Introduction to Observational Studies

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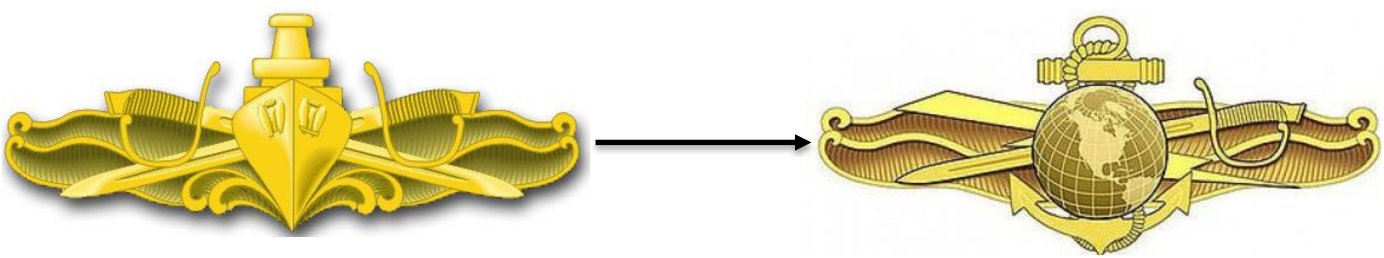
Outline

- Motivating example
- Observational studies vs. randomized experiments
- Observational studies: basics
- Some adjustment strategies
- Matching / stratification
- Difference-in-difference estimators
- Instrumental variables

Should Navy officers be denied lateral transfer by their supplying communities?

- A Navy officer can apply for a lateral transfer to another community if openings exist.
- The lateral transfer board ensures the receiving community gets the best and fully qualified officers.
- Transfer also needs approval from the supplying community.
- Officers who get denied may leave the Navy.
  - Reason for denial is not recorded in the data.



Navy officer lateral transfers and retention

What's the **causal effect** of being denied on retention?

Should supplying community quotas be reconsidered?

Navy officer lateral transfers and retention

- Problem: Officers who get denied could be:
  - Not best and fully qualified for the job
  - Not great at their job
  - Needed in their current job

- Denied officers could be ‘worse’ than those who get approved
  - Failure to promote correlated with denial and loss rate
  - Are they likely to leave the Navy anyway?

Navy officer lateral transfers and retention

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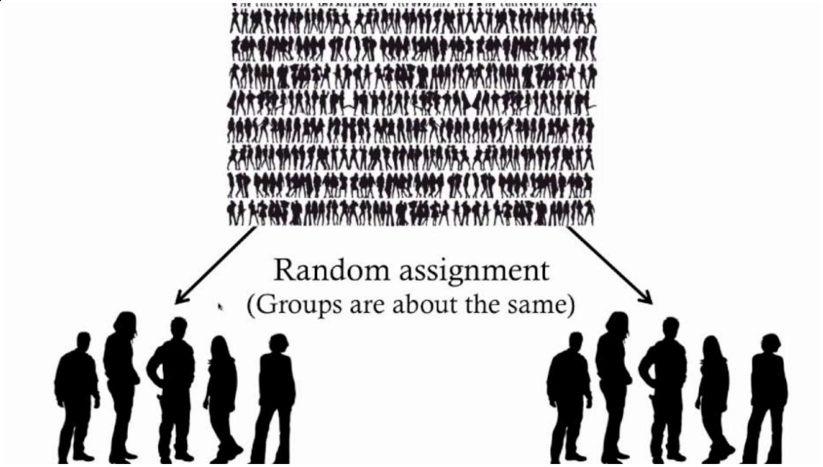
How do we adjust for **observed and unobserved** qualities?

Can we ever get to **causal** effects?

Randomized Experiments vs. Observational Studies

In a randomized experiment, 'treatment' is **randomly** assigned.

