Empirical Energy and Environmental Economics

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ARE 261

Lecture 1

August 2021

Course Objectives:

1. Develop an intuitive understanding of empirical methods and research designs used in the field of energy and environmental economics (EEE).
2. Review important empirical findings and lines of inquiry at the frontier of the EEE field.
3. Discuss/deliberate research design trade-offs in an EEE context.
4. Think critically about what lines of inquiry are under-explored (and why?)
5. Help you develop/chart your own research agenda.

Get excited about energy and environmental economics

- High stakes social problems and challenges.
- Substantive economic content.
- Great data (regulated industries, increasingly rich remote sensing data, etc)
- Opportunities to inform and impact real world policy decisions ...

My non-linear path to EEE

I went to college to study this...

but got really interested in this.

How did I get interested in electricity markets?

I was a Ph.D. student at UC Berkeley in the wake of the electricity crisis and the dawn of AB32.

Research areas that I have an enduring interest in..

- How are market-based environmental regulations working in practice? How could they work better?
- Interactions/collisions between economic and environmental regulation.
- The demand-side of electricity markets (e.g. energy efficiency programs; demand response programs; rate design)
- Incomplete carbon markets and GHG emissions ‘leakage’.

New research areas/projects I am excited about...

- Equity, incidence, and environmental policy
- Energy access in emerging economies
- The economics of distributed energy resources (super-wonky but super-important)
- Wildfire economics

I love my job

- Energy and environmental economists work on important challenges: climate change, air and water pollution, resource management, environmental justice.
- We get to introduce great students (undergraduates and graduates) to a compelling and policy-relevant field.
- Our work can directly inform market/policy design.
- Great way for a Type C to impact/shape policy/market reform.

Why are you all here?

Semester organization

- Lectures will focus on EEE applications of empirical methods.
- Two problem sets give you hands-on experience applying methods.
- Paper discussions are intended to help us connect the dots between methods and important applications.
- Research idea sketch - a commitment device. Commit to developing a new idea that is not your second year paper!

Paper discussions

Criteria for choosing papers:

- Address important questions (many leave room for improvement)
- Demonstrate important tools/methods – strengths and limitations.
- Examples of great scholarship

Our paper discussions will be organized around the following:

- What is the question and why is it interesting?
- Why is the existing literature incomplete, non-existent, and/or unresolved?
- How does the paper add value/insight?
- Advantages and limitations of chosen empirical strategy.

Discussion paper assignments

- Listed on the syllabus. But subject to change (with advanced warning).
- Please make one constructive/critical point about the assigned paper in a short (< 1 page) report to be submitted by noon on the class meeting day.
- Please email subject 'ARE 261 reading response'
- All students (auditors and graded) required to submit paper responses.

Research idea – where to find it?

Reading papers published in top economics journals can be inspiring ... but intimidating!

Research process: Where do good ideas come from?

- Classes: what are the important unanswered questions?
- Seminars: what does the seminar make me think about?
- Broad survey articles can stimulate ideas
- Read the news with an eye towards questions with substantive economics content.
- Talk to people .. and not just economist-people!

Keep at it! Lots of tail chasing in between the eureka moments...

Not all good questions lead to successful research papers

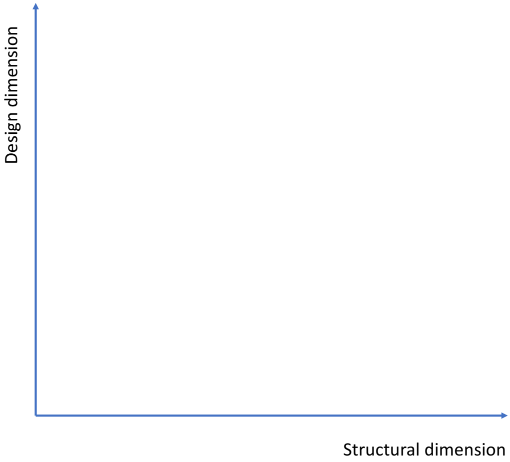
For every published paper, there are many other projects that died along the way.
Some reasons I've abandoned research ideas I was excited about:

- Research design underpowered (we'll talk about how to figure this out sooner versus later).
- Strange empirical results which were hard to credibly rationalize.
- Identification concerns hard to address/alleviate.
- Someone else got there first.

