Instrumental Variables Estimation

Courtney Van Houtven, PhD MSc

Department of Population Health Sciences
Duke University School of Medicine

Agenda & Learning Objectives

- Learning Objectives for Today
  - Understand Endogeneity
  - Understand value of adjusting for unobserved confounding
  - Understand tradeoffs b.t. using Instrumental Variables Estimation (IV) and not using it

What is Bias?

- Say we have a simple linear model where we want to know the effect of some variable X on some outcome Y

- $Y = \beta_{true}X + u$

- An estimated statistic β_{est} is said to be a biased estimate of the effect of X on Y if

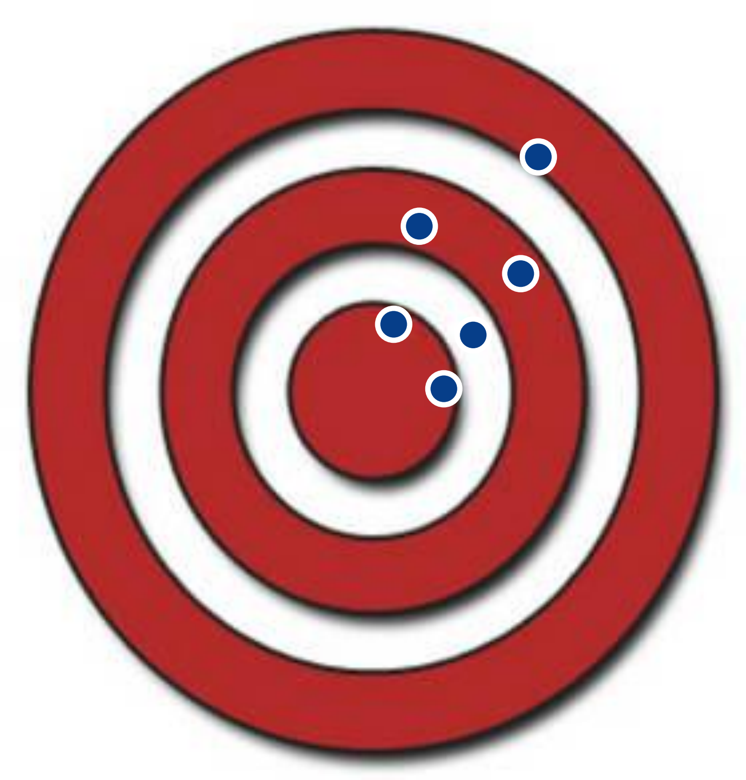
  $\beta_{est} \neq \beta_{true}$ or equivalently

  $\beta_{est} = \beta_{true} + \mathbf{b}$ where **b** is the bias in β_{est}

Visualizing Unbiasedness

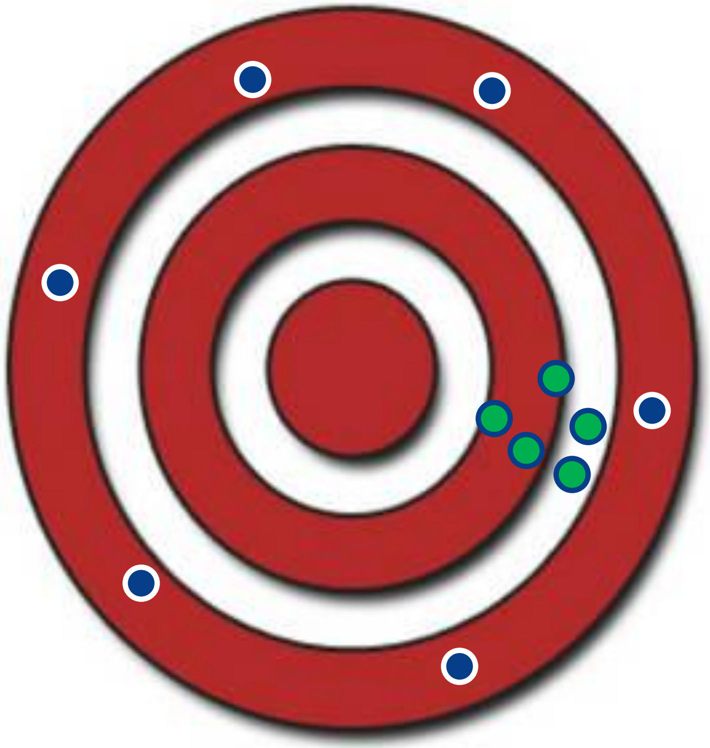
- Say the center of target is true value of what you are trying to estimate
  - E.g., incremental effect of public health insurance on inpatient utilization
- Bullet holes are estimates
- Gun is an estimator (i.e., OLS, GLM, MLE, etc)
- Un-biased means that in repeated shootings all bullets are centered around the bull's eye

What is a Biased Estimator?



- An estimator is biased if it systematically over- or under-estimates the true value

Efficiency



- Efficiency is also appealing in an estimator
- An estimator is efficient if all bullets are clustered tightly together. i.e., small variance-> small confidence intervals
- The blue bullets represent unbiased but inefficient estimators
- The green are biased but more efficient

Randomization Reduces or Eliminates Bias

- Bias depends on treatment allocation rule

- Randomization ensures that b=0 so

$$\beta_{est} = \beta_{true} + \mathbf{b} \quad \rightarrow \quad \beta_{est} = \beta_{true}$$

- In the absence of randomization, b ≠ 0

$$\beta_{est} = \beta_{true} + \mathbf{b}$$

Exogenous variables

- Exogenous:
  - Caused by factors or an agent from outside the system (exo = outside, genus = born)
    - Coin flip is exogenous to patient
  - Measures that cannot be chosen, such as age, sex, race, etc., and sometimes include policy variables.

