The Experimental Ideal

EC 425/525, Set 2

Edward Rubin

03 April 2019

Prologue

Schedule

Last time

Research basics, our class, and R

Today

Admin: Canvas exists. Updated class website.

Material: The Rubin causal model (not mine), Chapter 2 MHE. R basics.

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Future

Lab: Matrix work, regression, functions, simulation

Long run: Deepen understandings/intuitions for causality and inference.

Review

Research fundamentals

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Research fundamentals

Angrist and Pischke provide four **fundamental questions for research:**

1. What is the **causal relationship of interest**?
2. How would an **ideal experiment** capture this causal effect of interest?
3. What is your **identification strategy**?
4. What is your **mode of inference**?

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Research fundamentals

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Seemingly straightforward questions can be fundamentally unanswerable.

General research recommendations

More unsolicited advice:

- Be curious.
- Ask questions.
- Attend seminars.
- Meet faculty (UO + visitors).
- Focus on learning—especially intuition.[†]
- **Be kind and constructive.**

† *Learning* is not always the same as getting good grades.

The experimental ideal

The experimental ideal

What's so great about experiments?

Science widely regards **experiments as the gold standard** for research.

But why? The costs can be substantial.

Costs

- slow and expensive
- heavily regulated by review boards
- can abstract away from the actual question/setting

Benefits

So the benefits need to be pretty large, right?

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Example: Hospitals and health

Imagine we want to know the **causal effect of hospitals on health**.

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Research question

Within the population of poor, elderly individuals, does visiting the emergency room for primary care improve health?

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Empirical exercise

1. Collect data on *health status* and *hospital visits*.
2. Summarize health status by hospital-visit group.

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Example: Hospitals and health

Our empirical exercise from the 2005 National Health Inteview Survey:

Group	Sample Size	Mean Health Status	Std. Error
Hospital	7,774	3.21	0.014
No hospital	90,049	3.93	0.003

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Alternative conclusion: Perhaps we're making a mistake in our analysis… maybe sick people go to hospitals?

The experimental ideal

Potential outcomes framework

Let's develop a framework to better discuss the problem here.

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Potential outcomes framework

Let's develop a framework to better discuss the problem here.

- Binary treatment variable (*e.g.*, hospitalized): $\mathbf{D}_i = \mathbf{0}, \mathbf{1}$
- Outcome for individual i (*e.g.*, health): $\mathbf{Y}_i$

This framework has a few names...

- Neyman potential outcomes framework
- Rubin causal model
- Neyman-Rubin `"potential outcome"|"causal" "framework"|"model"`

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Research question: Does $\mathbf{D}_i$ affect $\mathbf{Y}_i$?

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The difference between these two outcomes gives us the **causal effect of hospital treatment**, *i.e.*,

$$\tau_i = \mathrm{Y}_{1i} - \mathrm{Y}_{0i}$$

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#problems

This simple equation

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leads us to ***the fundamental problem of causal inference.***

> We can never simultaneously observe Y_{1i} and Y_{0i}.

Most of applied econometrics focuses on addressing this simple problem.

Accordingly, our methods try to address the related question

> For each Y_{1i}, what is a (reasonably) good counterfactual?

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Solutions?

Problem We cannot directly calculate $\tau_i = \text{Y}_{1i} - \text{Y}_{0i}$.

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Proposed solution

Compare outcomes for people who visited the hospital $(\mathbf{Y}_{1i} \mid \mathbf{D}_i = 1)$
to outcomes for people who did not visit the hospital $\big(\mathbf{Y}_{0j} \mid \mathbf{D}_j = 0\big)$.

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$$\boldsymbol{E}[\mathrm{Y}_i \mid \mathrm{D}_i = 1] - \boldsymbol{E}[\mathrm{Y}_i \mid \mathrm{D}_i = 0]$$

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Q This comparison will return *an* answer, but is it *the* answer we want?

The experimental ideal

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Now write out our expectation, apply this definition, do creative math.

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The **first term** is *good variation*—essentially the answer that we want.

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The difference in the average untreated outcome between the treatment and control groups.

Selection bias The extent to which the "control group" provides a bad counterfactual for the treated individuals.

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> The goal of most empirical economic research is to overcome selection bias, and therefore to say something about the causal effect of a variable like $\mathbf{D}_i$.

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> The goal of most empirical economic research is to overcome selection bias, and therefore to say something about the causal effect of a variable like D_i.

Q So how do experiments—the gold standard of empirical economic (and scientific) research—accomplish this goal and overcome selection bias?

The experimental ideal

Back to experiments

Q How do experiments overcome selection bias?

The experimental ideal

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Q How do experiments overcome selection bias?

A Experiments break the link between potential outcomes and treatment.

In other words: Randomly assigning D_i makes D_i independent of which outcome we observe (meaning Y_{1i} or Y_{0i}).

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Difference in means with random assignment of D_i

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&\quad = E[\tau_i] && \text{Random assignment of } \mathrm{D}_i \text{ breaks selection bias.}
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The experimental ideal

Example: Training programs

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Challenges Participants self select. **+** Programs target lower-wage workers.