Get comfortable with pitching new ideas and getting feedback early and often...

Overview of 261 Module 1.

Conceptual framework:



Empirical strategy space

Design Dimension?

First part of this course emphasizes ‘design-based’ research strategies.

- Angrist and Pischke (2010) argue that the “credibility revolution” in empirical microeconomics defined by a “vigorous push for better and more clearly articulated research designs”
- Design-based papers emphasize the construction of a credible counterfactual to motivate causal questions and highlight the assumptions that are essential for identification.
- Emphasis on establishing a basis for credible causal inference.

Many causal questions drive research agendas in EEE..

What is the causal effect of x on y in sub-population N?

Intervention	**Outcome**	**Population**
Energy efficiency investment	Electricity consumption	Residential customers
Electricity access	Economic well-being	Rural households in Kenya
GHG emissions price	Firm-level emissions	Manufacturing firms
Air pollution	Mortality	People over 65
Conditional cash payments	Forest conservation	Rural landholders
Congestion pricing	Driving behavior	City drivers
Technology subsidies	green tech innovation	U.S. firms
etc.	etc.	etc.

The researcher's challenge

- What outcomes would have been observed at treated units in the absence of the intervention?
- What outcomes would have been observed among untreated units had they been treated?
- **Missing data problem:** These counterfactual outcomes not observable!
- We'll review a range of strategies used to tackle this identification problem:
  - Field experiments
  - Instrumental variables
  - DID/FE

1. Field experimental methods with EEE applications

Lecture topics:

- Research design fundamentals, power analysis, frontier methods
- EEE Applications:
  - Energy efficiency
  - Intersection of energy, environment, development.

Discussion papers:

- Fowlie, Meredith, Michael Greenstone, and Catherine Wolfram (2018). "Do Energy Efficiency Investments Deliver? Evidence from the Weatherization Assistance Program", Quarterly Journal of Economics.
- Hahn, Robert W., and Robert D. Metcalfe. 2021. "Efficiency and Equity Impacts of Energy Subsidies." American Economic Review.
- Carranza, Eliana and Robyn Meeks (2020). "Energy Efficiency and Electricity Reliability". Review of Economics and Statistics.

2. Quasi-experimental IV methods

Lecture topics:

- Hedonic regressions in theory and practice (review?)
- Causal impacts of air pollution

Discussion paper

- Deryugina, Tatyana, Garth Heutel, Nolan H. Miller, David Molitor, and Julian Reif (2019) "The Mortality and Medical Costs of Air Pollution: Evidence from Changes in Wind Direction." American Economic Review.

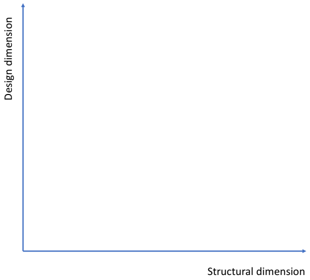
3. Differences-in-differences/Fixed effects

3 EEE applications:

- **Electricity demand**: Ito, Koichiro (2012). "Do Consumers Respond to Marginal or Average Price? Evidence from Nonlinear Electricity Pricing." American Economic Review.
- **Emissions markets and environmental justice**: Hernandez-Cortes, Danae and Kyle Meng (2020). "Do Environmental Markets Cause Environmental Injustice? Evidence from California's Carbon Market". NBER WP27205.

  Lo Prete, Chiara, Ashis Tyagi, and Qingyu Xu (2021) "California's cap-and-trade program and emission leakage in the Western Interconnection: comparing econometric and partial equilibrium model estimates"
- **Wildfire** : Baylis, Patrick and Judd Boomhower (2021) "Building Codes and Community Resilience to Natural Disasters".

The Structural Dimension



- Second half of the course investigates more 'structural' empirical methods.
- Emphasis on combining economic theory with explicit assumptions about structural errors in order to recover the underlying structural parameters or "primitives".

Imposing structure in empirical work: A toy example

$$y = \alpha + x\beta + \varepsilon \tag{1}$$

- Absent any additional structure, all we can really say about this equation is that it provides the best (i.e. squared prediction error minimizing) linear approximation of the conditional expectation function $E(y|x)$.
- Additional structure could support an economic interpretation.
- We need a basis for pushing beyond descriptive or statistical intepretations of linear regressions.
- **Where does this structure come from?**

Let's get us some structure!