Is something endogenous or exogenous?

- Depends on <u>conceptual model</u> and <u>perspective</u>

- Many discussions focus on whether policy variables are truly exogenous
  - If a state passes a ‘state subsidy on long-term care insurance’ policy it could change people’s purchase of long-term care insurance.
    - Do people move to those states to take advantage?
    - Do states that pass the subsidies also have sicker / healthier / wealthier people and different long-term care infrastructure / or different Medicaid policy?

Ways in which selection bias (endogeneity bias) can arise

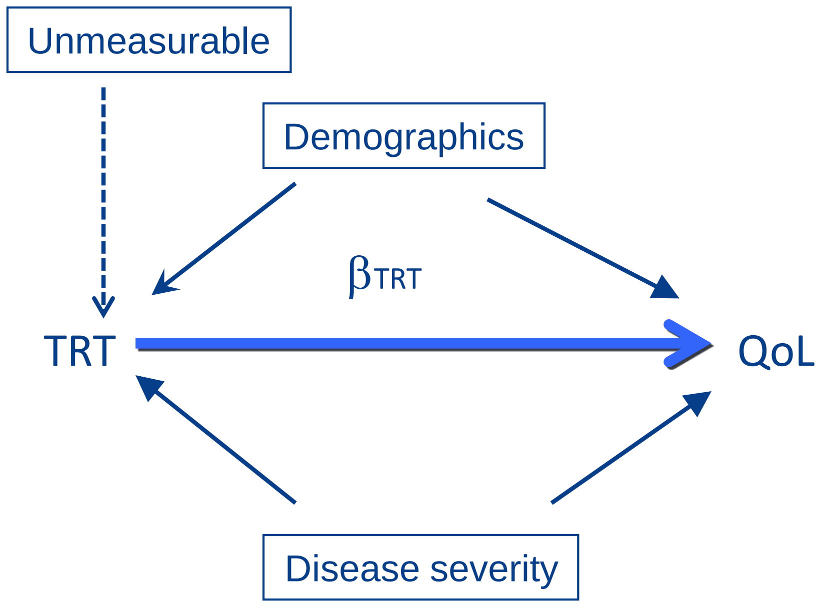
Sources of Selection Bias

- Goal: estimate β_{TRT} that is the effect of some treatment (e.g. case management program in emergency department (ED)) on quality of Life (QoL)

$$\mathrm{TRT} \xrightarrow{\beta_{\mathrm{TRT}}} \mathrm{QoL}$$

Sources of Selection Bias

- Easily measured variables
  - Demographics (Age, race, gender, etc.)
  - Assume that we've measured all these and they are RHS variables in a multivariate regression with QoL as the dependent variable
- Variables we could measure if we had enough time and money
  - Could abstract charts and measure all comorbid conditions for example
- Variables that for all practical purposes are unmeasurable
  - Measurement error
  - Idiosyncratic shocks to health (e.g., win lottery)
  - "Complex social factors"

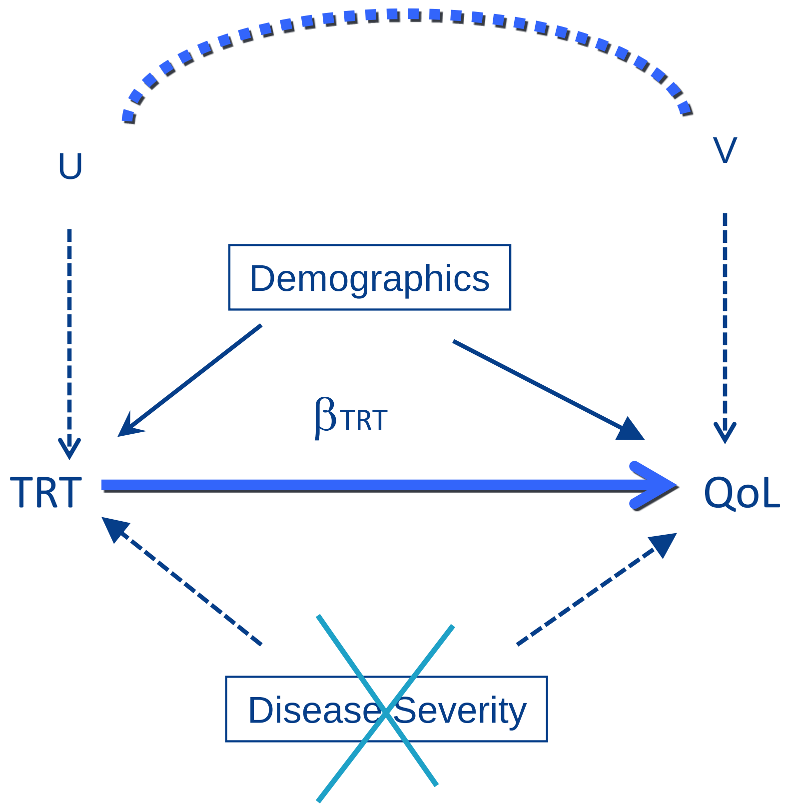


Selection Bias from Omitted Variables

- Omitted Variable Bias - error (U) is correlated with regressor through an important omitted variable (unobserved confounder)

- If disease severity is not measured, then it becomes a part of the error term and correlated with β_{TRT}