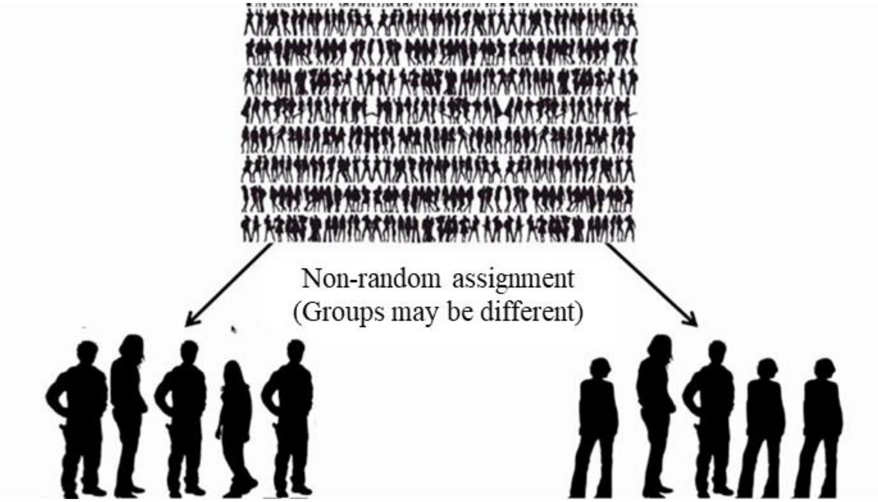
- Probability of being assigned to 'treatment' is the same for everyone (or everyone within a group).
- As n gets larger, observed and unobserved characteristics of the treated and control groups start approaching **balance.**
- Difference in outcomes can be attributed to treatment (**causation**).



Randomized Experiments vs. Observational Studies

In an observational study, ‘treatment’ assignment **may be** applied non-randomly.

- Different subjects may have **different probabilities of treatment assignment.**
- Observed and unobserved characteristics of treatment groups may not be balanced.
- Difference in outcomes between groups is much harder to attribute to treatment alone.



A bit of history

- 1950s and 1960s: interest in causal relationship between smoking and lung cancer
  - Establishment of the field of observational studies
- Cochran (1965) clarified the benefits of learning from reliably planned, measured, and analyzed observational studies.
  - He provided an infrastructure for planning and analysis.
- Cochran focuses on two main study characteristics:
  - The objective is to elucidate cause-and-effect relationships.
  - It is not feasible to use controlled experimentation.

Observational Studies: the basics

Cross-Sectional

- Individual-level data collected at a specific point in time

Case-Control

- Individual-level data collected for cases (subjects with the outcome of interest) vs controls

Cohort

- Following a cohort of subjects over time
- Can be prospective or retrospective

Ecological

- At least one variable is measured on the population level

Potential outcomes

Let r_{Ti} be the response of applicant officer i to being denied lateral transfer ('treatment') and r_{Ci} be the response of applicant officer i to being approved ('control'). Then the potential outcomes are:

- r_i=1 if officer leaves the Navy
- r_i=0 if officer stays in the Navy

For each officer i, potential outcomes and treatment effects are:

r_{Ti}	r_{Ci}	δ_i	Explanation
0	0	0	Officer stays in the Navy no matter what
0	1	-1	Approval causes the officer to leave the Navy
1	0	1	Denial causes the officer to leave the Navy
1	1	0	Officer leaves the Navy no matter what

The fundamental problem of causal inference

- For officer i, the treatment effect is $\delta_i = r_{Ti} - r_{Ci}$
- Average treatment effect (ATE) for the sample is $\frac{1}{n}\sum_{i=1}^{n} \delta_i$
- You could also estimate
  - Attributable effect
    - Number of events among treated subjects that were caused by the treatment (the number of officer losses that were caused by denials)
  - Average effect of treatment on the treated (ATT)
- **For each officer, we observe only r_{Ti} or r_{Ci} but never both**
- Sample treatment effect estimation is an issue of inference and not arithmetic

Causal inference – statistical questions

In randomized experiments

- Does denial ***cause*** officers to leave the Navy? (tests of no effect)
  - Fisher 1935 – randomization inference
- How much more likely is a denied officer to leave the Navy? (estimates of magnitude of the effect)

Causal inference – statistical questions

In observational studies

- What could the officers have done if approved or denied? (Potential outcomes framework)
  - Neyman 1923, Rubin 1974
- Adjustment for officer demographics and quality (overt biases)
  - Tests of no effect
  - Estimates of magnitude of the effect
- What if we missed something important? (sensitivity to hidden bias)

Some adjustment strategies

- Matching / Stratification
  - Propensity Scores
  - Prognostic Scores
- Difference-in-difference estimators
- Instrumental Variables

- Multiple other schools of thought
  - Recommended reading: *Causality* by Judea Pearl

Some standard assumptions

The Stable Unit Treatment Value Assumption (SUTVA)

