POLS 205
Political Science as a Social Science

Experiments & Observation

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What is a Research Design?

Components and Properties of Experiments

Some Common Experimental Designs

Natural Experiments

Field Experiments
What is a research design?

A research design is a plan to answer your research question, and includes:

1. A (causal) theory and implied hypotheses
2. A unit of analysis on which the hypotheses operate
3. A set of variables, including a dependent variable & covariates
4. A plan to collect these data
5. A plan to analyze these data

Today we focus on steps 4 and 5, and a single powerful strategy: experiments.
Key concepts for experiments

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**Intent to Treat**  In some experiments, subjects assigned to treatment group may evade treatment
Advantages & Disadvantages of Experiments

Well-designed experiments have three major advantages:

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**Isolate causal effects** Experiments can isolate the effect of covariates than tend to covary in the real world.
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**Low external validity**  Human awareness of the experimental environment often invalidates lab findings
A Closer Look at Internal Validity

Experiments are uniquely suited to make causal inferences:

- No chance of reverse causation because random assignment precedes treatment, it cannot cause it.
  - Note this assumes subjects stay in the study. If the effects of the treatment or control cause selective dropout, this does not hold.
- Limited effects of confounding variables. As sample size increases, treatment and control should have similar distributions on all confounding variables. Note this only holds on average.
  - In a given experiment, control and treatment may be unbalanced by chance, more likely if sample size is small.
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Other threats to interval validity can be solved through careful design

**Measurement Error**  The tests given to subjects may measure their results with error
If this error is random, results will still be valid on average

If this error is *correlated* with the treatment or confounders, the experiment will be invalidated
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**Testing Effects** Human subjects learn—and may get better at the “test” on their own!

This can include simply learning how to answer test questions quickly and efficiently

FYI: This is almost all SAT test prep does: give you tests until you get a “testing effect”
A Closer Look at External Validity

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Field experiments or natural experiments, perhaps?
Experimental design

To run an experiment properly, we must combine random assignment, treatment, and testing to ensure accurate causal inference.

But in the real world, these steps are expensive, so we also want to choose the design that maximizes interval validity subject to our budget constraint.

Consider the following designs:

1. Pre-test, post-test
2. Post-test
3. Multi-group
4. Case-control
Pre-test, Post-test Experimental Design

Classic experimental method is to test before and after treatment

By comparing in two directions:

1. Before and after the test for treated group
2. Between the treated group and the control

we can calculate the **Average Treatment Effect**, or **ATE**

(Why *Average* Treatment Effect?)
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(Why Average Treatment Effect? Because we want to remove random noise)
Pre-test, Post-test Experimental Design

Average Treatment Effect

$$\text{Average Treatment Effect} = \frac{1}{N_T} \sum_{i=1}^{N_T} (\text{Test}_{T1} - \text{Test}_{T0}) - \frac{1}{N_C} \sum_{j=1}^{N_C} (\text{Test}_{C1} - \text{Test}_{C0})$$
Post-test Experimental Design

- What if we can’t afford two waves of tests?
- What if we fear a very strong testing effect?
- What if we don’t want subjects to even know what we are testing until after the treatment?

Then we can just drop the pre-test altogether!

That is, if $N$ is large enough, the treatment and control should have the same pretest:

$$\text{Test}_{T_0} - \text{Test}_{C_0} \rightarrow 0 \text{ as } N \rightarrow \infty$$

This leads to a simplified research design.
Post-test Experimental Design

Randomize | Treat | Posttest
---|---|---
$N_{T}$ | $treat$ | $Test_{T1}$
$N_{All}$ | $time$
$N_{C}$ | $Test_{C1}$

Average Treatment Effect

$$= \frac{1}{N_{T}} \sum_{i=1}^{N_{T}} Test_{T1} - \frac{1}{N_{C}} \sum_{j=1}^{N_{C}} Test_{C1}$$
Longitudinal Experimental Design

Other extensions:

- What if we want to measure effects of treatment over time?
- Or effects of different treatments?
Longitudinal Experimental Design

Randomize Pretest Treat Posttest Posttest

\[ \text{Average Treatment Effect} = \frac{1}{N_T} \sum_{i=1}^{N_T} (\text{Test}_{T2} - \text{Test}_{T0}) - \frac{1}{N_C} \sum_{j=1}^{N_C} (\text{Test}_{C2} - \text{Test}_{C0}) \]
Multigroup Experimental Design