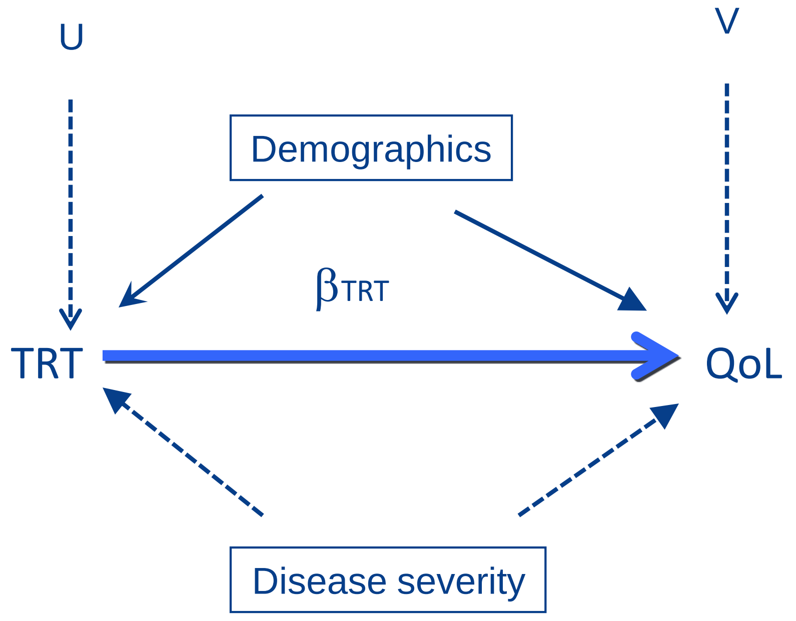
$$QoL = \beta_0 + \beta_{TRT} * TRT + (\beta_{DisSev} DisSev + v)$$



Selection Bias from Omitted Variables

- Sometimes the direction of bias can be determined
  - People with greater severity are more likely get TRT because they are repeat ED users and have a higher chance of being enrolled in study.
  - People w/ greater severity have lower QoL

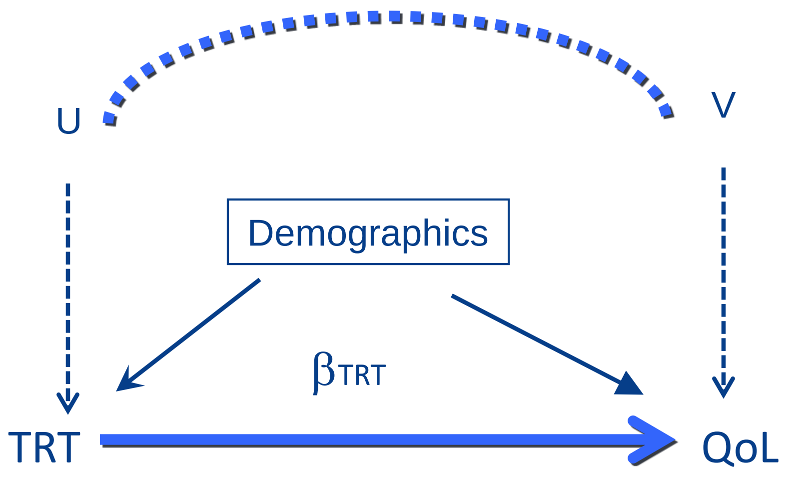
- If severity is omitted, then β_{TRT} has a negative bias
  - Biased toward negative infinity
  - TRT looks bad <u>not</u> because it is bad for you (i.e., $\beta_{true}<0$) but b/c more severe patients are more likely to get TRT
  - And severity is bad for you
  - In other words, if disease severity was controlled for, β_{TRT} would be higher in magnitude (e.g. more positive effect on QoL)



Ways to statistically address selection / endogeneity bias

Fundamental Problem of Selection Bias in Quasi-Experiments

- Problem: Cov(TRT, V) ≠ 0
  - We need to break this correlation in some way, but randomization isn't an option



What to do if you know there are still unmeasured confounders? Instrumental Variables Overview

- How does it work?
- What is an instrumental variable (IV) and why should you use it?
- Properties of good instruments
- Examples of instrumental variables
- How an instrumental variable analysis works
- Problems with IV analyses
  - Weak instruments
  - Marginal patient

Intuition behind Instrumental Variables

- Addresses issues of differences between treatment group in unobserved risk factors
- Due to correlation of treatment and unobserved confounder, don't compare two treatment groups according to what treatment they got (as in RCT) on basis of randomization
  - Instead, compare groups according to an instrument, which is uncorrelated with unobserved confounder, and then adjust for other differences between two groups.

Mechanistically, what does IV estimation mean?

- Model the Correlation between Treatment and the Error Term to “Break” the Correlation

- Exact approach depends on measures and estimation**
  - Linear models:
    - *Two stage least squares (2SLS) (continuous regressor, continuous regressand)*
  - Non-linear models (world of <u>binary TRT</u>):
    - *Two stage residual inclusion (2SRI) (discrete regressor and <u>discrete regressand</u>) (Terza Basu, Rathouz 2008) or*
    - *Linear Probability Model (Basu and Coe, 2018) if a rare discrete outcome.*
    - *Special regressor models (Lewbel 2000)*