- Each officer decides to stay or leave the Navy regardless of other officers' approval / denial or the approval process
- Potential outcomes for a subject are independent of treatment assignment for all other units and of the assignment mechanism
- SUTVA is usually assumed, but is rarely tested
- Interference between units can result in violations
    - Rubin (1990)

Some standard assumptions

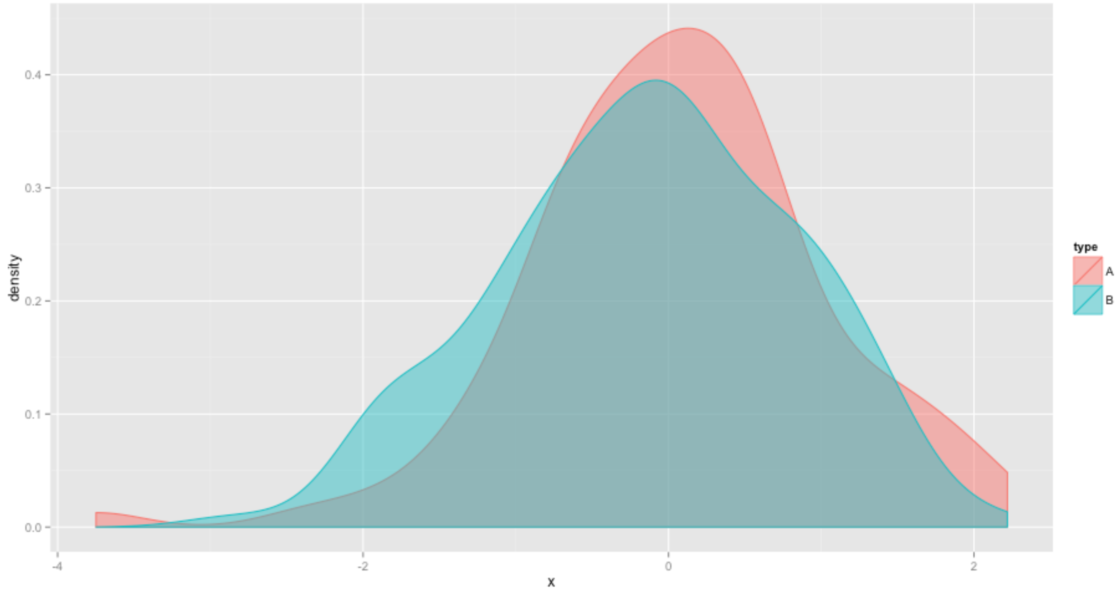
Strong Ignorability of Treatment Assignment

- Application approval or denial depends only on variables we measured and recorded
- A.k.a. Conditional Independence Assumption (CIA)
  - Rosenbaum and Rubin (1983)
- Assumes selection into treatment based on observed covariates
- Critical in matching, stratification, and covariance adjustment

Some standard assumptions

Common Support Condition

- Each officer can be approved and denied
- Probability of assignment to treatment is bounded away from zero and one
- Rosenbaum and Rubin (1983)



Curse of dimensionality

- There are a lot of variables that matter to approval (demographics, officer quality, accession source, etc.)
  - Concern about having to adjust for many potentially causal or "important disturbing variables" (Cochran 1965)

- 20 covariates each with just 2 levels results in over a million categories
  - Exact matches are hard to find
  - Approximate matches are hard to characterize
  - Rosenbaum and Rubin (1985)

- Hence the focus on dimension-reduction techniques
  - Propensity score (Rosenbaum and Rubin, 1983)
  - Prognostic score (Hansen, 2007)

Propensity scores

- In an experiment, we would compare officers who are similar in all important respects except for getting denied (the 'treatment').
- We can create such data configurations using *propensity score matching.*
  - Propensity score for each officer is the estimated probability of getting denied lateral transfer given their demographics and quality.
  - The propensity score the probability of "treatment" given observed covariates.
  - It reduces a multivariate **X** to a one-dimensional score.
  - Matching on it should balance variables between the two groups.
  - Matching can result in unbiased estimates of treatment effects.
  - Importantly, we can check whether matching 'worked' before we proceed with analysis of the impact of approval / denial.

