Research Methodology for Public Policy

Lecture 2 — The Importance of Research: Causality and Inference

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Welcome Back

Today's Agenda

- Returning to Lecture 1
  - What is (public policy) research?
  - The scientific method
  - Approaches to empirical research
  - The methods menu
- Main Event: Causality
  - Spurious correlations
  - Why causality is the heart of policy research
  - Correlation $\neq$ causation
  - The fundamental problem of causal inference
- Formalizing the core model
- Post-lunch R practicum

A few course notes

- I have already reduced number of problem sets from 5 to 4.
- You will receive the first one today and it will be due Friday. What time?
- Final project assignment will be introduced tomorrow

- Make sure you've read over the syllabus
- Complete readings before class

What Is (Public Policy) Research?

Social "Science"?

What are we actually doing when we do this kind of research?

- A search for truth about how the social and political world works
- An attempt to describe and explain social and political phenomena . . . humans are complicated
- A reasonably standardized set of procedures ("the scientific method") that lets a community of researchers work cumulatively
- A social purpose: the hope that better understanding leads to better policy

Where Policy Research Sits: Subfields

Empirical **Political Science** into a Three broad subfields — public policy research draws on all of them:

- **Comparative politics**: comparisons across countries or regions
- **American politics**: behavior, institutions, and history within one political system
- **International relations**: trade, conflict, and political economy at the global scale
- **(Quantitative) Methods**: developing the tools — statistics, computational methods, game theory — that the other subfields rely on *(EMPS Ch. 1.1)*
- Generally, political science values theoretical contributions(Slanchev reading), whereas public policy values policy relevance.(ie less concern about why, but only if it works)

What Big Questions Does the Field Ask?

Why are some countries democratic and others aren't? Does democratic rule make people better off? What leads to cooperation between countries? Why do people vote and participate in politics as they do? What factors are associated with global environmental cooperation?

- These questions are *big* — progress is real, but rarely final
- "A different interpretation can lead to a different finding" — e.g., what counts as a "best" political outcome: stability, or responsiveness? *(EMPS Ch. 1.2)*
- Public policy research narrows these big questions into something testable

What Kinds of Questions Does Policy Research Ask?

- **Descriptive:** What does the world look like? (How many households are food insecure?)
- **Causal:** What causes what? (Does a cash transfer *reduce* food insecurity?)
- **Evaluative:** Did a policy work? (Did the transfer program achieve its goal, and at what cost?)

Advocacy vs. Analysis

- **Politics / advocacy** uses rhetoric and persuasion to move people toward a point of view
- **Policy research** uses the scientific method to try to uncover the true state of the world
- Both matter in public life — but this course is about the second one
- Good policy analysts can still be persuasive; they are persuasive *because* their evidence is credible
- Our focus here is analysis - ie we adopt the mindset of objective scientists

Quality Research -> Effective Public Policy

- We need to know foundational truths about how the social world works in order to make meaningful policy interventions
- Policies based on faulty research won't work

Banning Ice Cream won't prevent shark attacks

Using the Scientific Method

The Scientific Method: Popper's Legacy

- We owe much of modern empirical social science to philosopher **Karl Popper**, who pushed scholars toward **falsification** and toward having an explicit *method* for inquiry
- EMPS adapts this into a seven-part structure we will use to read — and to write — research, all term
- *(EMPS Ch. 1.4)*

The Seven Elements: Puzzle and Theory

- **Puzzle:** the research question — "research leads us to expect X, but we observe Y," or two competing arguments that disagree
- "A puzzle is something that is not only unanswered, but interesting. It can somehow tell us about the world in a broader way, even if the question itself is quite narrow." *(EMPS Ch. 1.4)*
- **Theory:** the proposed explanation — usually an outcome explained by some important factor (more on this in Lecture 4)

The Seven Elements: Hypotheses Through Conclusions

- **Hypotheses & implications:** the *testable* predictions that follow from the theory
- **Evidence / test:** how the claim is evaluated — a regression, a difference of means, interview data
- **Falsifiability:** could this theory, in principle, be proven wrong?
- **Conclusions:** what did the study actually find, and how far does that finding generalize?