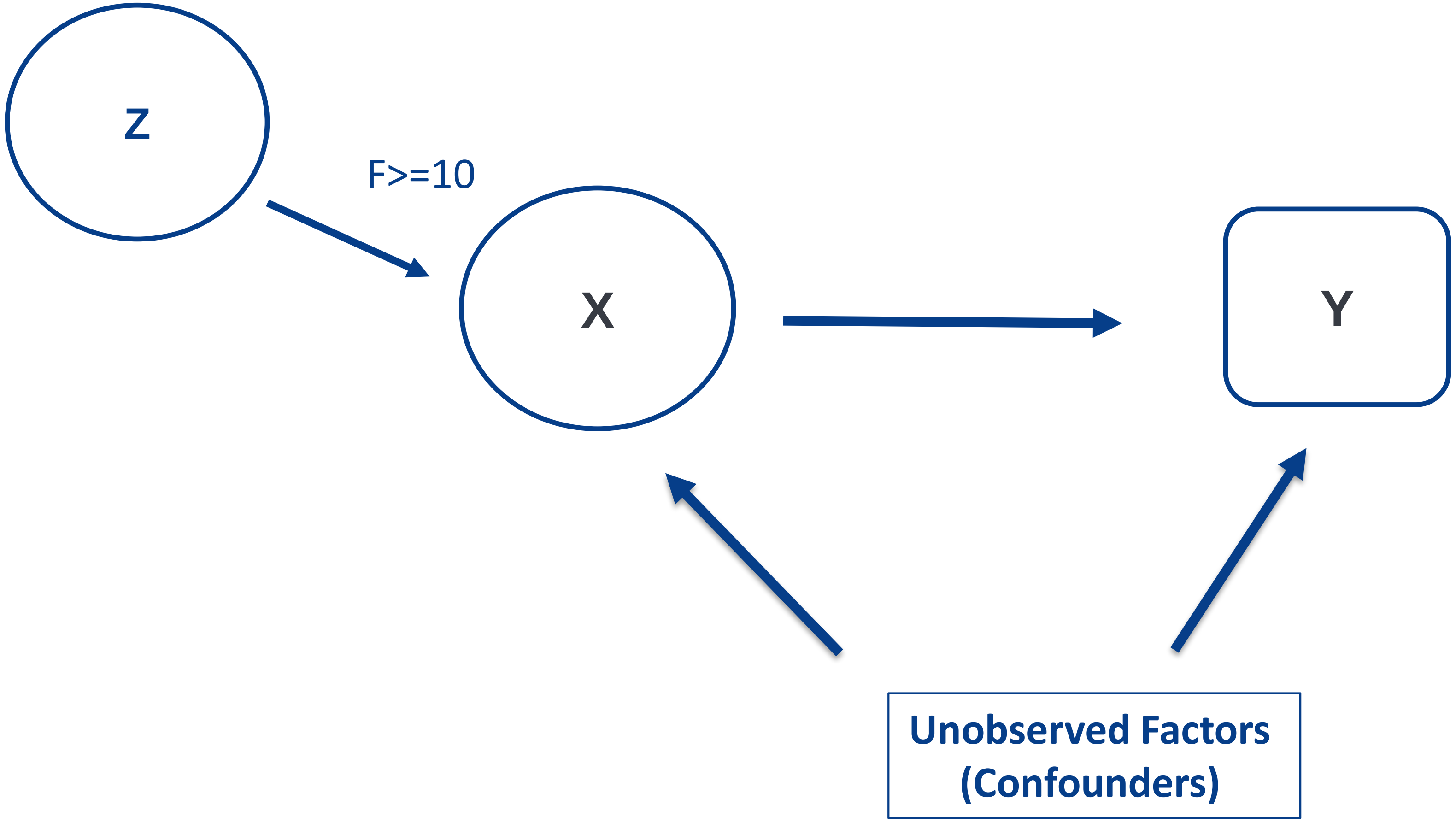
**Talk to an economist or statistician

Properties of Strong Instruments

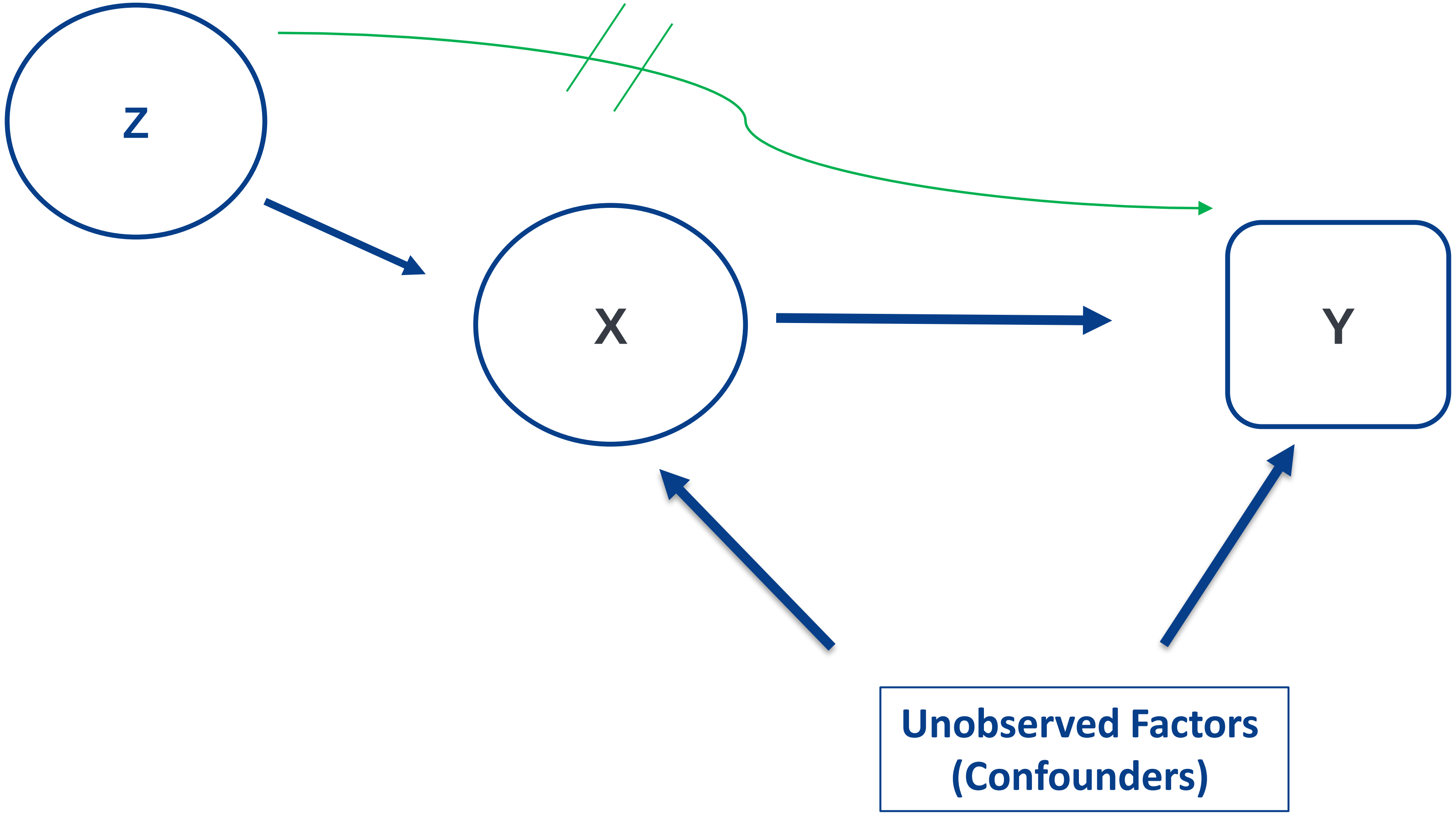
- Two most important properties of good IVs
  - Correlated with treatment
  - Uncorrelated with outcome (except perhaps through treatment)

Goldman 2001 JASA

THE IV (Z) STRONGLY PREDICTS RECEIPT OF TREATMENT



