# Causal Inference in Education Policy Research

*MLDS Research Series*

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# Outline

- Introduction and Context
- Causal Inference, the Counterfactual, and the "Fundamental Problem of Causal Inference"
- Three Approaches to Evaluate Cause in Observational Studies
  - Condition on Covariates
  - Instrumental Variable Estimation
  - Regression Discontinuity Analysis
- Recommendations
- References for More Information

# Introduction

- Data, too often, are turned into "information" that can be misleading
  - "…many college students who take developmental education classes… fail to graduate. Only 28% of two-year college students who took at least one developmental course earned a degree or certificate within 8.5 years, compared to 43% of non-remedial students…" *(USA Today, July 25, 2013)*
  - "Financial aid can make or break a college education…any student headed to study at a private school with financial gaps over $3,000 would be at significant risk of not graduating." (*www.bottomline.org*)

# Introduction

- "employment and finances [are seen] as the main reasons for departure…nearly 40 percent of students who worked full time while enrolled dropped out within three years, compared to 19 percent of students who worked part time and 13 percent who did not work." *(Demos, 2011)*

- "The evidence is clear: Undergraduates enrolled full-time — specifically, 30 or more credits completed in their first year — are more likely to graduate on time than students who complete fewer credits per year." *(Complete College America, 2013)*

# Introduction

- These examples focus on bivariate relations:
  - Taking a remedial course and earning a degree/certificate
  - Having unmet financial need and graduating
  - Working and dropping out of college
  - Enrollment in 30 credits and time-to-degree

- *"Correlation does not imply causation"*

  …what can we do instead?
- First, we need an understanding of the concept of causal inference and the counterfactual

# Causal Inference

- In order to attribute "cause" -- or measure the Treatment Effect of a given "treatment" -- we need to see the person under both conditions

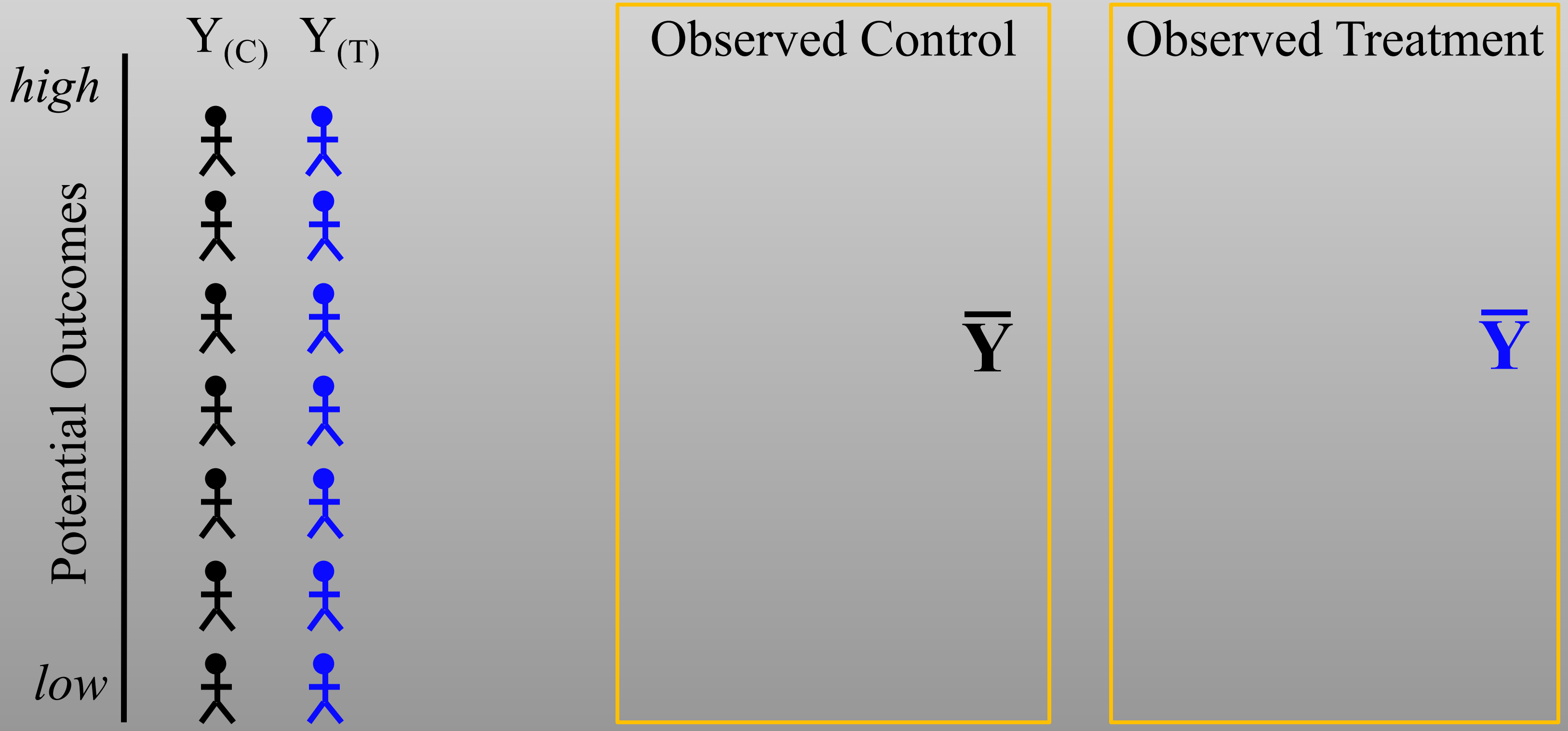
| no college | college |
|---|---|
| ? | ? |