The experimental ideal

Example: Training programs

How do we formalize these concerns in our framework?

The experimental ideal

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Observational program evaluations

$$E[\text{Wage}_i \mid \text{Program}_i = 1] - E[\text{Wage}_i \mid \text{Program}_i = 0] =$$

$$\underbrace{E[\text{Wage}_{1i} \mid \text{Program}_i = 1] - E[\text{Wage}_{0i} \mid \text{Program}_i = 1]}_{\text{Average causal effect of training program on wages for participants, } i.e., \bar{\tau}_1} +$$

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The experimental ideal

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If the program attracts/selects individuals who, on average, have lower wages without the program (sort of the point of the program), then we have negative selection bias.

The experimental ideal

Example: Training programs

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So even if the program, on average, has an positive wage effect (in the participant group), *i.e.*, $\bar{\tau}_1 > \mathbf{0}$, we will detect a lower effect due to the negative selection bias.

The experimental ideal

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The experimental ideal

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If the bias is sufficiently large (relative to the treatment effect), our estimate will even get the sign of the effect wrong.

Related While observational studies typically found negative program effects, several experiments found positive program effects.

The experimental ideal

Example: The STAR experiment

The Tennessee STAR experiment is a famous/popular example of an experiment that allows us to answer an important social/policy question.

Research question Do classroom resources affect student performance?

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Research question Do classroom resources affect student performance?

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Treatments

1. *Small* classes (13–17 students)
2. *Regular* classes (22–35 students) plus part-time teacher's aide
3. *Regular* classes (22–35 students) plus full-time teacher's aide

Example: The STAR experiment

First question Did the randomization balance participants' characteristics across the treatment groups?

The experimental ideal

Example: The STAR experiment

First question Did the randomization balance participants' characteristics across the treatment groups?

Ideally, we would have pre-experiment data on outcome variable.

Unfortunately, we only have a few demographic attributes.

Table 2.2.1, MHE

	Treatment: Class Size			
Variable	**Small**	**Regular**	**Regular + Aide**	**P-value**
Free lunch	0.47	0.48	0.50	0.09
White/Asian	0.68	0.67	0.66	0.26
Age in 1985	5.44	5.43	5.42	0.32
Attrition rate	0.49	0.52	0.53	0.02
K. class size	15.10	22.40	22.80	0.00
K. test percentile	54.70	48.90	50.00	0.00

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Demographics appear balanced across the three treatment groups.

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The three groups differ significantly on attrition rate.

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The randomization generated variation in the treatment.

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The small-class treatment significantly increased test scores.

The experimental ideal

The STAR experiment

The previous table estimated/compared the treatment effects using simple differences in means.

We can make the same comparisons using regressions.

Specifically, we regress our outcome (test percentile) on dummy variables (binary indicator variables) for each treatment group.

The experimental ideal

Example of our three treatment dummies.

i	y_i	Trt_{1i}	Trt_{2i}	Trt_{3i}
1	y_1	1	0	0
2	y_2	1	0	0
$\vdots$	$\vdots$	$\vdots$	$\vdots$	$\vdots$
ℓ	y_ℓ	1	0	0
$\ell+1$	$y_{\ell-1}$	0	1	0
$\vdots$	$\vdots$	$\vdots$	$\vdots$	$\vdots$
p	y_p	0	1	0
$p+1$	y_{p+1}	0	0	1
$\vdots$	$\vdots$	$\vdots$	$\vdots$	$\vdots$
N	y_N	0	0	1

The experimental ideal

Regression analysis

Assume for the moment that the treatment effect is constant[†], *i.e.*,

$$\mathrm{Y}_{1i} - \mathrm{Y}_{0i} = \rho \quad \forall \boldsymbol{i}$$

You'll often hear econometricians say "homogeneous" (*vs.* "hetergeneous").

The experimental ideal

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$$\color{#e64173}{\text{Y}_{1i}} - \color{#6A5ACD}{\text{Y}_{0i}} = \color{orange}{\rho} \quad \forall \boldsymbol{i}$$

then we can rewrite

$$\text{Y}_i = \color{#6A5ACD}{\text{Y}_{0i}} + \text{D}_i \left(\color{#e64173}{\text{Y}_{1i}} - \color{#6A5ACD}{\text{Y}_{0i}} \right)$$

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The experimental ideal

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as

$$\text{Y}_i = \underbrace{\alpha}_{=E[\text{Y}_{0i}]} + \text{D}_i \underbrace{\rho}_{\text{Y}_{1i} - \text{Y}_{0i}} + \underbrace{\eta_i}_{\text{Y}_{0i} - E[\text{Y}_{0i}]}$$

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The experimental ideal

Regression analysis

$$\mathrm{Y}_i = \alpha + \mathrm{D}_i \rho + \eta_i$$

Now write out the conditional expectation of $\mathbf{Y}_i$ for both levels of $\mathbf{D}_i$

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Take the difference...