IV (Z) HAS NO INDEPENDENT RELATIONSHIP WITH THE OUTCOME



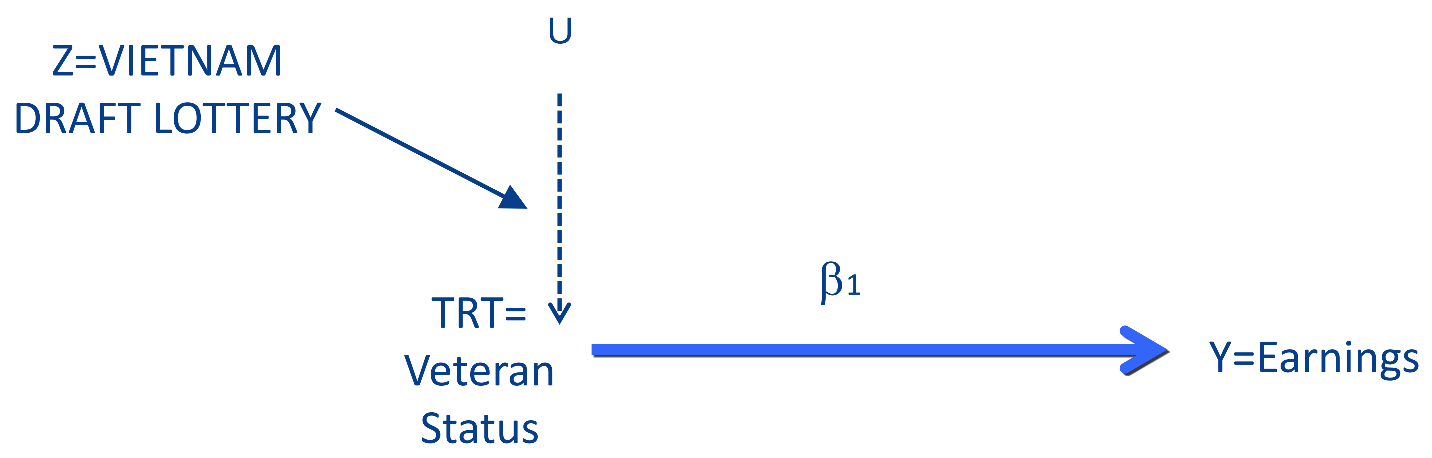
Properties of Strong Instruments

- Other necessary properties
  - **Uncorrelated with difference in potential outcomes
  - Monotonicity
  - SUTVA
  - **Only pathway from instrument to outcomes is through treatment