Treatment effect of college on earnings = ? - ?

- "Fundamental Problem of Causal Inference" – we never obtain the counterfactual in social science
- If we can assume that treatment assignment is unrelated to *potential outcomes*, then the Average Treatment Effect gives us an estimate of the Treatment Effect

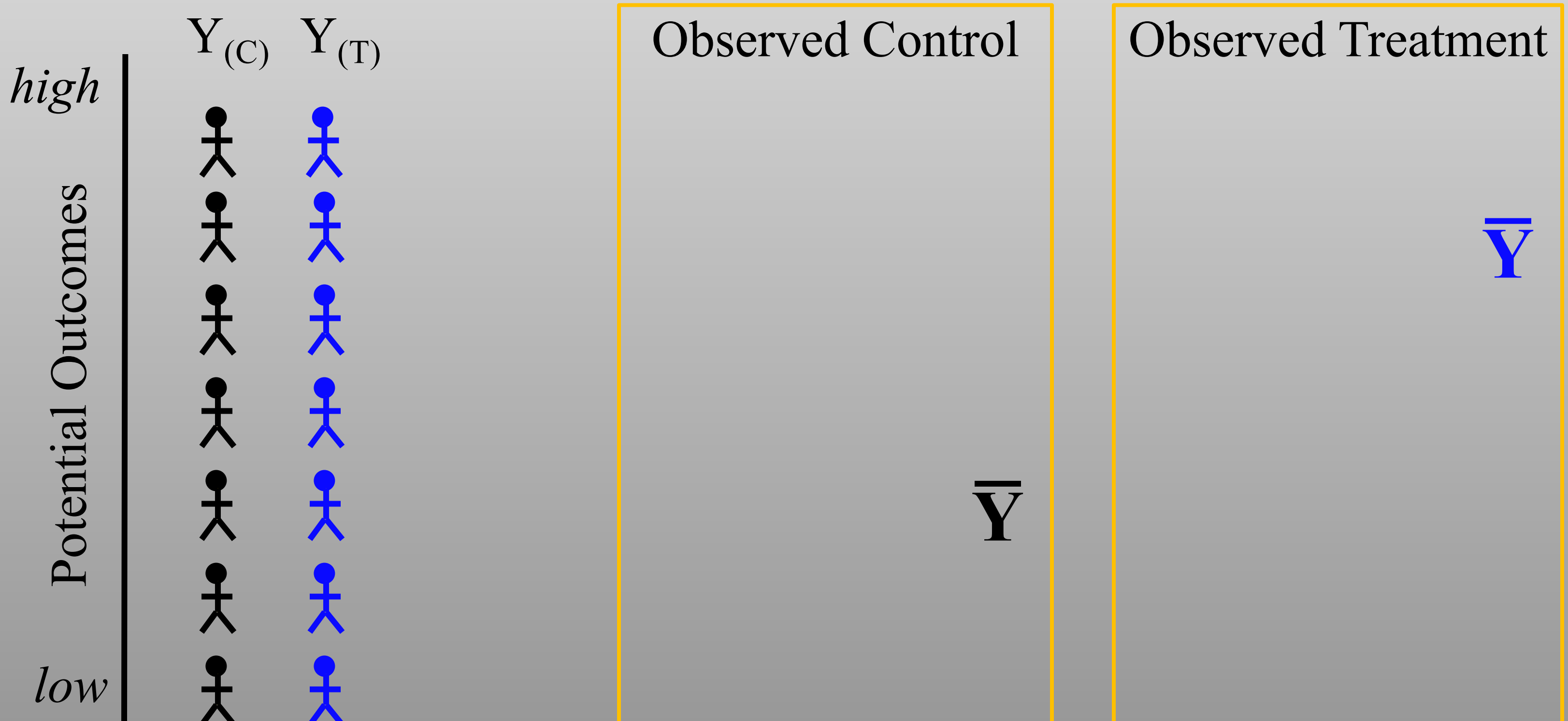
# Causal Inference

- We can obtain an unbiased estimate of the Average Treatment Effect (ATE) with a well-designed random assignment study



# Causal Inference

- However, with observational studies, Treatment Assignment tends to be related to potential outcomes (it is *endogenous*)

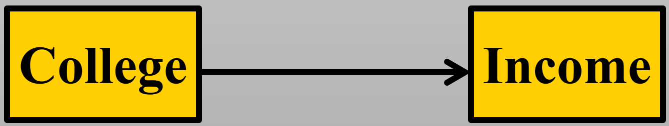


# Causal Inference

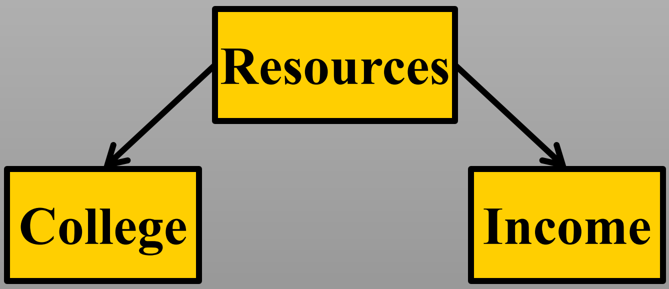
- Aug 27, 2013, there was a great piece by Dylan Matthews in the Washington Post: *The Tuition is Too Damn High: Part II Why College is Still Worth It*

