# POL332: Using Data to Understand Politics

Shamel Bhimani

Fall 2025

## Contents

**1 Introduction to Causality** **2**
1.1 Chapter I – Kosuke Imai. Quantitative Social Science: An Introduction. Princeton: Princeton University Press, 2017. . . . . 2
1.1.1 Introduction to Causality . . . . . 2
1.1.2 Causal Effects and the Counterfactual . . . . . 2
1.1.3 Randomized Controlled Trials . . . . . 2

**2 Natural Experiments** **3**
2.1 Chapter II – Kosuke Imai. Quantitative Social Science: An Introduction. Princeton: Princeton University Press, 2017. . . . . 3
2.1.1 Observational Studies . . . . . 3
2.1.2 Sample Average Treatment Effect for the Treated (SATT) . . . . . 4

# 1 Introduction to Causality

## 1.1 Chapter I – Kosuke Imai. Quantitative Social Science: An Introduction. Princeton: Princeton University Press, 2017.

### 1.1.1 Introduction to Causality

**Experimental Data:** examines how a treatment causally affects and outcome by assigning varying values of the treatment variable to different observations, and measuring their corresponding values of the outcome.

**Contingency Table:** Summarizes the relationship between the treatment variables and the outcome variable.

**Binary Variable/Dummy Variable:** Takes the value of 1 if a condition is true and 0 if the condition is false. The sample of a binary variable equals the sample proportion of 1s. This means that the true observations can be conveniently calculated as the *sample mean*, or *sample average*.

To calculate the sample mean:

$$\mu = \frac{\sum_{i=1}^{n} x_i}{n}$$

Where:

$x_i$ represents each individual value or data point in the sample;
$n$ represents the total number of observations or data points in the sample.

### 1.1.2 Causal Effects and the Counterfactual

Causal inference is the comparison between the factual and the counterfactual, i.e., what actually happened and what would have happened if a key condition were different. Unfortunately, we would never observe this counterfactual outcome, because changing one key variable and keeping the rest the same may, in some cases, affect internal validity.

For each observation $i$, we can define the **casual effect** of a binary treatment $T_i$ as the difference between two potential outcomes, $Y_i(1) - Y_i(0)$, where $Y_i(1)$ represents the outcome that would be realized under the treatment condition ($T_i = 1$) and $Y_i(0)$ deontes the outcome that would be realized under the control condition ($T_i = 0$).

The **fundamental problem of causal inference** is that we observe only one of the two potential outcomes, and which potential outcome is observed depends on the treatment status. Formally, the observed outcome $Y_i$ is equal to $Y_i(T_i)$.

This simple framework of causal inference also clarifies what is and is not an appropriate causal question. Characteristics like gender and race, for example, are called *immutable characteristics*, and many scholars believe that causal questions about these characteristics are not answerable. In fact, there exists a mantra which states, "No causation without manipulation". However, immutable characteristics *can* and have been studied. Instead of tackling the task of directly estimating the causal effect of race, researchers use *perception scores* of the unit of analysis.

### 1.1.3 Randomized Controlled Trials

In a **randomized controlled trial (RCT)**, each unit is randomly assigned either to the treatment or control group. This randomization of treatment assignment guarantees that the average difference in outcome between the treatment and control groups can be attriobuted solely to the treatment, because the two groups

are on average identical to each other in all pretreatment characteristics.

**Sample Average Treatment Effect:** is defined as the sample-average of individual-level causal effects (i.e., $Y_i(1) - Y_i(0)$). Formally, in the potential outcomes framework:

Let $Y_i(1)$ = potential outcome for unit $i$ if treated;
Let $Y_i(0)$ = potential outcome for unit $i$ if untreated;
The individual treatment effect is:

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

The Sample Average Treatment Effect (SATE) is then:

$$SATE = \frac{1}{n}\sum_{i=1}^{n}(Y_i(1) - Y_i(0))$$

where $n$ is the sample size.

The SATE is not directly observable. For the treatment group that received the treatment, we observe the average outcome under the treatment but do not know what their average outcome would have been in the absence of treatment for the same unit (the fundamental problem of causal inference). The same problem exists for the *control group* because this group does not receive the treatment and as a result, we do not observe the average outcome that would occur under the treatment condition.

In order to estimate the average counterfactual outcome for the treatment group, we may use the observed average outcome of the control group. Similarly, we can use the observed average outcome of the treatment group as an estimate of the average counterfactual outcome for the control group. This suggests that SATE can be estimated by calculating the difference in the average outcome between the treatment and control groups, or the *difference-in-means estimator*.

