1994
1996
1998

Time Series Analysis

- Figure 1 reveals that real benefits have declined dramatically over time, while average hours have risen substantially.
- Apparently supports the theory that TANF benefit cuts should increase labor supply.
- There are problems, however.
- Two sub-periods (1968-1976, and 1978-1983) show negative effect on labor supply, or zero effect.
- Highlights difficulty that when there is a slow moving trend (benefit declines), it is very difficult to infer causal effect of this on another variable.

Time Series Analysis

- Many potential explanations for the changes, too, such as:
  - Greater acceptance of women in workplace.
  - Better child care options.
  - Changes in social norms about working.
  - Other government program like the earned income tax credit.
  - Economic growth.

Quasi-Experiments

- ***Quasi-experiments*** are changes in the economic environment that create roughly identical treatment and control groups for studying the effect of that environmental change.
  - This allows researchers to take advantage of randomization created by *external forces*.
- Basic approach is to let outside forces do the randomization for us. In some cases, the situation happens naturally.
  - Suppose, for example, that Arkansas cut its TANF benefit by 20% in 1997, and that we had a large sample of single mothers in Arkansas in 1996 and 1998.
  - At the same time, imagine that Louisiana's benefits remained unchanged.

Quasi-Experiments

- In principle, the alteration in the states' policies has essentially performed our randomization for us.
  - The women in Arkansas who experienced the decrease in benefits are the *treatment group*.
  - The women in Louisiana whose benefits were unchanged are the *control*.
  - By computing the change in labor supply across these groups, and then examining the difference between treatment (Arkansas) and control (Louisiana), we can obtain an estimate of the impact of benefits on labor supply that is free from bias.

Quasi-Experiments

- Imagine we simply studied single mothers in Arkansas alone.
- Arkansas has essentially performed an "experiment" where single mothers in 1996 are the control group, and those in 1998 are the treatment group.
- In practice, this comparison runs into the criticisms that confront us with time series analysis.
  - For example, the national economy was growing exceptionally fast during this period.

Quasi-Experiments

- Because of these concerns about national trends, the quasi-experimental approach includes the extra step of comparing the treatment group for whom the policy changed to a control group for whom it did *not*.
- Single mothers in Louisiana did not experience the TANF cut, yet benefited from the growth in the economy.

Quasi-Experiments

- That is, by examining hours of work in Arkansas, we obtain:
  - $\text{HOURS}_{AR,1998}$-$\text{HOURS}_{AR,1996}$
  - This contains *both* the ***treatment effect*** and the bias from the economic boom.
- In contrast, by examining hours of work in Louisiana, we obtain:
  - $\text{HOURS}_{LA,1998}$-$\text{HOURS}_{LA,1996}$
  - This contains *only* the effect of the economic boom.

Quasi-Experiments

- By subtracting the change in hours of work in Louisiana from that in Arkansas, we control for the bias caused by the economic boom.
- We obtain a causal estimate of the effect of TANF benefits on hours of work.
- An example is given in **Table 1**, first focusing on Arkansas alone.

Table 1

Using Quasi-Experimental Variation
Arkansas

	1996	1998	Difference
Benefit Guarantee	$5,000	$4,000	-$1,000
Hours of Work Per Year	1,000	1,200	200

Quasi-Experiments

- While benefits fell by 20%, hours of work increased by 20%; the implied elasticity of labor supply with respect to benefits levels is -1.
- This is larger than the -0.67 elasticity estimate found in the randomized trial in California.

Quasi-Experiments

- There is likely to be bias in this "first-difference," because there was major economic growth during this period.
  - Thus, single mothers in Arkansas may have increased their work effort even if TANF benefits had not fallen.
- We examine single mothers in the neighboring state of Louisiana, in the bottom panel of **Table 1**.

Table 1

Using Quasi-Experimental Variation			
Arkansas			
	1996	1998	Difference
Benefit Guarantee	$5,000	$4,000	-$1,000
Hours of Work Per Year	1,000	1,200	200
Louisiana			
	1996	1998	Difference
Benefit Guarantee	$5,000	$5,000	$0
Hours of Work Per Year	1,050	1,100	50

Quasi-Experiments

- This approach yields the ***difference-in-difference*** estimator – the difference between the changes in outcomes for the treatment group that experiences an intervention and a control group that does not.
- We are taking the difference in labor supply changes in these states in an attempt to purge the estimate of bias (due to the growing economy).
  - While cross-sectional analysis would suggest that the reduction in welfare benefits leads to a 100-hour increase in work, the difference-in-difference analysis suggests a 150-hour increase.

Quasi-Experiments

- The difference-in-difference estimator is:

$$\left(HOURS_{AK,1998} - HOURS_{AK,1996}\right) - \left(HOURS_{LA,1998} - HOURS_{LA,1996}\right)$$

- The second term, for Louisiana, nets out the bias from the growing economy.
- Thus, the causal effect of TANF benefit cuts would be a 150-hour increase in labor supply.

Quasi-Experiments: Problems with quasi-experimental analysis

- This approach also has problems, however.
  - It is possible that the economic boom affected Arkansas differently than it did Louisiana.
  - More generally, single mothers may be different across states.
- We can never be completely certain that we have purged the treatment-control comparisons of bias.

Recap: trials of ERT

- ERT is the estrogen replacement therapy, which is a popular treatment for women who have gone through menopause.
  - Menopause is associated with many negative side effects.
  - ERT reduces those by mimicking the estrogen produced before the onset of menopause.
- Concern about ERT: Does it raise the risk of heart disease?
- A series of studies (from 1980s) compared women who did and did not underwent ERT.
- They found no higher risk, and, in fact, if anything, ERT lowered the risk of heart attacks.
- Do you see the problem?

Trials of ERT. The problem.

- Women who underwent ERT are more likely to be under a doctor's care, lead healthier lifestyle, have more income: all of these are associated with a lower chance of heart problems.
- Randomizes trials of ERT.
  - 1991. National Institute of Health appoints its first female director, Dr. B. Healy. She sponsors a randomized trial of ERT.
  - 16000 women ages 50-79 participate.
  - Supposed to last 8.5 years, stopped after 5.2.
  - ERT did raise the risk of hart disease (and of invasive breast cancer).
  - Lead to more careful recommendations.