The Causal Inference Problem and the Rubin Causal Model

Lecture 2

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Exp Class Lectures

Definition (Treatment Variable)

The principal variable that we expect to have a causal impact.

- In general we can denote the two states of the world that a voter can be in as "1" and "0" where 1 refers to being informed and 0 refers to being uninformed or less informed.

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- In general we can denote the two states of the world that a voter can be in as "1" and "0" where 1 refers to being informed and 0 refers to being uninformed or less informed.
- Let $T_i = 1$ if an individual is in state "1"; $T_i = 0$ otherwise.

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- Useful to think of T_i as an endogenous variable,
- which is a function of a set of observable variables, Z_i,
- a set of unobservable variables, V_i,
- as well as sometimes a manipulated variable, M_i, which may be manipulated by a researcher or by nature. What is this? ...

What is the Manipulated Variable?

Definition (Manipulated Variable)

A variable that has an impact on the treatment variable that can be manipulated either naturally or by an experimenter.

Definition (Experimental Manipulation)

When the manipulated variable is fixed through the intervention of an experimentalist.

Definition (Natural Manipulation)

When the manipulated variable is part of nature without intervention of an experimentalist.

The Dependent Variable

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- Denote Y_{i1} as the voting choice of i when informed and Y_{i0} as the voting choice of i when uninformed.

The Dependent Variable

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A variable that represents the effects that we wish to explain. In the case of political behavior, the dependent variable represents the political behavior that the treatment may influence.

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- For example, Y_{ij} might be a function of a voter's partisan affiliation, an observable variable and it might be a function of a voter's value for performing citizen duty, an arguably unobservable variable.
- Note that we assume that it is possible that Z_i and X_i overlap & could be the same and that U_i and V_i overlap & could be the same (although this raises problems with estimation as discussed in the following Chapters).

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- Table 3.1 presents a summary of this notation, which is used throughout Chapters 3-5.

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- So we make the distinction between the two.

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- View that ethnicity or gender cannot be a treatment variable conflates the difficulty in identifying causal effects with defining causal effects.
- It maybe that identifying the causal effect of gender, race or ethnicity on something like earnings or, in political science voting, is difficult, but that does not mean it isn't an interesting question that we can imagine asking.

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- Subjects are shown candidate images and their brain activations are measured. The comparison is between winning and losing candidates. Subjects' brains appear to respond.
- Is this an experiment? No manipulation of the images.
- But there is intervention in the DGP and considerable control over the choices of subjects.

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- The main issue in causal inference is figuring out how to measure δ_i.

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The Causal Inference Problem & Observational Data

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- Thus, with observational data the observed voting choice of an individual, Y_i at a given point in time is given by: $Y_i = T_i Y_{i1} + (1 - T_i)\, Y_{i0}$
- As a result, we cannot observe directly the causal effect of information on any given individual's voting choice since for each individual we only observe one value of Y_i. How can we deal with this problem? ...

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- Winship & Morgan (1999, page 664) summarize causal inference in a single question (using our notation): "Given that δ_i cannot be calculated for any individual and therefore that Y_{i1} and Y_{i0} can be observed on mutually exclusive subsets of the population, what can be inferred about the distribution of the δ_i from an analysis of Y_i and T_i?"

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- At this point RCM requires thinking theoretically or hypothetically in order to measure causal effects.

Definition (Between-Subjects Experimental Design)

Subjects in an experiment make choices in only one state of the world.

Definition (Within-Subjects Experimental Design)

Subjects in an experiment make choices in multiple states of the world.

Definition (Multiple-Choice Procedure)

Subjects in a within subjects experimental design make choices in multiple states of the world simultaneously.

Definition (Strategy Method)

A version of the multiple-choice procedure in which subjects choose a strategy to be implemented in an experiment testing a game theoretic situation. The strategy is a set of choices conditional on hypothetical information or previous choices that subjects may face when the choice situation occurs in the experiment.

Definition (Decision Method)

When subjects in an experiment evaluating a game theoretic model make choices when the decision situation for the choice occurs in the experiment given knowledge of the information available at that time and actual previous choices made by other subjects.

Cross-Over Procedures & the Importance of Sequence

Definition (Cross-Over Procedure)

Subjects make choices in states of the world sequentially.

Design versus Analysis

Figure: Stages in Experimental Research

Design versus Analysis

Definition (Design Stage)

The period before an experimenter intervenes in the DGP in which he or she makes decisions about the design of the experiment such as the extent to use experimental control and/or random assignment.

Definition (Analysis Stage)

The period after data has been generated either by an experiment or without experimental intervention in which a researcher uses statistical tools to analyze the data such as statistical control and statistical methods that attempt to simulate random assignment.

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- Other measures will discuss later ...

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  - Treatment of unit i only affects the outcome of unit i (thus it does not matter how many others have been treated or not treated) (Note this means it is a "local" effect, can't be aggregated, something OFTEN ignored)
  - For ATE and ATT, the treatment is homogeneous across voters.

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  - Assumes a recursive model of causality. It cannot measure the causal effects of outcomes that occur simultaneously.

Is RCM Good or Bad?

- What do you think?