The Seven Elements: "Do I Buy It?"

- The final, evaluative step: your own critique of the method, execution, or case
- "To criticize something, you must first understand what is being argued." *(EMPS Ch. 1.4)*
- *All research is flawed, it is just flawed in different ways*
- We will use exactly this structure — Puzzle, Theory, Hypotheses, Evidence, Falsifiability, Conclusions, Do I Buy It? — to take notes on every reading this term
- Your final project will be structured around these elements

Approaches to Empirical Research

Epistemological approaches

Epistemology - how we (humans) know things about the world

- **Objectivism**
  - Basic statement of knowledge: Meaning and reality exist independently (outside) of any particular consciousness.
  - There are fundamental, knowable truths about the world.
  - Almost all quantitative research and a lot of qualitative
- **Subjectivism**
  - Basic statement of knowledge: There is no meaning or knowable reality independent of the meaning or reality constructed by particular consciousnesses.
  - There is no reality we can know

Epistemological approaches

Epistemology - how we (humans) know things about the world

- **Constructivism**
  - Basic statement of knowledge: People construct meaning from facts, events, and the reality out there.
  - Places on emphasis on interactions between people and the "intersubjective understandings" they create

Two Broad Traditions

Qualitative

- Few cases, studied in depth
- Interviews, process tracing, case studies, ethnography
- Strength: mechanism, context, meaning
- This approach tends to be more common in European social science . . . and Asia

Quantitative

- Many cases, summarized with numbers
- Surveys, experiments, large-N regression
- Strength: pattern, generalizability, precision
- Strength of "American-style" social science
- *. . . I believe these skills are unique/vauled and will give you an advantage throughout your career in*

The Broader Methods Menu in Political Science

Families of method:

- Surveys
- Experiments
- Large-N (statistical) analysis / Observational
- Small-N (case-based) analysis
- Game theory
- Social network analysis
- Machine learning

Where This Course Spends Its Time

- This course covers **Large-N analysis** (most of the term), **Experiments** (Lecture 9), and **Small-N / qualitative methods** (Lectures 10–11)
- "The key focus [is] whether the tool is appropriate for the job." Researchers usually specialize, but should be conversant in several.
- The research question should choose the method — not the reverse
- Expectation for academic social scientists to learn different methods - this class gives you the foundation

Why Not Just Pick One Tradition?

> *"There has been a bit of a divide that's arisen within the discipline… However, there is some movement toward what is termed a 'mixed method' or 'multi-method' approach in which both quantitative and qualitative data are used in a research project." (EMPS Ch. 1.3.2)*

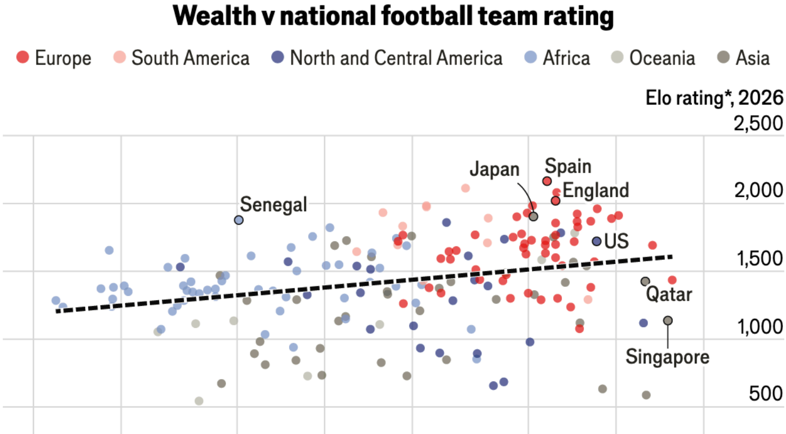
- Each method has advantages and disadvantages; combining methods lets you lean on one method's strengths to cover another's weaknesses
- The cost: you (or your team) need real proficiency in more than one toolkit — still worth it for many of the best questions in policy research