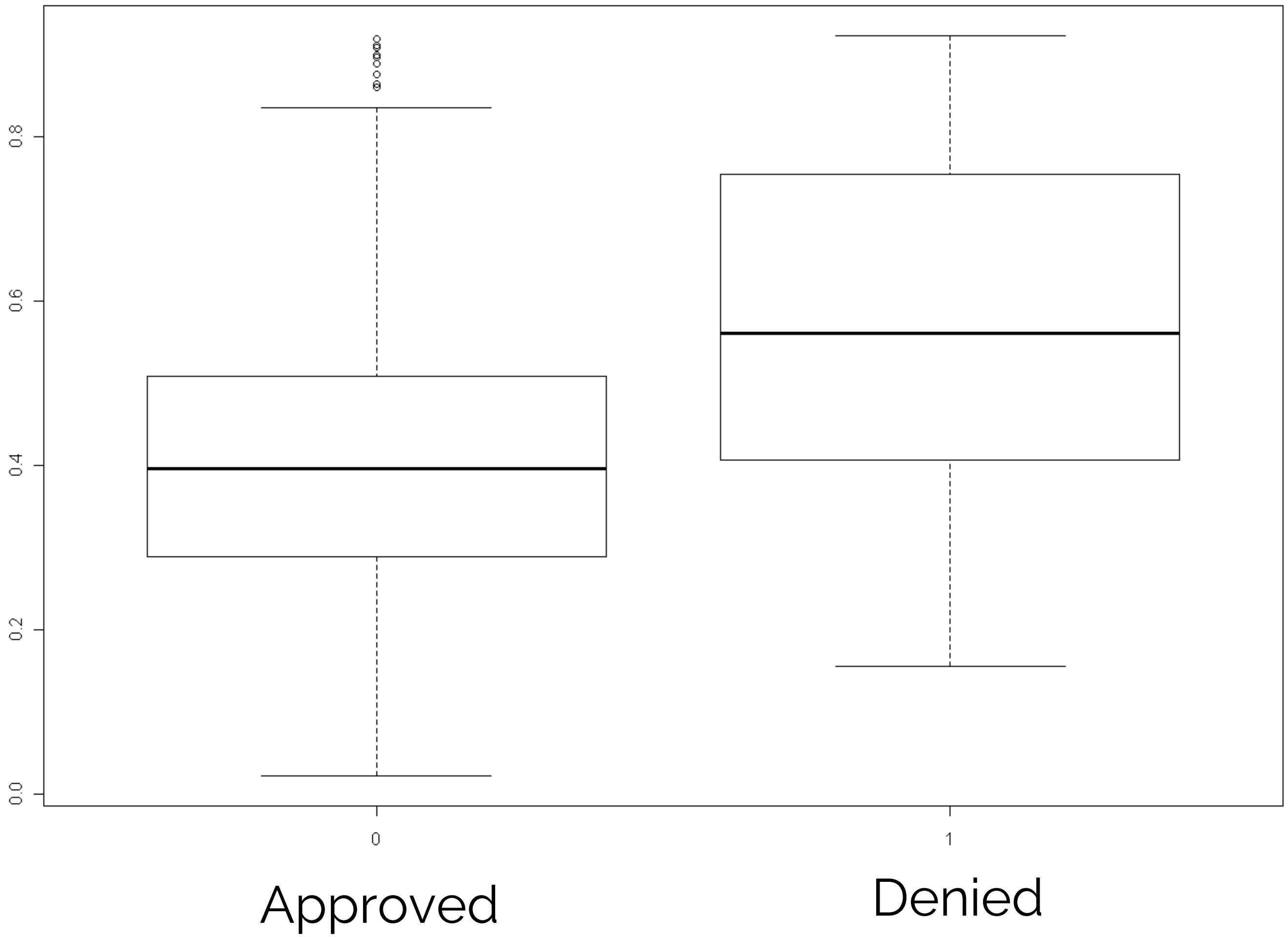
Propensity scores

- Vary with covariates for each officer
- Can be higher for denied officers (treated subjects)
- Overlap is important!
- Are an estimated quantity and that's OK
  - Subclassification on the propensity score should balance the observed covariates that went into its estimation.
- Within subclasses, the joint distribution of observed covariates should be similar between treated and control subjects.

Propensity score shortcomings (Rubin 1997)

- They only help adjust for observed covariates, and unobserved to the extent that they are correlated with observed.
- They work better in large samples.
- Covariates related to treatment assignment and not the outcome are treated the same as the ones strongly related to the outcome and not treatment.
- Misspecification is difficult to diagnose, and the consequences of it are elusive.