Suppose our OLS regression is motivated as a Cobb-Douglas production function summarizing the technical relationship between inputs to production and outputs :

$$Q_t = AL_t^{\alpha} K^{\beta}. \tag{2}$$

Taking logs we get:

$$\log Q_t = \log A + \alpha \log L_t + \beta \log K_t. \tag{3}$$

Suppose we go out and collect data on output Q_t and labor and capital inputs (L_t and K_t) and we estimate the following:

$$\log Q_t = \log A + \alpha \log L_t + \beta \log K_t + \varepsilon_t \tag{4}$$

Can we interpret our estimates of α and β as estimates of the parameters of the Cobb Douglas production function?

More structure needed...(if the economic model does not perfectly rationalize the data!)

- The statistical properties of the error term have important implications for how we interpret the estimated coefficients.
- The source of the error (data generating process) will have implications for the assumptions we can credibly make about its statistical properties.
- The most convenient assumption: $\varepsilon_t \sim N(0, \sigma^2)$.
- Why might this assumption be violated?

Upshot

This very simple example was intended to fix ideas with respect to the following questions

- **What is a "structural model"?**
  A model that explicitly combines theoretical structure/assumptions with statistical assumptions in order to estimate or "recover" the parameters of a model or function from the joint density of economic data (in this case $f(x, y)$).
- **Where does the "structure" come from?**

Upshot

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- **What is a "structural model"?**
  A model that explicitly combines theoretical structure/assumptions with statistical assumptions in order to estimate or "recover" the parameters of a model or function from the joint density of economic data (in this case $f(x, y)$).
- **Where does the "structure" come from?**
  - Economic theory ... but Cobb–Douglas production function was not developed on the basis of a physical understanding of production.
  - Other sources (such as engineering, atmospheric science, behavioral psychology, biology, etc.) can help us model the processes and constraints that play a role in generating the data.

How is structure used to identify the parameters?

Five (not-so-)easy steps!!

- Write down a sensible theoretical model (e.g. a production function relating inputs and outputs).
- Be explicit about what we can and cannot observe.
- Think about the processes that give rise to "structural errors". Impose (and substantiate if possible) assumptions about the statistical properties of these errors.
- Derive statistical objects/estimands from the model.
- Identify the parameters that best match or rationalize the data we observe (conditional on the assumed structure).

4. Discrete Choice Models: Logit

Lecture topics:

- Discrete choice modeling fundamentals
- The conditional logit model

Discussion papers:

- Davis, Lucas (2021) What Matters for Electrification? Evidence from 70 Years of U.S. Home Heating Choices
- Burgess, Robin, Michael Greenstone, Nicholas Ryan, Anant Sudarshan (2020). "The Role of Decentralized Solar in Completing Indian Electrification"

5. Differentiated product markets

Lecture topics:

- Random taste variation and the mixed logit model
- Structural models of differentiated product markets (BLP)

Discussion papers:

- Grigolon, Laura, Mathias Reynaert, and Frank Verboven (2018). "Consumer Valuation of Fuel Costs and the Effectiveness of Tax Policy - Evidence from the European Car Market", *American Economic Journal: Economic Policy*.
- Ito, Koichiro and Shuang (2019) "Zhang Willingness to Pay for Clean Air: Evidence from Air Purifier Markets in China. *Journal of Political Economy*.

6. Housing markets and environmental justice

Lecture topics:

- Neighborhood choice
- Environmental justice and hedonic/sorting models.

Discussion papers

- Depro, Brooks, Christopher Timmins, and Maggie O'Neil (2015) "White Flight and Coming to the Nuisance: Can Residential Mobility Explain Environmental Injustice?," Journal of the Association of Environmental and Resource Economists 2, no. 3 (September 2015): 439-468.
- Taylor, Dorceta. "Market Dynamics Residential Mobility, or Who Moves and Who Stays" Toxic Communities: Environmental Racism, Industrial Pollution, and Residential Mobility. NYU Press, 2014.