Experiments

- Ideal version: the fully randomized controlled trial (RCT)
- **Good for:** identifying causation cleanly
- **Often weaker on:** generalizability and external validity (does the lab or pilot result hold up "in the wild"?)
- We'll spend a full session on this (Lecture 9)

Large-N Analysis

- Look for systematic patterns across a large number of cases
- Usually implemented through some form of **regression**
- Lets us ask: holding other things constant, how much does X matter for Y?



Causality: The Heart of This Course

Causation Is Key

$$X \longrightarrow Y$$

Our goal in this course is **inference**:

- **Inference** is using facts we *do* know to learn facts we *don't*
- **Descriptive inference**: using data to learn about the state of the world
- **Causal inference**: using data to learn about *how* the world works
- Our focus for most of the course will be **causal inference**

The Goal of Policy Research

- Underlying nearly everything we do: the concept of *causality*
- Deterministic causality (it always happens) vs. **probabilistic** causality (it happens more often, on average)
- The recurring logical structure: "all else equal (*ceteris paribus*), an increase in X causes an increase in Y"
- We will learn the tools to set up *and* test causal claims like this
- A recurring tension: establishing causality convincingly often costs us some generalizability

What Can Research Actually Tell Us?

Two Different Questions, Always

EMPS frames every research finding as answering two distinct questions at once:

1. What relationship does *this* dataset support? (internal to your study)
2. How far does that relationship *generalize* beyond your data? (external to your study)

(EMPS Ch. 1.5)

Support for Hypotheses

- If your sample shows a statistically significant relationship, you have **support** for your hypothesis — not "proof"
- If it doesn't, you have a *failure to find support* — not "disproof"
- "If you had a statistically significant relationship, you would find support for your hypotheses. If you failed to have a statistically significant relationship, you would not find support for your hypotheses." *(EMPS Ch. 1.5.1)*
- Both outcomes are informative. Neither is final.

Generalizability

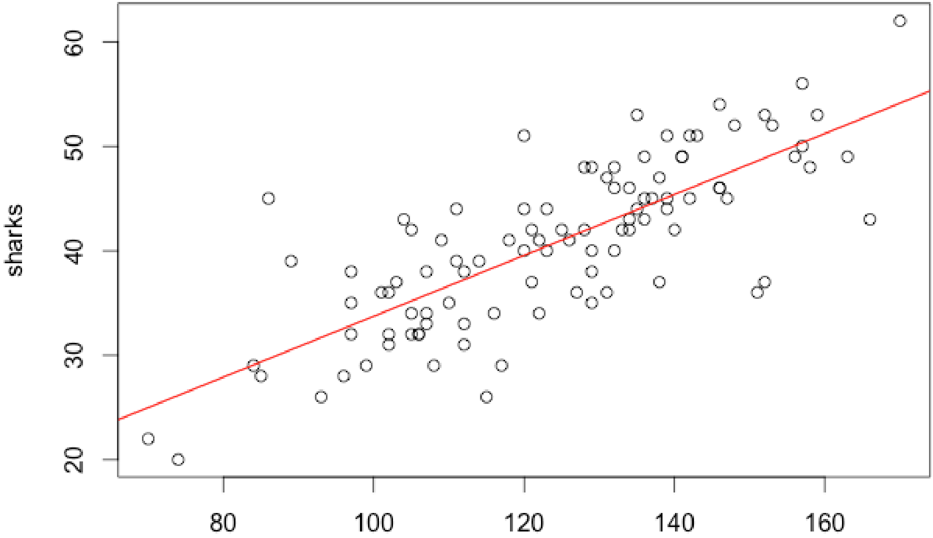
- The real prize is rarely the sample itself — it's the **population** the sample represents
- "While your sample of, say, 1600 data points may be interesting, it's really only interesting in that it can tell us about the 327 million other data points we don't know anything about." *(EMPS Ch. 1.5.2)*
- This is exactly why *how* you sample (Lecture 5) matters as much as *what* you find
- Being precise about uncertainty *is* part of being a good policy analyst, not a weakness