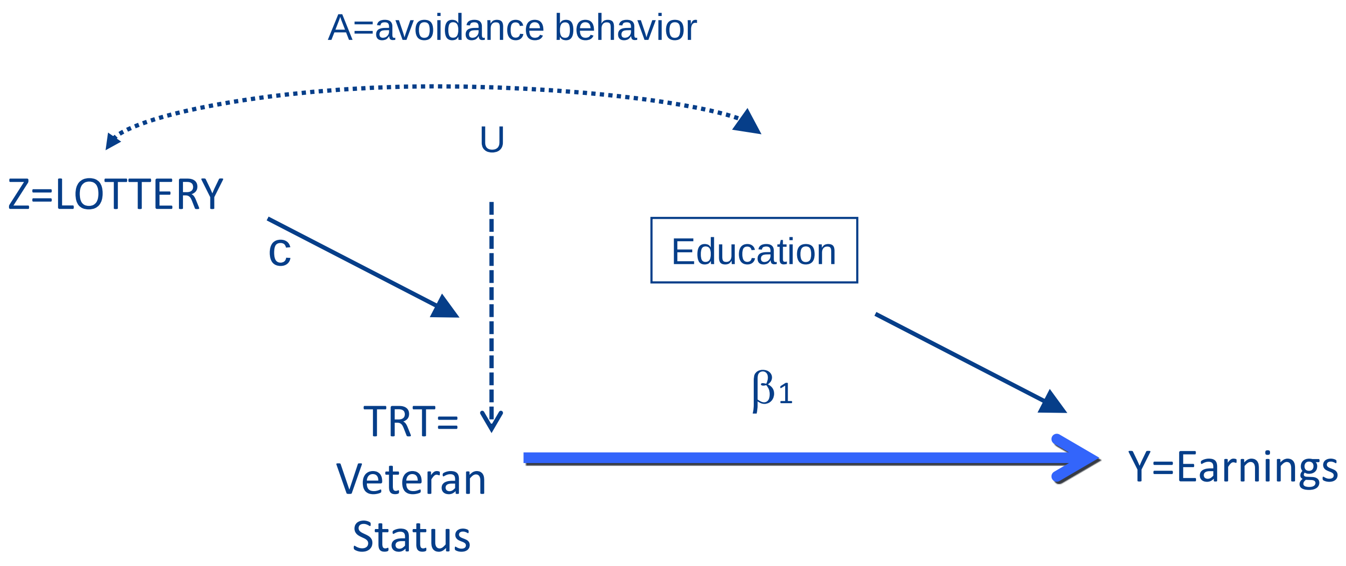
  - **=more important

Goldman 2001 JASA

Want to measure impact of being a Veteran on lifetime earnings. Is instrument independent of Difference in Potential Outcomes?



Instrument is Independent of Difference in Potential Outcomes ??



- If draft-avoidance behavior is correlated with lottery numbers and with variables related to earnings besides veteran status, then lottery-based instruments will be correlated with the regression error in the outcome equation (Angrist et al, 1990)

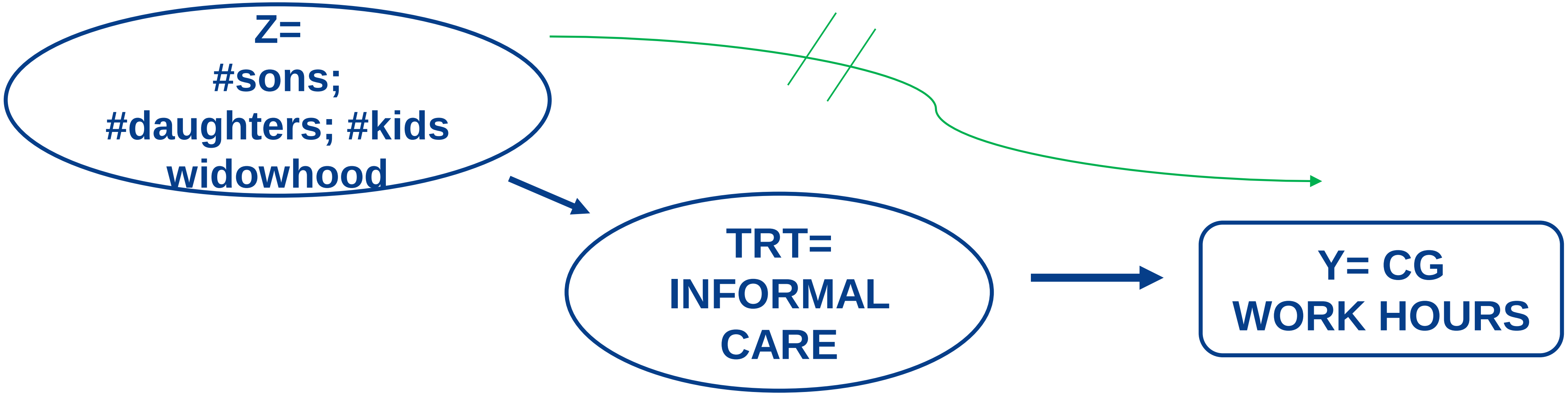
Potential Instruments

- Distance*
- Physician Preference
- Examiner for social programs
- Family structure
- Policy changes

*McClellan M, McNeil BJ, Newhouse JP. Does More Intensive Treatment of Acute Myocardial Infarction in the Elderly Reduce Mortality? Analysis Using Instrumental Variables. *JAMA.* 1994;272(11):859–866. doi:10.1001/jama.1994.03520110039026

Need IV approaches in many applied research ?s: Informal Care

- Does informal care affect health care use/health outcomes of care recipients?
  – Often these decisions are made simultaneously…
- Does informal care affect work of does taste for work affect caregiving?