Time permitting: Dynamic discrete choice

Lecture topics:

- Fundamentals of dynamic discrete choice
- Review a classic: Rust (1987)

Discussion papers:

- Bell, Samuel, Kelsey Jack, Chris Severen, Elizabeth Walker (2020). "Technology Adoption under Uncertainty: Take-up and Subsequent Investment in Zambia" The Review of Economics and Statistics.
- Meredith Fowlie, Mar Reguant, and Stephen P. Ryan (2016). "Market-based Emissions Regulation and Industry Dynamics". Journal of Political Economy.

Section 1

Field Experiment Fundamentals

The rise of field experiments in environmental economics

- Experimental methods have taken their rightful place in our empirical methods tool kit.
- Assigning a treatment or intervention at random ensures that there is no systematic variation in unobserved factors across treated and untreated units.

"An advantage of field experiments is tht they lend themselves easily to a routinized programme of evidence-based research"
– List and Metcalfe, 2016

- This is both a feature and a bug...

A Noteworthy Nobel!!!

But the enthusiasm is not universal

But the enthusiasm is not universal

- Researchers look for good experiments (actual or quasi) versus good questions. These papers are playing ‘small ball’ while the big questions go unanswered because they are out of reach.
- In more structural empirical work, estimated parameters have a clear economic interpretation. Field experimental studies can get sloppy.
- Some have argued that these studies generate idiosyncratic results that have little predictive value beyond the context of the original experiment.

Some critiques and questions

"RCTs of 'what works', even when done without error or contamination, are unlikely to be helpful for policy unless they tell us something about why it works, something to which they are often neither targeted nor well-suited."
– Deaton, 2008

"Black-box experimental evaluations.. pose a serious threat to the accumulation of knowledge about the behavior of persons and institutions. Because they are not conducted within a behaviorally coherent framework of analysis, the evidence from experiments does not accumulate."
– Heckman and Smith, 1995

"Has the randomista revolution gone too far?"
– Oriana Bandiera, December 2019

Why spend two lectures on experimental research designs?

For the RCT consumer

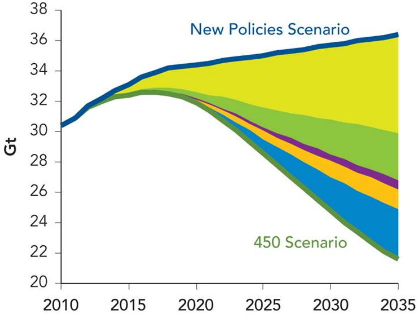
- Think clearly about research design/causal inference more generally.
- Become a more informed consumer of RCT papers.

For the RCT producer

- RCTs have huge advantages...
- ...but they are not a panacea
- Wrinkles, triumphs, head aches, cautionary tales

The application we'll start with: Energy efficiency!

Energy efficiency expected to play a critical role in climate change mitigation

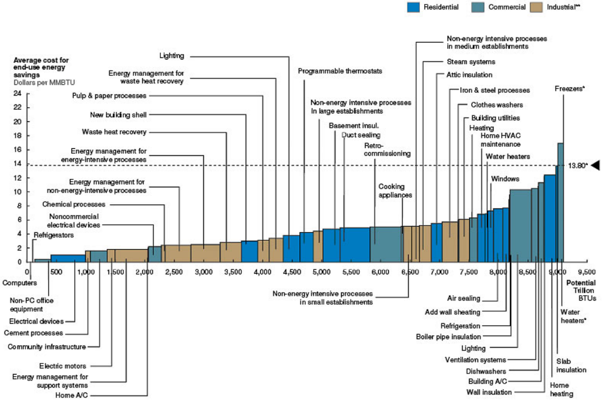


	Abatement 2020	Abatement 2035
Efficiency	72%	44%
Renewables	17%	21%
Biofuels	2%	4%
Nuclear	5%	9%
CCS	3%	22%
Total (Gt CO_2)	2.5	14.8

Source: IEA World Energy Outlook
** Note all carbon mitigation strategies depicted are zero carbon.

Where to direct new investments in energy efficiency?

U.S. Energy Efficiency Supply Curve - 2020



* Average price of avoided energy consumption at the industrial price; $35.60/MMBTU represents the highest regional electricity price used; new build cost based on AEO 2008 future construction costs

** Our 49th source of savings, refining processes, offers no NPV-positive savings

Source: EIA AEO 2008, McKinsey analysis

* IEA estimate of global spending on incremental energy efficiency investments (global).