**We see a correlation…**


**We may be tempted to conclude…**

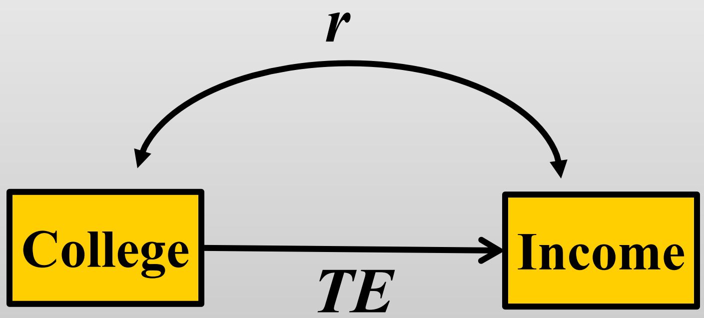



**A different reason for the correlation…**



# Causal Inference in Observational Studies

We would like to estimate the treatment effect (*TE*)…




But with observational studies, there is also a relation (*r*) between the treatment assignment and the potential outcome…

If we naively estimate the effect of T on Y, then our estimate is biased… it will be *TE* + *r*

# Approaches to Evaluate the Causal Effect

- Three approaches we will introduce today:
  - conditioning on covariates
  - instrumental variable estimator
  - regression discontinuity estimator

- Each of these approaches differ on:
  - “who” is included in the analysis
  - the required type of auxiliary information / data
  - statistical (and conceptual) assumptions