# 2 Natural Experiments

## 2.1 Chapter II – Kosuke Imai. Quantitative Social Science: An Introduction. Princeton: Princeton University Press, 2017.

### 2.1.1 Observational Studies

Although RCTs can provide an internally valid estimate of causal effects, in many cases social scientists are unable to randomize treatment assignment in the real world for ethical and logistical reasons. Here, we consider Observational Studies.

**Observational Studies:** Researchers simply observe naturally occurring events and collect and analyze the data, without direct intervention.

- In such studies internal validity is likely to be compromised because of possible selection bias.
- External validity is often stronger than that of RCTs.
- Findings are more generalizable.

**Cross-Section Comparison Design:** More commonly known as a **cross-sectional study**, is a type of observational research that analyzes data from a population, or a representative subset, at a single point in time. It is used to measure the prevalence of an outcome and its associated factors in a specific population.

The important assumption of observational studies is that the treatment and control groups must be comparable with respect to everything related to the outcome other than the treatment.

**Confounding Variables:** A pretreatment variable that is associated with both the treatment and the outcome variables is called a **confounder** and is a source of **confounding bias** in the estimation of the treatment effect.

**Self-selection Bias:** Confounding bias due to self-selection into the treatment group is called *selection bias*. Selection bias often arises in observational studies because researchers have no control over who receives the treatment.

- The lack of control over treatment assignment means that those who self-select themselves into the treatment group may differ significantly from those who do not in terms of observed and unobserved characteristics.
- This makes it difficult to determine whether the observed difference in outcome between the treatment and control groups is due to the difference in the treatment condition or the differences in confounders.

In observational studies, the possibility of confounding bias can never be ruled out. However, researchers can try to address it by means of *statistical control*.

**Statistical Control:** Confounding bias can be reduced through statistical control whereby the researcher adjusts for confounders using statistical procedures. Some methods of statistical control are:

- **Subclassification:** The idea is to make the treatment and control groups as similar to each other as possible by comparing them within a subset of observations defined by shared values in pretreatment variables or a subclass.

In observational studies, the data collected over time are a valuable source of information. Multiple measurements taken over time on the same units are called *longitudinal data* or *panel data*.

- Longitudinal data often yield a more credible comparison of the treatment and control groups than *cross-section data* because the former contain additional information about changes over time.

**Before-and-after Design:** Examines how the outcome variable changed from the pretreatment period to the post-treatment period for the same set of units. The design is able to adjust for any confounding factor that is specific to each unit but does not change over time. However, the design does not address possible bias due to time-varying confounders.

**Difference-in-Differences Design:** Extends the before-and-after design to address the confounding bias due to time treends. The key assumption behind the DiD design is that the outcome variable follows a parallel trend in the absence of treatment.

- Under the DiD design, the sample average causal effect estimate is the difference between the observed outcome after the treatment and the counterfactual outcome derived under the parallel time-trend assumption.
- The quantity of interest under the DiD design is called the *sample average treatment efect for the treated (SATT)*.

### 2.1.2 Sample Average Treatment Effect for the Treated (SATT)

The SATT is the difference between the average outcome of the treated group with the treatment and the average outcome the sample group *would have had* if they had not been treated.

The formula can be expressed as:

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

Where:
$Y_i(1)$ is the potential outcome for individual $i$ if they receive the treatment;

$Y_i(0)$ is the potential outcome for individual $i$ if they do not receive the treatment (the counterfactual);
$D_i - 1$ indicates that individual $i$ is in the treatment group;
$E[.]$ is the expectation operator, which in this context means we are taking the average over the individuals in the specified group.

A key challenge in calculating the SATT is that we can never observe both potential outcomes for the same individual at the same time. We only observe the outcome for the treated group with the treatment. The counterfactual – what would have happened to the treated group without the treatment – is unobserved.

Therefore, to estimate the SATT, we need to find a suitable comparison group of untreated individuals that can serve as a proxy for the counterfactual outcome of the treated group. A common way to express the estimation of SATT using observed data is:

$$SATT = \frac{1}{n_1} \sum_{i=1}^{n} T_i[Y_i(1) - Y_i(0)]$$

Where:
$T_i$ is the binary treatment indicator variable;
$n_1 = \sum_{i=1}^{n} T_i$ is the size of the treatment group.