What works, what doesn't, and why?

- Decisions to invest in energy efficiency improvements are widely believed to be affected by multiple market failures (e.g. environmental externalities, imperfect information, behavioral biases).
- Governments are increasing support for energy efficiency policies.
- How can we estimate the causal effect of an energy efficiency improvement on energy consumption?

What works, what doesn't, and why?

- Decisions to invest in energy efficiency improvements are widely believed to be affected by multiple market failures (e.g. environmental externalities, imperfect information, behavioral biases).
- Governments are increasing support for energy efficiency policies.
- How can we estimate the causal effect of an energy efficiency improvement on energy consumption?
  - Simulation models/'structural' engineering estimates
  - Quasi-experimental designs (e.g. instrumental variables, regression discountinuities, differences-in-differences)
  - Experimental research designs (e.g. randomized control trials, randomized encouragement designs)

Approach 1: Build a structural model

- Model energy consumption in a residential building.
- Calibrate the model to simulate energy consumption under different conditions/scenarios.
- These "engineering estimates" are used to:
    - Predict savings from efficiency interventions.
    - Inform policy design.
    - Estimate untapped EE potential across the economy .

source:Rocky Mountain Institute

Strengths? Limitations?

Strengths? Limitations?

Recent studies have documented how ex ante projections can significantly over-estimate ex post realized savings.

Some likely explanations include:

- Failure to capture/model behavioral responses to efficiency improvements (e.g., rebound).
- Overly optimistic assumptions about technology performance.
- Imperfections in implementation/installation.
- Calibration errors.

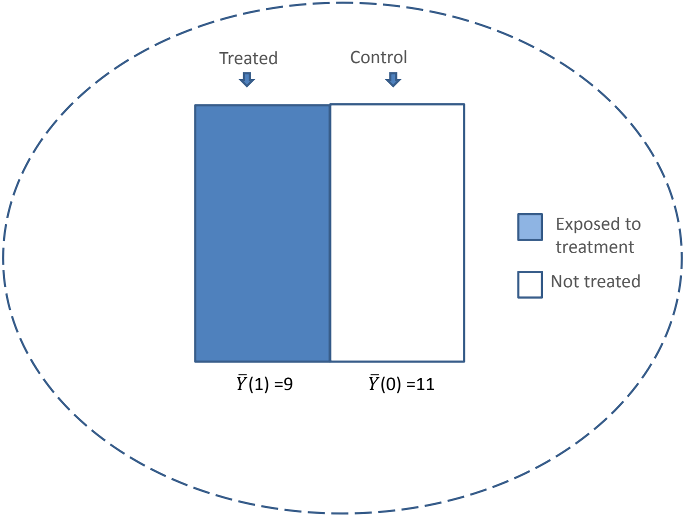
Approach 2: Estimate counterfactual using non-experimental data

- Observe energy consumption at households that have adopted an energy efficiency improvement (e.g. improved insulation, high-efficiency furnaces) and those who have not.
- Identify observationally similar households (i.e. similar energy consumption, demographics) across adopters and non-adopters.
- How can we use these data to estimate the causal effect of the efficiency improvement on energy consumption?
- Concerns about this identification strategy?

Why Worry?

- Even after controlling for a rich set of observable household characteristics, there remains lots of unexplained variation in household electricity consumption patterns, appliance adoption choices, etc.
- Even small differences in unobservable factors/trends can confound the effects we are interested in detecting.

Approach 3: Randomized Control Trial



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The gold standard?

- Assigning treatment at random ensures that there is no systematic variation in unobserved factors across treated and untreated groups.
- Even when impossible, it's good idea to approach causal inference problems with a careful consideration of what the ideal experiment would look like.
- When possible, this approach can be very powerful.. but not always as straightforward as it looks.
- Identification predicated on some important design details and assumptions...

Overview of the Fundamentals

- Potential outcomes framework (review for consistent notation)
- Identifying assumptions
- Imperfect compliance with assignment
- Power analysis

The Potential Outcomes Framework

- The ‘potential outcomes framework’ provides an intuitive theoretical foundation/structure for field experimentation.
- Review the conceptual framework/elementary mathematics that we will use to frame causal questions and derive causal estimands.
- Review assumptions that must be met if a research design is to yield credible estimates of causal impacts.