Officer Propensity Scores



Source: The Navy Officer Lateral Transfer Process and Retention: A Matched Analysis, Pinelis & Parcell, JSM 2011

Prognostic Scores

- Basic idea: Not all covariates are created equal.
  - Balancing covariates strongly related to the outcome may be more important (Hansen 2008).
- The prognostic score measures the relationship between observed variables and potential outcomes.
  - First, retention (the outcome) is modeled just for officers who got approved (in the control group).
  - Then, the obtained model is used to predict retention (the response) for officers who got denied (in the treated group).
  - The fitted values from the model are the prognostic score.
- Allows the comparison of officers who would have responded similarly to being approved.
- Controversial practice of using outcomes at this stage of the analysis.

Stratification and Matching

- An attempt to 'recover' the hidden block-randomized experiment from observational data (Hansen, 2009)

- Stratification first addressed by Cochran (1968)

- Matching options
  - On covariates
  - On propensity or other scores
  - Within calipers

- Matching algorithms
  - Greedy / nearest-neighbor
  - Optimal

Balance assessments

How do you know if matching / stratification worked?

- Are observed covariates any more balanced than they were before?
- Unobserved covariates balance to the extent that they are correlated with observed covariates that got balanced.

Balance assessments

To test balance or not?

- Unresolved debate in statistical literature
- Population hypothesis tests
- Randomization inference

Inference

- Standard inference approaches apply
- Randomization inference (tests of no effect)
  - Fisher exact test
  - Wilcoxon's signed rank and rank sum tests
  - Mantel-Haenszel-Birch test
  - Logrank test
- Parametric techniques
  - ANOVA (comparing groups)
  - Regression (estimating treatment effects)
- Nonparametric covariance adjustments (Rosenbaum 2002)

Sensitivity Analysis

Basic questions:

- How big of an effect does my missing variable have to have in order to break down my result?
- How likely is a variable like that to exist?

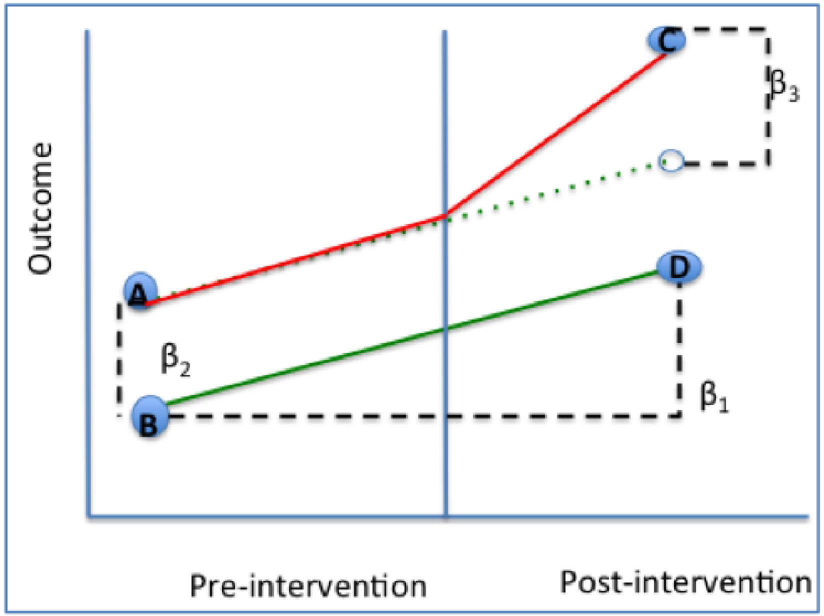
Difference-in-Difference Estimators

- Compares the average change in outcome for the treatment group to the average change in outcome for the control group
- Uses panel data to compare differences using longitudinal analyses
- Assumptions:
  - Standard OLS assumptions
  - SUTVA
  - Parallel trends assumption (in the absence of treatment, the difference between the ‘treatment’ and ‘control’ group is constant over time)

Difference-in-Difference Estimators

Usually implemented as an interaction term between time and treatment group dummy variables in a regression model