Focusing on Causality: Spurious Correlation

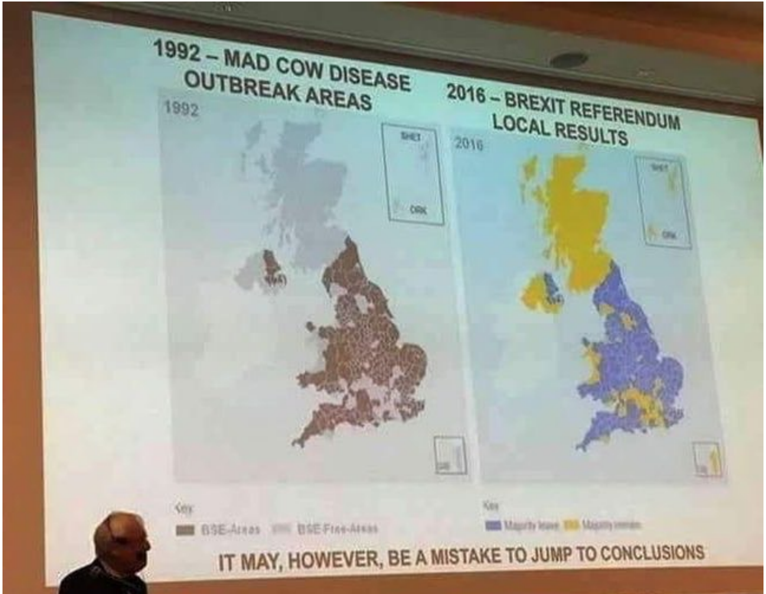
Correlation - When Two Things Move Together...

- ...it's tempting to assume one causes the other
- Sometimes that's right. Often it isn't.
- A few examples — some silly, all instructive — before we get formal

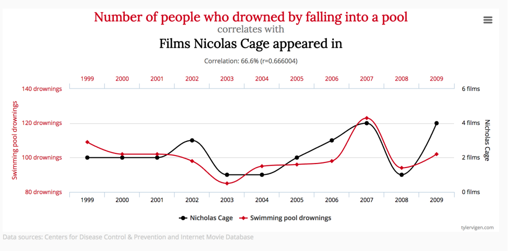
Example

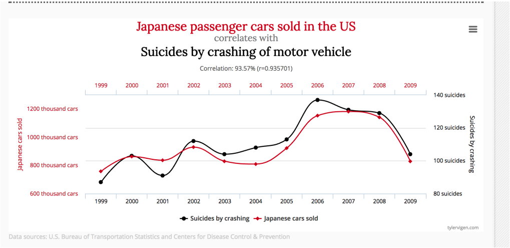


Example


1992 – MAD COW DISEASE OUTBREAK AREAS
1992
2016 – BREXIT REFERENDUM LOCAL RESULTS
2016
Key
BSE-Areas
BSE-Free-Areas
Key
IT MAY, HOWEVER, BE A MISTAKE TO JUMP TO CONCLUSIONS

