Data, Causality, Stats Review

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Today's plan

1. Review reading topics
   1.1 Types of data
   1.2 How type of data informs us about causality
   1.3 Statistics review
2. In-class activity: Working with data in R

Types of data

Experimental vs. Observational

- **Experimental data:**
  - Data from controlled experiments
  - e.g. a biologist experiments with two genetically identical plants
  - Relatively uncommon in the social sciences
- **Observational data:**
  - a.k.a. Nonexperimental data; Retrospective data
  - Data collected passively, after observing some outcomes
  - Collectors act as **observers** of what has happened
  - e.g. Census Bureau surveys households and asks about income & education

Cross-sectional, Time series, and Longitudinal Data

- **Cross-sectional:** Data on multiple units collected at a single point in time

- **Time series:** Data on one unit collected at a multiple points in time

- **Longitudinal:** Multiple units are followed over multiple time periods

    - “Longitudinal” a.k.a. “Panel”

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  - e.g. OU Class of 2019, surveyed each academic year
  - "Longitudinal" a.k.a. "Panel"

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How the type of data informs us about causality

How the type of data informs us about causality

- Experimental data can be cross-sectional, time series, or longitudinal
- The two ideas are not related
- Experimental/Observational tells us how confident we can be that correlation $\Rightarrow$ causation
- Cross-Sec/Time-Series/Panel tells us how to correctly compute correlation

Stats Review

Sampling

- Cross-sectional data is a **random sample** from some population
- We look at data because we want to learn something about the population
  - e.g. Estimate a statistic
  - e.g. Test a hypothesis
- A random sample:
  - is representative of the population of interest
  - gives us the best chance of learning about the population

Estimators and Estimates

- **Estimator of θ:** Some rule that assigns each random sample a value of θ
  - e.g. Sample average, $\overline{Y} = \frac{1}{N}\sum_{i=1}^{N} Y_i$
  - in this case, the *population parameter* is μ (the sample mean); $\overline{Y}$ estimates it
- **Estimate of θ:** the value the estimator spits out given a random sample
- Estimates depend on the sample $\Rightarrow$ estimates are random variables
  - **Sampling distribution:** The distribution of estimates (given all samples)
  - can characterize it by using summary stats (mean, variance, etc.)

Bias

- **Bias of an estimator W:** $\text{Bias}(W) = E(W) - \theta$
  - i.e. if we take a bunch of samples, the average of all estimates $= \theta$
  - $\overline{Y}$ is an unbiased estimator of μ
  - $\frac{1}{N-1}\sum_{i=1}^{N}\left(Y_i - \overline{Y}\right)^2$ is an unbiased estimator of σ^2
- But some poor estimators are unbiased
- And some great estimators are biased
- So bias isn't everything; but all else equal, we like unbiased estimators

Sampling Variance and Efficiency

- Bias focuses on the average of an estimator's sampling distribution
- It's also important to think about the *variance* of the sampling distribution
  - e.g. Variance$\left(\overline{Y}\right) = \frac{\sigma^2}{N}$
- An estimator is **efficient** if it has a lower sampling variance than all other estimators
- As econometricians, we should be using *unbiased* and *efficient* estimators!

Asymptotic Properties of Estimators

- **Asymptotic** means ”infinite-sample”
- A good way to evaluate an estimator is to look at its properties as $N \to \infty$
- An estimator W is **consistent** if its sampling distribution becomes more and more centered on θ as $N \to \infty$ (see: Law of Large Numbers)
- W is **asymptotically normal** if its sampling distribution increasingly resembles a Normal distribution as $N \to \infty$ (see: Central Limit Theorem)
- The best estimators are those that are CAN: Consistent and Asymptotically Normal

Hypothesis Testing

- **hypothesis testing:** A method to answer yes/no questions using a sample of data
  - e.g. Are Asian-Americans discriminated against in admissions to Harvard?

- Define null (H_0) and alternative (H_a or H_1) hypotheses
  - e.g. let $\theta = \mu_a - \mu_w$ be the difference in admissions rates of white and Asian Harvard applicants
  - if discrimination, then should have $\theta < 0$

$$H_0 : \theta = 0$$
$$H_a : \theta < 0$$

  - How low of T needed to conclude discrimination? (depends on $\text{Var}(T)$!)

Significance and Power

- **significance level:** our tolerance for making a Type I error (rejecting H_0 when we shouldn't)

- **power:** likelihood of *not* making a Type II error (failing to reject H_0 when we should)

- Set a significance level α (e.g. 5%)

- α quantifies our tolerance to make a Type I error

- Subject to α, want to maximize power

- There is a trade-off between power and significance

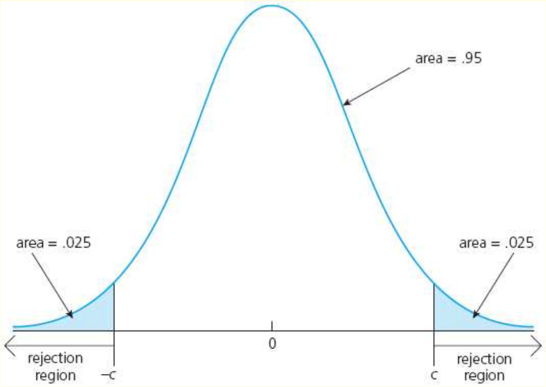
What goes into a hypothesis test

- Need two things to conduct a hypothesis test:

    1. **Test statistic (T):** Some function of the sample of data

    2. **Critical value (c):** Value of T such that we reject H_0 if, e.g. $|T| > c$

- c is implicitly a function of the significance level α



A two-sided test with $\alpha = 0.05$ (Wooldridge Fig. C.6)

Steps to performing a hypothesis test

- Declare a significance level (5% is most common)
- Determine if your H_a is one- or two-sided (two-sided most common)
- Determine what distribution your test statistic will have (t is most common)
- Given T and α, compute critical value
- Compute the value of T for your sample
- If $|T| > c$, reject H_0; otherwise, fail to reject H_0

Example: Discrimination in Harvard admissions

- Recall our hypothesis test introduced earlier:

$$H_0 : \theta = 0$$
$$H_a : \theta < 0$$

  where $\theta = \mu_a - \mu_w$ is the Asian-White difference in admissions rates

- Suppose our sample of data contains $N = 10,000$ applicants from each group.

- Let $\alpha = 0.05$. What is c?

  - Look up c in a t distribution table

  - For one-tailed test with $9,999$ degrees of freedom, $c = -1.65$

Example: Discrimination in Harvard admissions

- Suppose $\bar{y}_a - \bar{y}_w = -0.06$; and $\text{se}\left(\bar{y}_a - \bar{y}_w\right) = 0.01$

$$
\begin{aligned}
t &= \frac{\text{estimate} - \text{null}}{\text{std. err.}} \\
&= \frac{-0.06 - 0}{0.01} \\
&= -6
\end{aligned}
$$

- $-6 < -1.65$ so we reject H_0
- conclude that there is evidence of discrimination against Asian-Americans

p-values

- Often, the outcome of the hypothesis test will be summarized by the p-value instead of comparing T and c.

- **p-value:** The largest significance level at which we could conduct the test and still fail to reject H_0.

- Reject H_0 if $p < \alpha$

Hypothesis testing in R

- R will compute test statistics, critical values, and p-values automatically
- We'll practice this in more detail next time