Van Houtven and Norton, JHE, 2004, 2005; Van Houtven, Coe, Skira, JHE 2013

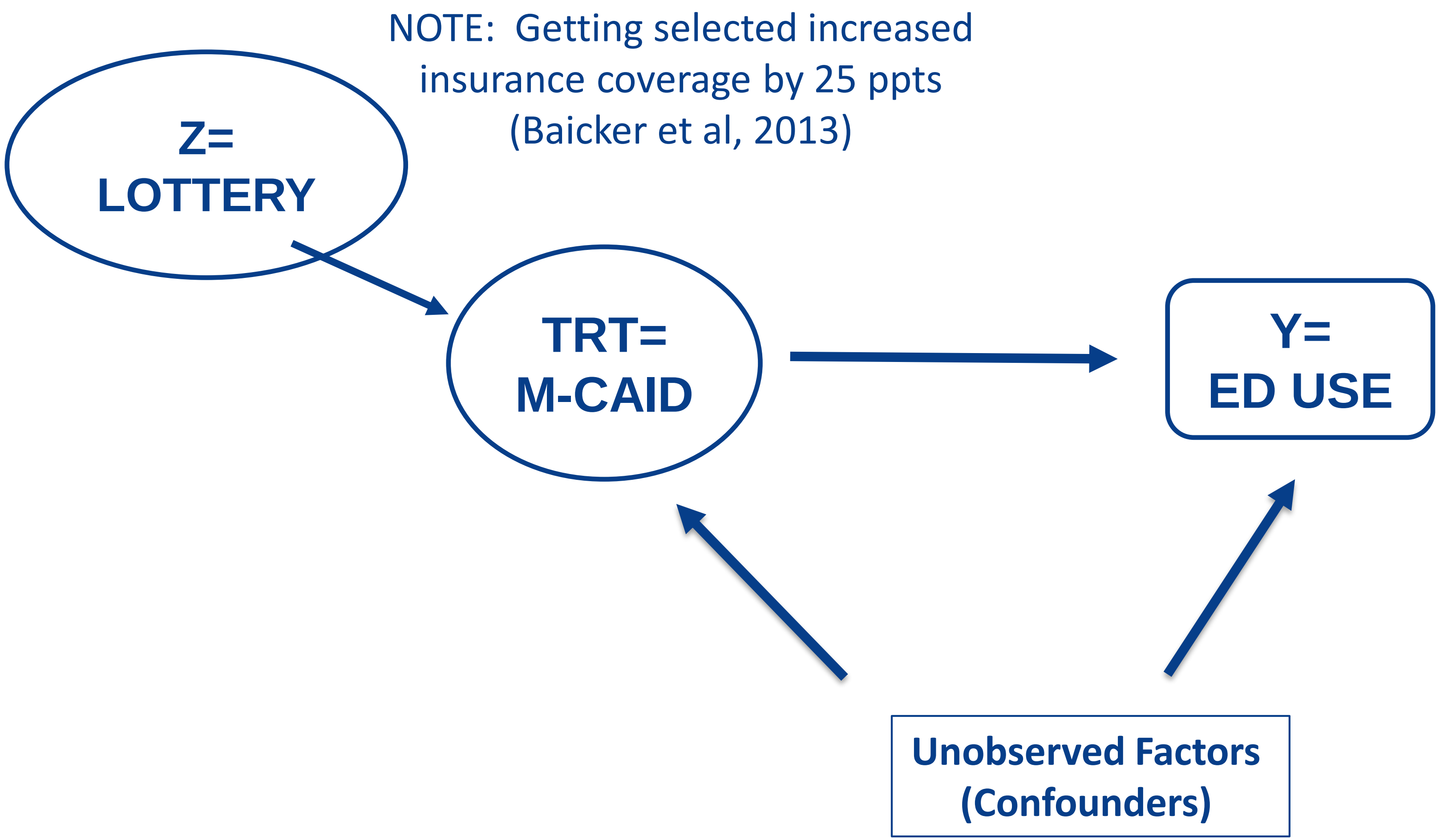
IV of Policy changes or structure

The Oregon Medicaid Experiment

- Lottery
  - Waiver to operate lottery
  - 5-week sign-up period, heavy advertising (Jan-Feb 2008)
  - Low barriers to sign-up, no eligibility pre-screening
  - Limited information on list
  - Randomly drew 30,000 out of 85,000 on list (March-Oct 2008)
  - Those selected given chance to apply
    - Treatment at household level
    - Had to return application within 45 days
    - 60% applied; 50% of those deemed eligible → 10,000 enrollees