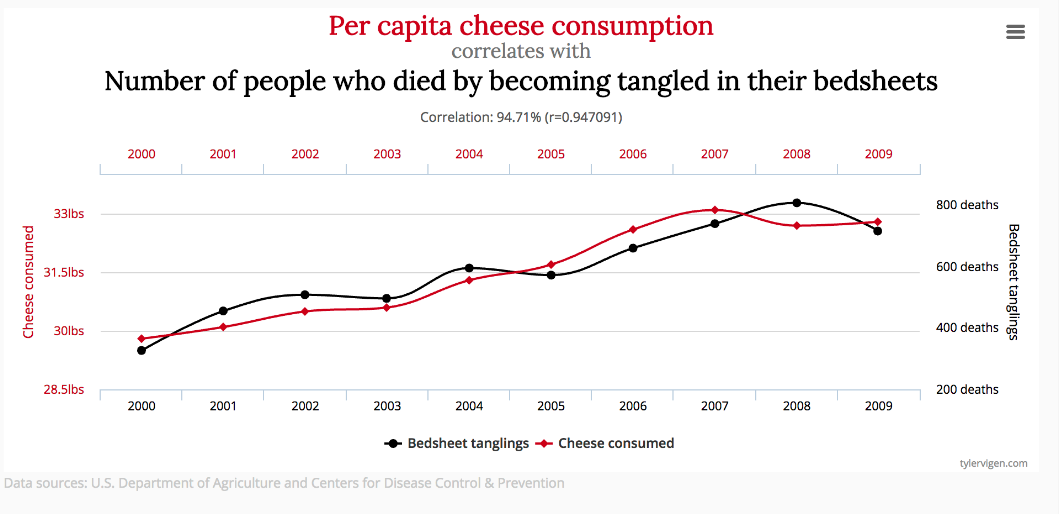
More From the Internet





- Statistician Tyler Vigen built an entire website cataloging pairs like these
- The pattern holds for *thousands* of variable pairs, if you look hard enough

Midwesterners love cheese



- With enough variables and enough time periods, *some* pairs will move together by

What Went Wrong?

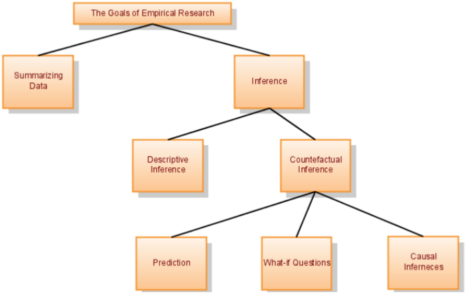
- Two variables can move together because of pure coincidence, a shared underlying cause, or genuine causation
- "In the end, there is no magical statistical procedure that can show causality; each problem requires the application of careful thought." *(EMPS Ch. 2)*
- Our job as researchers is to figure out *which one* we're looking at — that's what the rest of today is about

Why Causality Matters

Most Interesting Policy Questions Are Causal

- Does democracy improve health or economic outcomes?
- Do politicians change policy because of public opinion?
- Does foreign aid reduce violence?
- Does representation improve women's rights?
- Does education increase youth political participation?
- Does *[your policy of interest]* actually work?

Where Causal Inference Fits



- Political scientist Gary King's framework splits research goals into description and explanation
- Causal inference — the most demanding branch — is usually what policymakers want answered

A Classic Illustration: Hospitals

- IV (treatment): going to the hospital
- DV (outcome): five-year survival
- We would likely find: people who go to the hospital have **lower** five-year survival, on average
- Does going to the hospital *cause* lower survival?

A Classic Illustration: Hospitals

- IV (treatment): going to the hospital
- DV (outcome): five-year survival
- We would likely find: people who go to the hospital have **lower** five-year survival, on average
- Does going to the hospital *cause* lower survival? **No.**
- This is exactly why we can't read causation directly off a raw correlation

Holding "All Else Equal"

- EMPS calls this the dilemma of **ceteris paribus** — holding all else equal
- "This [is] also known as the dilemma of holding all else equal ('ceteris paribus'), and it is the fundamental problem of causal inference." *(EMPS Ch. 2)*
- Everything we do for the rest of the course is, in some sense, a strategy for approximating ceteris paribus without time travel