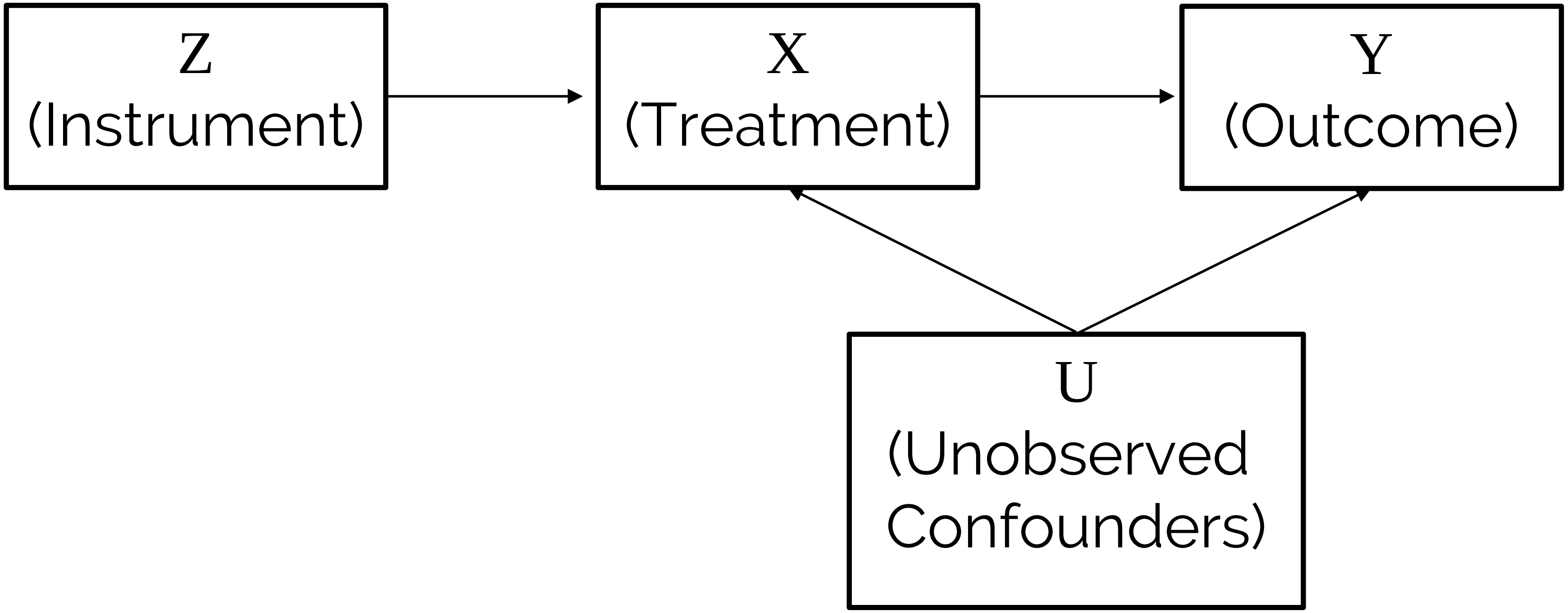
Coefficient	Calculation	Interpretation
β_0	B	Baseline average
β_1	D-B	Time trend in control group
β_2	A-B	Difference between two groups pre-intervention
β_3	(C-A)-(D-B)	Difference in changes over time



Source: https://www.mailman.columbia.edu/research/population-health-methods/difference-difference-estimation

Instrumental variables

Concept introduced in 1928 by Philip G. Wright in a book called *The Tariff on Animal and Vegetable Oils*