# Conditioning on Covariates

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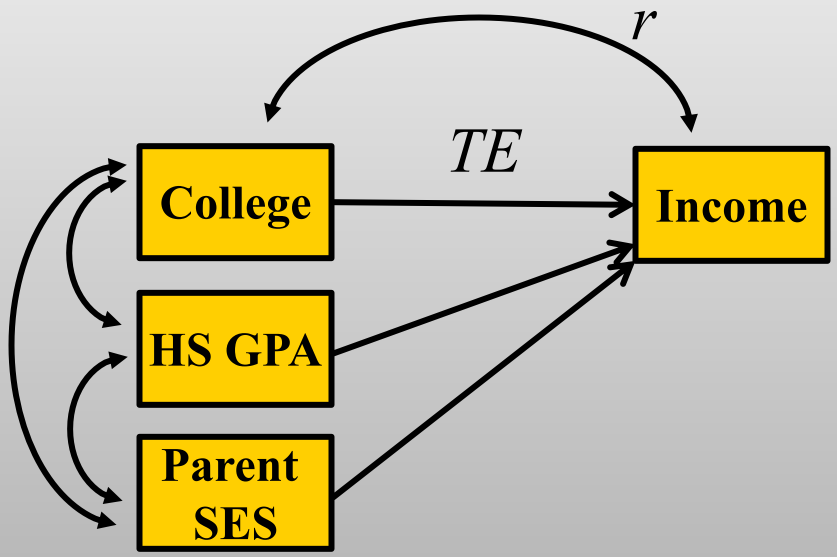
# Conditioning on Covariates

- We can address selection bias in our observed data by using other data that we know about the participants
- Using the other data (*which we call "covariates"*), we can:
  - adjust for differences in a multiple regression framework
  - stratify people by levels of the covariates and examine the effect of treatment within strata
  - match on the covariates to create groups that only differ on the treatment variable

# Controlling for Covariates Using Multiple Regression




**Assumptions:**

1) Covariates have eliminated the relation between College and Income residual (ignorability)
2) Correct functional form of relation of covariates and outcome
3) Relation of College and Income same at all levels of covariates
4) Homoscedastic spread of observations over the outcome/covariate space