Correlation $\neq$ Causation

Three Ways to Think About Why

1. **Selection**: people who go to the hospital are sicker to begin with
2. **Confounding**: an unmeasured variable (severity of illness) drives *both* going to the hospital *and* survival
3. **Comparability**: the treated and untreated groups differ in ways that go beyond the treatment itself

If A and B Are Related, Three Stories Remain

$$A \to B \qquad\qquad B \to A \qquad\qquad C \to A \text{ and } B$$

- $A =$ democracy, $B =$ income: does democracy raise income? Does income raise the odds of democratizing? Or does some C (colonial history, institutions) drive both?
- Telling whether A and B are *related* is comparatively easy
- Telling these three stories apart is the hard part of causal inference

Four Questions to Ask of Any Causal Claim

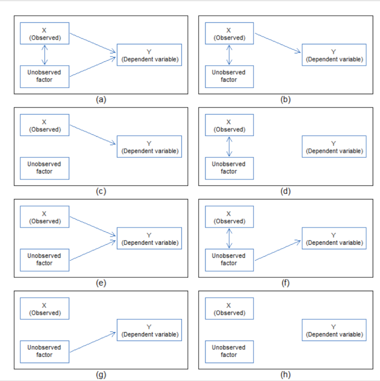
EMPS Ch. 2 frames this as a sequence of questions, illustrated with Fox News viewership (X) and Republican voting (Y):

1. Is there a relationship between X and Y at all?
2. What is the *direction* — could Y be causing X (**reverse causality**)?
3. Is some **confounding variable** Z driving both?
4. Could the relationship simply be **spurious** — showing up by chance?

Worked Example from EMPS: Fox News and Partisanship

- Theory: watching Fox News (X) causes higher Republican voting (Y)
- "Both Fox News viewership (X) and partisanship (Y) could be a function of age (Z). Old people watch more Fox News, and they are also more Republican." *(EMPS Ch. 2)*
- "What we thought is a relationship between watching Fox news and voting is actually just a reflection of a different set of relationships." *(EMPS Ch. 2)*
- This is also called **omitted variable bias** — we'll return to it formally later this lecture
- How could ask a similar question using an experiment?

Confounding in the Wild



- The same X–Y–Z logic recurs across dozens of configurations
- Step one of any empirical project: ask what Z's might be lurking

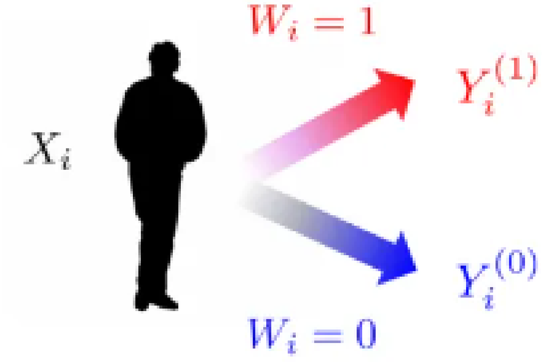
Why Random Assignment Helps

If *we*, the researchers, decide who gets the treatment — by a coin flip:

- Reverse causation is ruled out (treatment came first, by design)
- "Through randomization we can make — on average — all other things equal across treatment and control group [...] these two groups are even similar across variables we cannot observe." *(EMPS Ch. 2)*
- There is no selection effect — we assigned the groups, units didn't select themselves
- This is why experiments are often called the "gold standard" for causal claims (Lecture 9)

The Fundamental Problem of Causal Inference

Potential Outcomes



The Problem, Stated Simply

- For any unit i, imagine two **potential outcomes**: $Y_i(1)$ if treated, $Y_i(0)$ if untreated
- The causal effect for unit i is $Y_i(1) - Y_i(0)$
- **We only ever observe one of these for each unit** — the other is *counterfactual*
- This is the **fundamental problem of causal inference** *(EMPS Ch. 2)*