The Potential Outcomes Framework

- The conceptualization of causality is tied to a treatment (or manipulation) applied to a unit i.
- A unit can be a firm, a person, a collection of people (e.g. a classroom), a county, etc. The same firm, person observed at different times is often conceived of as a different unit.
- The critical feature of a "unit" (however it is defined) is that treatments can vary across (but not within) units.
- For the binary treatment case, the potential outcome framework pre-supposes the existence of two well defined states to which all units could potentially be exposed: $D_i = 1$, $D_i = 0$.

Potential Outcomes

- Let $Y_i(1)$ denote the outcome that would be realized at unit i if it receives the treatment;
- Let $Y_i(0)$ denote the outcome if unit i does not receive the treatment.

The unit-level causal effect of the treatment can be defined as:

$$\tau_i = Y_i(1) - Y_i(0).$$

- The comparison of potential outcomes for the same unit at the same point in time defines the treatment effect.
- Straightforward to generalize this framework to the multiple treatment case.

Notation basics

The connection between the outcome we observe and the underlying potential outcomes:

$$Y_i = Y_i(0) + (Y_i(1) - Y_i(0))D_i$$

- We only observe one potential outcome per unit, so we cannot directly calculate individual causal effects.
- Fundamental challenge of causal inference is to construct our best estimate of the counterfactual outcomes we cannot observe.
- This requires observing multiple units in different treatment states.

We've already made an important assumption...?

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Stable unit treatment value assumption (SUTVA) allows us to write:

$$Y_i(D_i)$$

The potential outcome $Y_i(t)$ for any unit i exposed to treatment t is "stable". It does not vary with the mechanism used to assign treatments, or the particular allocation of treatment, or the treatment status of other units.

For every treatment assignment vector $D \in \mathrm{D}$, the potential outcome that would be observed if unit i is exposed to treatment $D_i = t$ is always $Y_i(t)$.. If this is true, we can write the potential outcome for i as simply $Y_i(t)$.

Assignment Mechanism

When we use the potential outcomes framework as the basis for causal inference, it is critical to define (or make assumptions about) the mechanism that determines which potential outcomes we observe for each unit.

- The 'assignment mechanism' determines which units get treated (and which potential outcomes we researchers observe).
- For a binary treatment and a population of N units indexed by $i = 1..N$. we can interpret the $NX1$ vector of treatment indicators D as a vector of treatment 'assignments'.
- The matrix $\mathbf{D}$ contains all possible assignment vectors.

Assignment Mechanism

- The "assignment mechanism" is the function that assigns probabilities to all possible $N - vectors$.
- In general, these probabilities can depend on covariates X and potential outcomes Y(0) and Y(1).
- Imbens and Rubin formalize three restrictions or properties of assignment mechanisms which are important for causal inference. These restrictions serve as the organizing framework for their great book on causal inference.

Classical assignment mechanisms

- Individual conditional probabilities sum to one:

$$\sum_{D \in \{0,1\}^N} \mathrm{Pr}(\mathrm{D}|\mathrm{X}, \mathrm{Y}(0), \mathrm{Y}(1)) = 1 \tag{5}$$

- Probabilistic assignment: Unit-level probabilities of assignment to treatment all lie between 0 and 1:

$$0 < Pr(D_i = 1|X, Y_{obs}) < 1$$

- Unconfounded assignment (does not depend on potential outcomes):

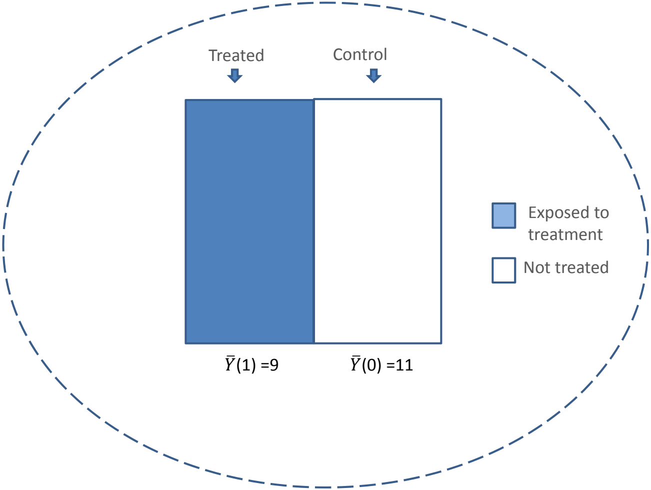
$$Pr(D|X, Y(0), Y(1)) = Pr(D|X),$$

implies potential outcomes are, conditional on X, missing at random.