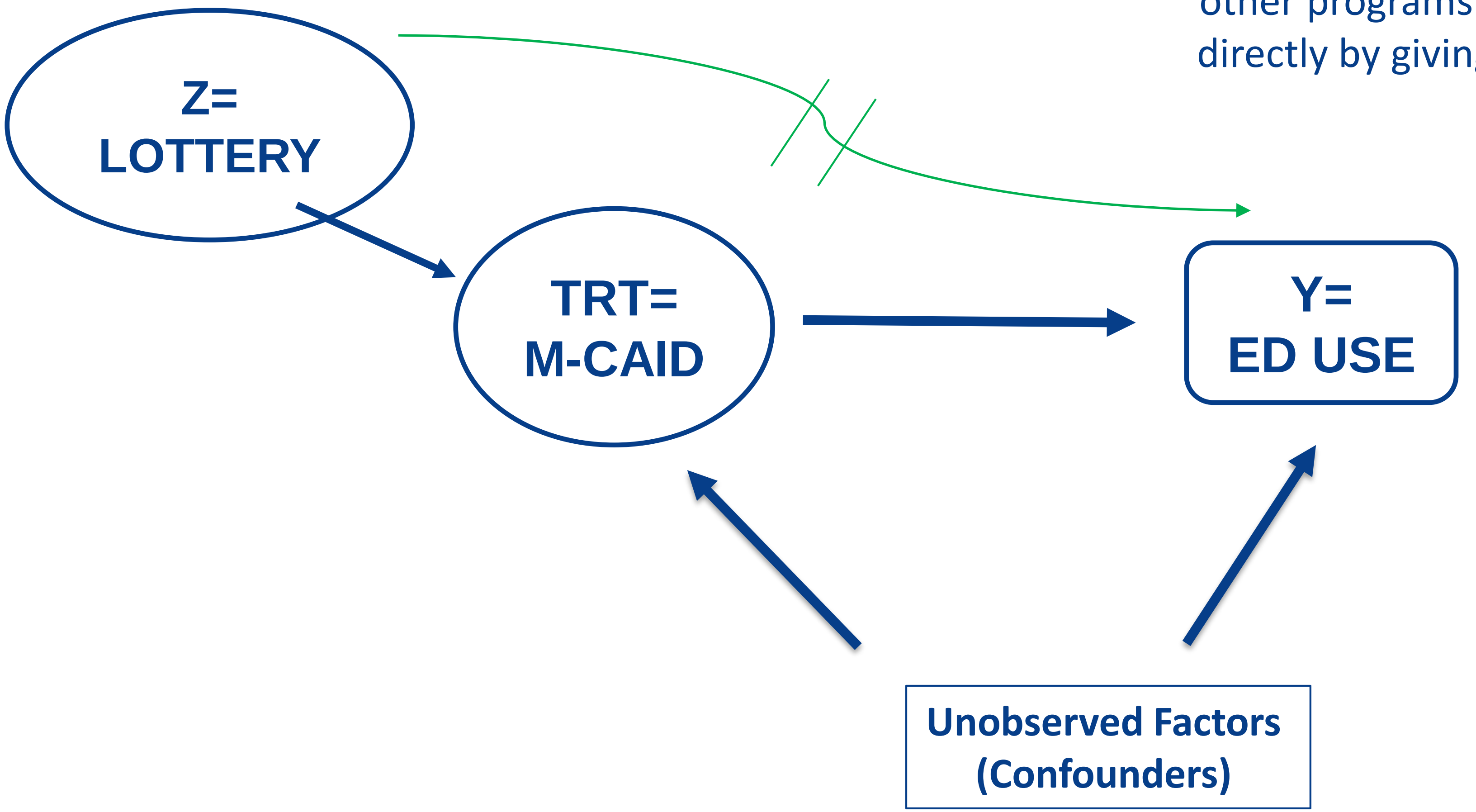
Reprinted http://www.nber.org/oregon/index.html

THE IV STRONGLY PREDICTS RECEIPT OF TREATMENT



THE IV NOT DIRECTLY RELATED TO OUTCOME

NOTE: Lottery could have independently affected outcomes through participation in other programs (e.g. Meals on Wheels) or directly by giving a ‘warm glow’ for having won …



Results: Access & Use of Care

Gaining insurance resulted in increased probability of hospital admissions, primarily driven by non-ED admissions.

	CONTROL	RF Model (ITT)	IV Model (LATE)	P-Value
Any hospital admission	6.7%	+.50%	+2.1%	.004
--Admits through ED	4.8%	+.2%	+.7%	.265
--Admits NOT through ED	2.9%	+.4%	+1.6%	.002

SOURCE: Hospital Discharge Data

Overall, this represents a 30% higher probability of admission, although admissions are still rare events.

Reprinted http://www.nber.org/oregon/index.html

Problems with Instrumental Variables

1. Weak Instruments can accentuate bias
2. Assumption that instrument is uncorrelated with errors in outcome equation is untestable
3. Marginal patient and local average treatment effects

1. Weak Instruments: Rule of Ten

- Run an OLS of the treatment on Xs and the instruments.
  - If F-test on the instruments is >=10 you are ok
  - If F-test < 10, then weak instrument and try again

- General rule: Weak instrument generates more biased estimate than result without instrument
  - Your system of equations will not be identified or only identified through functional form if a non-linear model = bad

Instrumental Variables and the Marginal Patient

- LATE is <u>different from ATE</u>, not necessarily worse:
  - LATE is good for addressing policies changes
  - Have to think about the marginal patient – e.g. the patient who changed behavior based on the IV (e.g. results generalize to those individuals invoked to buy LTCI due to the tax subsidy for LTCI)
- This is not so different from problems of many RCTs
  - Only people who enroll in the RCTs provide information to ATE, so they are marginal patients
  - You don’t know who outside the trial is like these marginal patients

Interpreting IV Results

- When IV results differ from original regression
  - Possibility #1: If strong IV, then IV results are unbiased while original results are likely biased
  - Possibility #2 (less likely): Given likely heterogeneous treatment effect, it is possible that IV results and original results are both correct but they simply generalize to different patients with different treatment effects
- When IV results are the same as original results, original results are likely unbiased by unobserved confounders
  - NOTE: IV result generalizes to marginal patients and original result has benefit of generalizing broadly

Key point to remember

- Instrumental variable methods try to capitalize on controlling for **unobserved** information.
- If you can find a good instrument, you may be able to get a reduction in bias in estimates that simply cannot be achieved with propensity score approaches.
- Problem is usually finding a good instrument.
- Beware efficiency losses….

Summary

- How selection bias (from unobservables) arises
- Motivation: What is an instrumental variable (IV) and why should you use it?
  - "IV analyses trade one set of unverifiable assumptions (no unmeasured confounding) for another (unconfounded instruments)" Rassen 2009
- Properties of good instruments
- Examples of instrumental variables
- How an instrumental variable analysis works
- Problems with IV analyses
  - Work with statistician or economist if you want to go down this road

QUESTIONS?