*Important Clarification: Randomness, Randomization, and Random Samples

- **Randomness**: an event whose outcome is not deterministic (a coin flip)
- **Randomization**: the researcher deliberately uses a random process to assign treatment
- **Random sample**: a sample drawn so every unit in the population has a known, nonzero chance of selection
- These three ideas get conflated constantly — they answer *different* questions (who's in your data vs. who gets treated)

How We Get Around It

- We cannot observe individual-level causal effects directly
- But under the right design, we *can* estimate **average** causal effects across groups
- Strategy: construct (or find) a comparison group that approximates the “missing” counterfactual
- This logic underlies every method this course covers: experiments, quasi-experiments, regression with controls, and more

The Three Pillars of Causality

QUANT Ch. 1 lists the basis for any causal claim in a theory:

1. **Time Ordering**: the cause precedes the effect, $X \to Y$
2. **Co-Variation**: changes in X are associated with changes in Y
3. **Non-Spuriousness**: there is no variable Z that causes both X and Y

- We can only assume this through random assignment or an "as-if random" process
- Notice: this is the *same* logic as "Correlation $\neq$ Causation," just stated as a positive checklist

#Building our model

Building Blocks - Important key terms

- Y_i — dependent / outcome variable: the thing we want to explain
- X_i — independent / explanatory variable: the thing doing the explaining
- ϵ_i — the error term: everything affecting Y that isn't X (usually a lot!) — not directly observable

The Core Model

$$Y_i = \beta_0 + \beta_1 X_i + \epsilon_i$$

REMEMBER THIS

Our core statistical model is

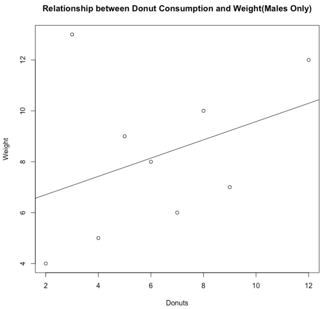
$$Y_i = \beta_0 + \beta_1 X_i + \epsilon_i$$

1. β_1, the slope, indicates how much change in Y (the dependent variable) is expected if X (the independent variable) increases by one unit.
2. β_0, the intercept, indicates where the regression line crosses the Y-axis. It is the value of Y when X is zero.
3. β_1 is almost always more interesting than β_0.

- β_0: the constant — predicted Y when $X = 0$
- β_1: the slope — how much Y changes per one-unit change in X

An Illustration

$$\text{WeightGain}_i = \beta_0 + \beta_1\,\text{DonutConsumption}_i + \epsilon_i$$



- This line is a *description* of the data, not yet a causal claim
- Whether β_1 is causal depends on whether donut consumption is uncorrelated with everything else hiding in ϵ_i (overall diet, exercise, genetics...)

Endogeneity: The Technical Version of "Correlation $\neq$ Causation"

- **Endogeneity**: X_i is correlated with the error term ϵ_i
- Usually because an omitted **confounder** affects both X and Y
- If X_i is endogenous, $\hat{\beta}_1$ is **biased** — it picks up the confounder's influence too, not just X's
- Goal: find or create **exogeneity** — a setting where X_i is unrelated to ϵ_i

```r
# illustrative only -- the mechanics of fitting this come in Practicum
model <- lm(weight_gain ~ donut_consumption, data = diet_study)
```

Key Terms & Looking Ahead

Key Terms from Today

- Epistemology
- Causation vs. correlation
- Counterfactual / ceteris paribus
- Random assignment
- Selection problem
- Confounding / omitted variable bias
- Spuriousness / reverse causality
- Endogeneity / exogeneity
- The core model
- Internal / external validity
- Identification strategy

Before Next Session

Lecture 3: Research Questions and Literature Reviews

- Read: EMPS, Ch. 3 (*Theory*)
- Read: QRM, Ch. 4 & Ch. 9 (*Finding a Research Question*; *Reviewing the Literature*)

Discussion

If you can't randomize, what would you need to believe about your data to make a causal claim anyway?

Questions?

See You in the Practicum