Randomize | Pretest | Treat | Posttest
---|---|---|---
$N_T$ | $Test_{T0}$ | $treat$ | $Test_{T1}$
$N_{All}$ | $N_T'$ | $Test_{T'0}$ | $treat'$ | $Test_{T'1}$
$N_C$ | $Test_{C0}$ | | $Test_{C1}$

time

Average Treatment Effect  
\[
= \frac{1}{N_T'} \sum_{i=1}^{N_T'} (Test_{T'1} - Test_{T'0}) - \frac{1}{N_C} \sum_{j=1}^{N_C} (Test_{C1} - Test_{C0})
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Case-Control Experimental Design

My favorite experimental design (strongly recommended over previous):

1. Gather all controls and confounders as you would for an observational study
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7. Report Average Treatment Effect
Case-Control Experimental Design

<table>
<thead>
<tr>
<th>Randomize</th>
<th>Pretest</th>
<th>Treat</th>
<th>Posttest</th>
<th>Posttest</th>
</tr>
</thead>
<tbody>
<tr>
<td>Subject(_{Ti})</td>
<td>Test(_{T0i})</td>
<td>treat</td>
<td>Test(_{T1i})</td>
<td>Test(_{T2i})</td>
</tr>
<tr>
<td>N(_{All})</td>
<td>match on covariates</td>
<td></td>
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Average Treatment Effect \(= \frac{1}{N_T} \sum_{i=1}^{N_T} [(Test\(_{T1i}\) - Test\(_{T0i}\)) - (Test\(_{C1i}\) - Test\(_{C0i}\))]\)
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Case-control solves three problems at little cost:

1. Impossible to be unbalanced on observables, even with random assignment!
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3. If you think treatment effect is heterogenous as a function of observables, can report *Local* Average Treatment Effect by looking at a subset of cases.
Case-Control Experimental Design

Case-control shares with other experimental designs these problems:

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Case-control shares with other experimental designs these problems:

1. If random assignment on unobservables if unbalanced, could be biased
2. If drop out is non-random with respect to unobservables, could be bias

Solution to both is to expand sample size!
Alternatives to Experiments

Suppose we can’t do a lab experiment or want higher external validity

Alternative research designs:

1. **Natural Experiment**: Find a case where nature assigned a random treatment
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2. **Field Experiment**: Assign a treatment to people in a real-world environment
3. **Matching**: Use case-control matching with (non-random) naturally assigned variation
4. **Regression**: Use observational data and control for *every* confounder
Naturale Experiments

Find a case where nature assigned a random treatment, measure average treatment effect

Key: Convincing other scientists treatment assignment is unrelated to all confounders

Examples:

1. Snow’s cholera map
2. 2000 Presidential election, Palm Beach ballot
Natural Experiment 1: Snow’s cholera map

The pipes of each Company go down all the street... A few houses are supplied by one Company and a few by the other, according to the decision of the owner or occupier at that time when the Water Companies were in active competition. In many cases a single house has a supply different from that on either side. Each company supplies both rich and poor, both large houses and small; there is no difference either in the condition or occupation of the persons receiving the water of either company...

It is obvious no experiment could have been designed which would more thoroughly test the effect of water supply on the progress of cholera than this.

John Snow (1885: 74-75)
Natural Experiment 2: Palm Beach ballot

2000 Presidential election between Bush & Gore came down to Florida

Florida was achingly close:
537 votes in the last tally before the US Supreme Court called the election

But in populous, Democratic Palm Beach, at least 3400 voters picked conservative third party candidate Pat Buchanan, 3 to 8 times more than he expected

What happened?
One explanation: poor ballot design led many Gore voters to accidently punch Buchanan
Natural Experiment 2: Palm Beach ballot

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Appears to be an excellent natural experiment: assignment of ballot uncorrelated with essentially every other political variable
Palm beach Buchanan vote a huge outlier: can’t be explained by any other variable
Field experiments

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Requires a field-manipulable variable.
Field experiment example: New Haven voter turnout

Don Green & Alan Gerber (1999, PNAS) conducted a voter turnout experiment in New Haven

Randomly encouraged some voters to vote through door canvasing
Compared to an unvisited control group
Found a 6% increase in turnout!

Potential problem: Told some voters election would be close (it wasn’t)

Can political scientists use field experiments widely?

Another problem (noticed by Kosuke Imai): Random assignment turned out to be very non-random—results change a lot if corrected

Case-control assignment would have solved this problem
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Next time... 

Non-experimental methods:

Matching (both qualitative & quantitative)

Regression