$$E[\mathrm{Y}_i \mid \mathrm{D}_i = 1] - E[\mathrm{Y}_i \mid \mathrm{D}_i = 0]$$

The experimental ideal

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$$\begin{aligned} & E[Y_i \mid D_i = 1] - E[Y_i \mid D_i = 0] \\ & \quad = \rho + \underbrace{E[\eta_i | D_i = 1] - E[\eta_i \mid D_i = 0]}_{\text{Selection bias}} \end{aligned}$$

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$$E[\text{Y}_i \mid \text{D}_i = 1] - E[\text{Y}_i \mid \text{D}_i = 0] = E[\eta_i | \text{D}_i = 1] - E[\eta_i \mid \text{D}_i = 0]$$

Again, our estimate of the **treatment effect** (ρ) is only going to be as good as our ability to shut down the **selection bias**.

Selection bias in regression model: $E[\eta_i | \text{D}_i = 1] - E[\eta_i \mid \text{D}_i = 0]$

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The experimental ideal

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There is something in our disturbance η_i that is affecting Y_i and is also correlated with D_i.

The experimental ideal

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There is something in our disturbance η_i that is affecting $\mathbf{Y}_i$ and is also correlated with $\mathbf{D}_i$.

In other metrics-y words: Our treatment $\mathbf{D}_i$ is endogenous.

The experimental ideal

Solutions and covariates

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Another potential route to identification is to condition on covariates in the hopes that they "take care of" the relationship between $\mathbf{D}_i$ and whatever is in our disturbance η_i.

Without very clear reasons explaining how you know you've controlled for the "bad variation", clean and convincing identification on this path is going to be challenging.

The experimental ideal

Covariates

That said, covariates can help with two things:

1. Even experiments may need **conditioning/controls**: The STAR experiment was random *within school*—not across schools.

2. Covariates can soak up unexplained variation—**increasing precision.**

The experimental ideal

Covariates

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Now that we've seen regression can analyze experiments, let's estimate the STAR example...

Table 2.2.2, MHE

Explanatory variable	**1**	**2**	**3**
Small class	4.82	5.37	5.36
	(2.19)	(1.26)	(1.21)
Regular + aide	0.12	0.29	0.53
	(2.23)	(1.13)	(1.09)
White/Asian			8.35
			(1.35)
Female			4.48
			(0.63)
Free lunch			-13.15
			(0.77)
School F.E.	F	T	T

The omitted level is *Regular* (with part-time aide).

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Results without other controls are very similar to the difference in means.

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School FEs enforce the experiment's design and increase precision.

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Additional controls slightly increase precision.

R

Object types/classes

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- `TRUE`, `T`, `FALSE`, and `F` are `logical` (as is the result of `3 > 2`).

The `class(x)` function tells you the class of object `x`.

Structure

In addition to having types/classes, objects have some type of structure.

- `1:3`, `c(1, 2)`, and `seq(2, 8, 2)` each produce a `numeric`-class `vector`.

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- `matrix(data = 1:15, ncol = 5)` creates a `matrix` with class from `data`.
- `data.frame(x = 1:2, y = c("a", "b"), z = T)` produces a `data.frame` with three columns and two rows. The first column (`x`) is `numeric`; the second column (`y`) is `character`, and the third column (`z`) is logical.

Our `matrix`

```r
matrix(data = 1:15, ncol = 5)
```

```
#>      [,1] [,2] [,3] [,4] [,5]
#> [1,]    1    4    7   10   13
#> [2,]    2    5    8   11   14
#> [3,]    3    6    9   12   15
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Our first `data.frame`!

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#>   x y    z
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Notice how `R` helps 'fill' out the columns when lengths don't match.

Packages

Straight out of the box, `R` has a ton of useful features, but it really gets its power from the additional packages (libraries) that users create.

- **Open-source greatness** Users find needs and create amazing solutions.
- ***Caveat utilitor*** There are a lot of packages, each with a lot of functions. Mistakes can happen.
- **Open-source greatness$_2$** Again, `R` is open source: Check the code!

Packages

Straight out of the box, `R` has a ton of useful features, but it really gets its power from the additional packages (libraries) that users create.

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Examples `ggplot2` (plotting), `dplyr` (data work that can link with SQL), `sf` and `raster` (geospatial work), `lfe` (high-dimensional fixed-effect regression), `data.table` (fast and efficient data work)

Installing packages

Once you find a function/package that you need to install,[†] you'll typically install it via `install.packages("newAmazingPackage")`.[††]

We'll use the package `dplyr` throughout the course. Let's install it.

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# Install 'dplyr' package
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Aside Notice the comment above the actual code (R uses `#` for comments).

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Now all functions contained in `dplyr` are available (until you close R).

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Package management

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[Enter] The `pacman` package... for package management, of course.

After installing (`install.packages("pacman")`), you can

- Install and load packages via `p_load(package1, ... , packageN)`
- Update packages via `p_update()`

The `p_load` paradigm is especially helpful for collaboarations or projects across multiple machines.

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