Classical assignment mechanisms

- The most basic form of random assignment allocate treatments such that each subject has the same probability of treatment.
- In this case, treatment status is statistically independent of the subject's potential outcomes and background attributes X.
- When economists run 'controlled' experiment, they rarely (if ever?) have everything under control! The one important thing they do control is the assignment mechanism.

RCTs (properly implemented) are classical assignment mechanisms



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Randomization improves validity of estimates

Internal validity:

Randomization improves validity of estimates

Internal validity: the confidence with which we can state that the impact we estimate was caused by the treatment being evaluated (versus some other factors).

External validity:

Randomization improves validity of estimates

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External validity: The extent to which a study's results can be generalized/applied to other subjects or settings.

Construct validity:

Randomization improves validity of estimates

Internal validity: the confidence with which we can state that the impact we estimate was caused by the treatment being evaluated (versus some other factors).

External validity: The extent to which a study's results can be generalized/applied to other subjects or settings.

Construct validity:The extent to which the experimental treatment mimics the real-world intervention of interest.

Identification of causal effects

- The potential outcome framework can accommodate lots of heterogeneity (i.e. to each her own treatment effect).
- The summary statistic most often estimated is the average treatment effect, either for the entire population or for some sub-population.
- The average treatment effect is defined as:

$$ATE = \frac{1}{N}\sum_{i=1}^{N}\tau_i = \frac{1}{N}\sum_{i=1}^{N}(Y_i(1) - Y_i(0))$$

Estimating the average treatment effect

If a unit is selected at random, its expected treatment effect is equal to the difference between the expected value of a randomly selected $Y_i(1)$ and the expected value of a randomly selected $Y_i(0)$:

$$E[Y_i(1) - Y_i(0)] = E[Y_i(1)] - E[Y_i(0)],$$

Given random assignment of treatment, this can be rewritten as:

$$E[Y_i(1)] - E[Y_i(0)] = E[Y_i(1)|D_i = 1] - E[Y_i(0)|D_i = 0]$$

The terms $E[Y_i(1)|D_i = 1]$ and $E[Y_i(0)|D_i = 0]$ can be estimated using experimental data.

$$E[Y_i(1)] - E[Y_i(0)] = \frac{1}{N}\sum_{i=1}^{N}(Y_i(1)) - \frac{1}{N}\sum_{i=1}^{N} Y_i(0)$$

Identification assumptions?

If we interpret the difference in outcomes across treated and control groups as an unbiased estimate of the causal impact of the treatment, what are we assuming?

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- Ignorable assignment of the treatment D_i:

$$(Y_i(1), Y_i(0)) \perp D_i$$

  This assumption satisfied by design in a well implemented RCT.

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- Ignorable assignment of the treatment D_i:

$$(Y_i(1), Y_i(0)) \perp D_i$$

  This assumption satisfied by design in a well implemented RCT.

- Stable unit treatment value assumption (SUTVA). Allows us to write:

$$Y_i(D_i)$$

  Examples of SUTVA violations??

Interference between units

Examples:

- Impact of vaccinations on health outcomes
- Impact of energy efficiency investments on non-adopters
- Impact of air quality information provision on health outcomes
- Impact of electrification on income

Interference between units

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- Impact of electrification on income

If potential outcomes are a function of the entire treatment assignment vector (versus just individual treatment status) we can no longer claim to observe units in all relevant treatment states because we observe only one realization of the assignment.

Making lemonade out of SUTVA lemons...

- Social scientists are increasingly interested in substantive phenomena that lead to SUTVA violations.
- In order to make an empirical analysis of SUTVA meaningful, we must make precise assumptions about the channels through which SUTVA is violated.
- **Cue structure**! We need to impose some structure on the social networks under study (and the mechanism(s) for interference).
- Experiments designed to estimate spillovers can open up an exciting set of research questions.
- We'll discuss one such paper next week...