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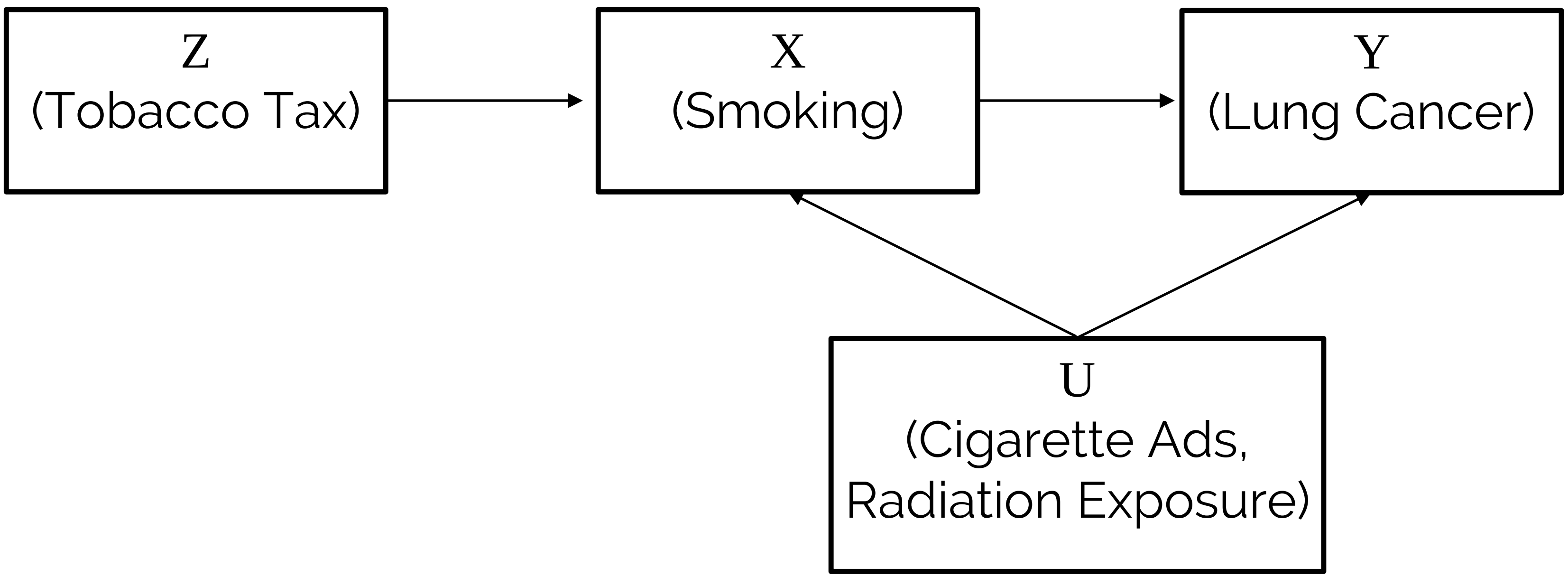

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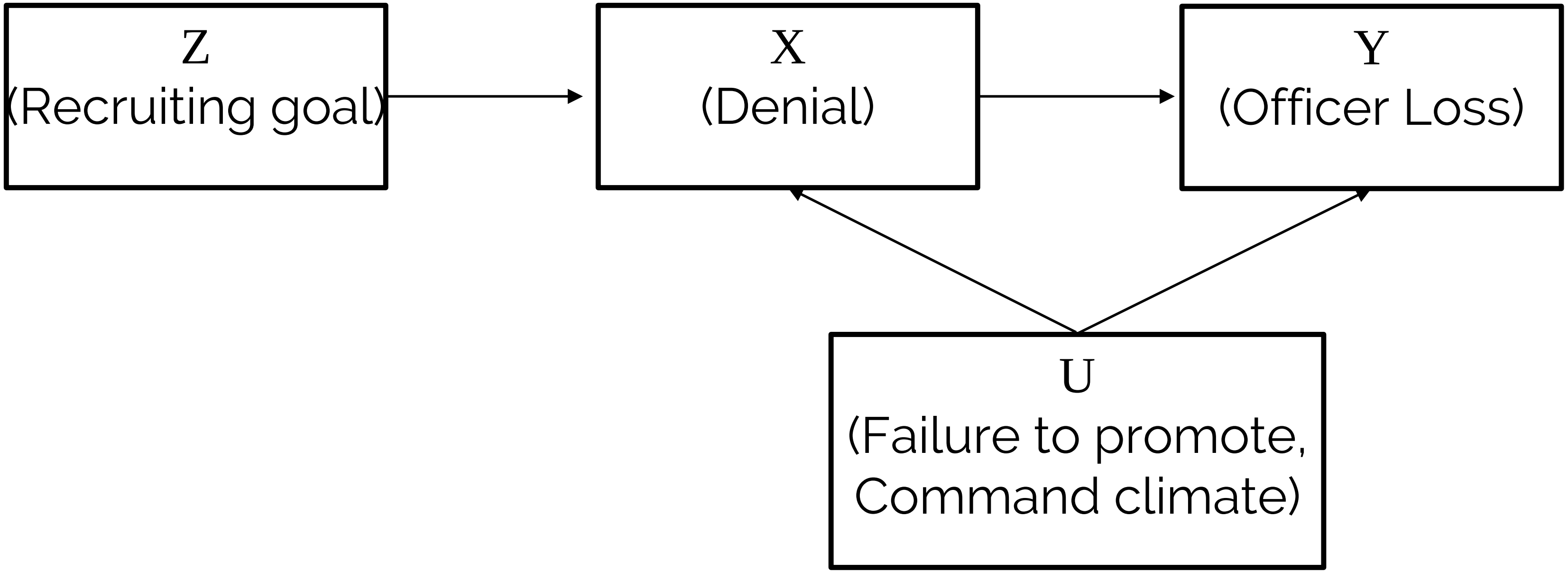
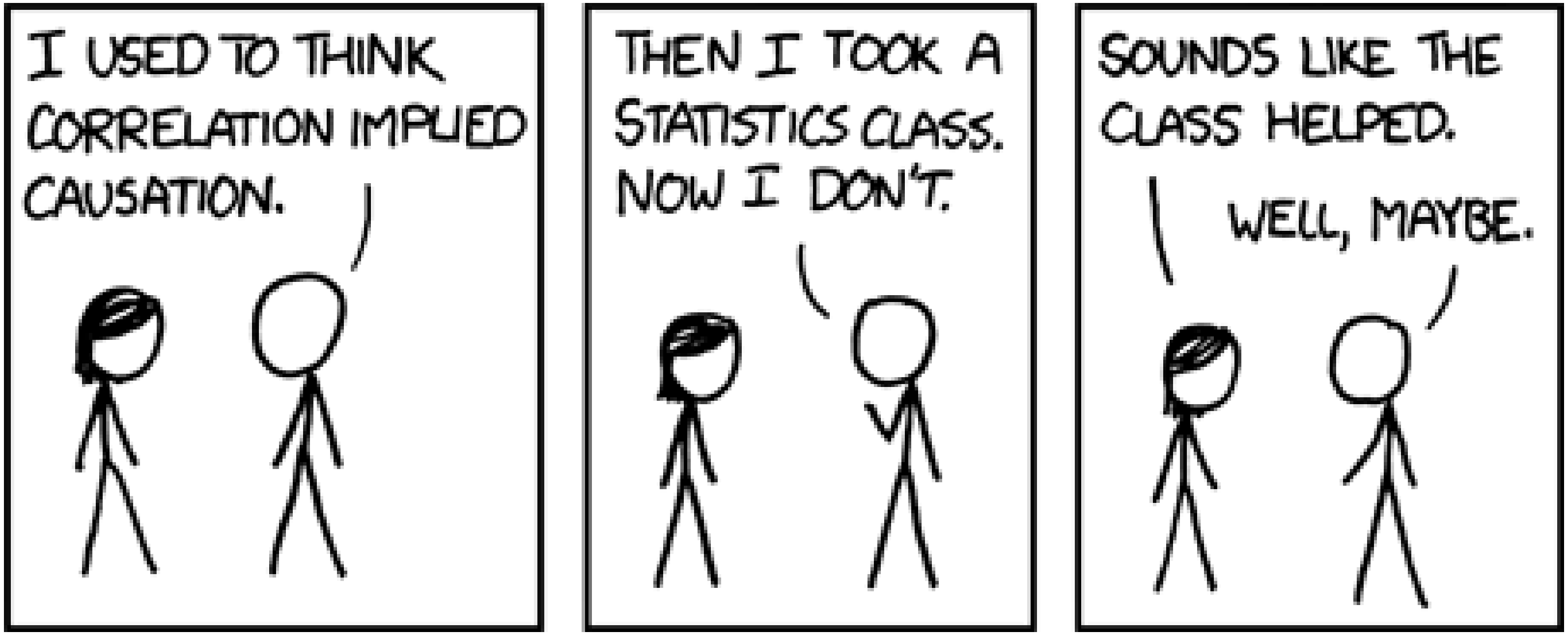


Instrumental variables

- Basic idea: in $y_i = \beta x_i + u_i$, x_i are correlated with u_i
- To estimate β, we can use IV z_i and two stage least squares regression to replace x_i with $\widehat{x_i}$ that are correlated with x_i but not with u_i
  - First, regress X on Z
    - Predicted values from this regression are $\widehat{x_i}$
  - Then regress Y on $\hat{X}$
    - Resulting estimates of β are consistent
    - Can also be interpreted as a Generalized Method of Moments estimator

Conclusion


I USED TO THINK CORRELATION IMPLIED CAUSATION.
THEN I TOOK A STATISTICS CLASS. NOW I DON'T.
SOUNDS LIKE THE CLASS HELPED.
WELL, MAYBE.