**Provides us with the "ATE" – the average treatment effect if all people were exposed to the treatment**

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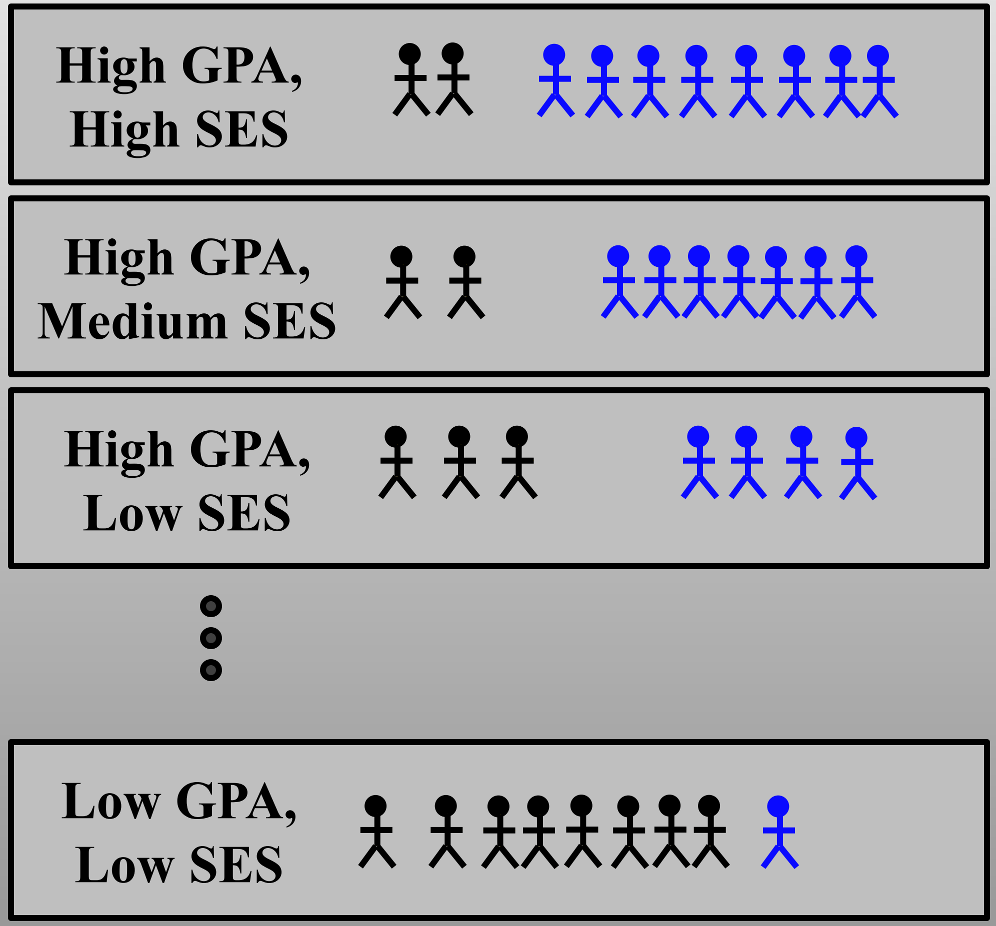
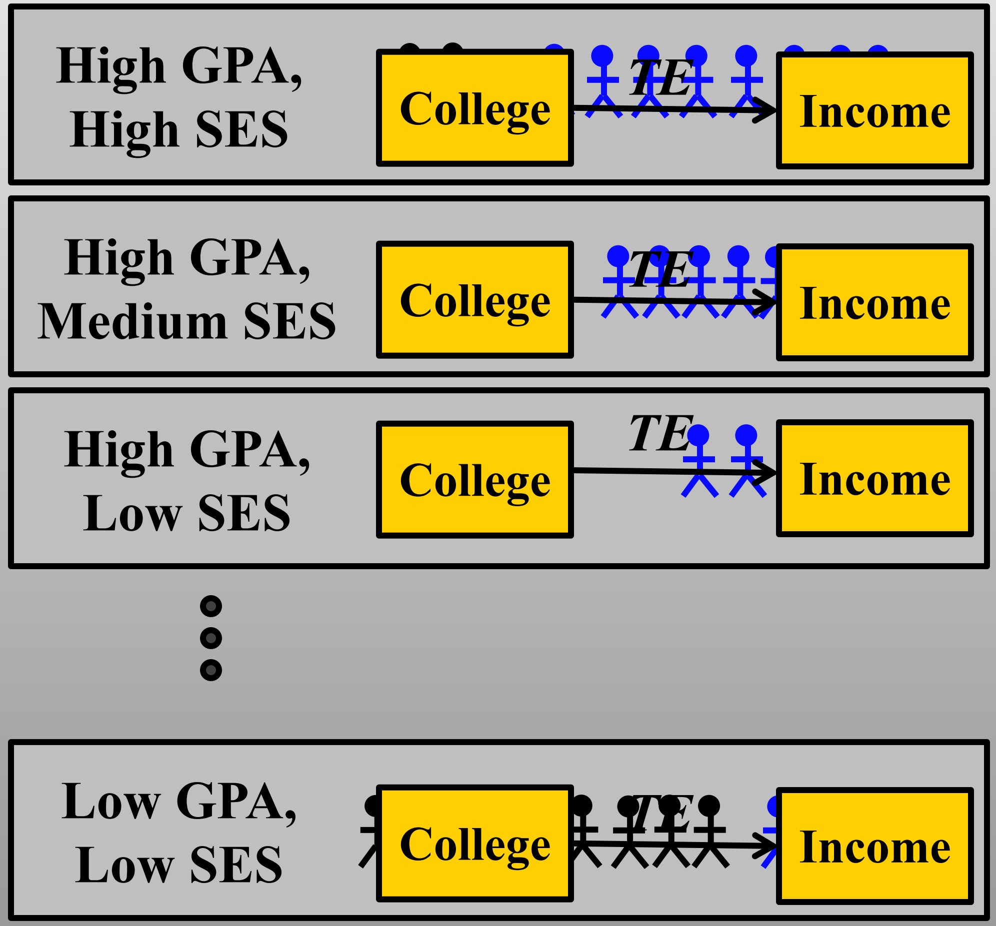
# Controlling for Covariates Using Multiple Regression

- What if all high GPA and high SES students went to college and low GPA and low SES students did not go to college?
- We would be comparing completely different groups – no overlap (*referred to as "common support"*) – but we would not "see" it when we run this regression analysis
- Additionally, we never know whether we have met assumptions about functional form (*we cannot separate the evaluation of it from possible treatment effects given that both are included in the model simultaneously*)

# Controlling for Covariates Using Stratification



# Controlling for Covariates Using Stratification



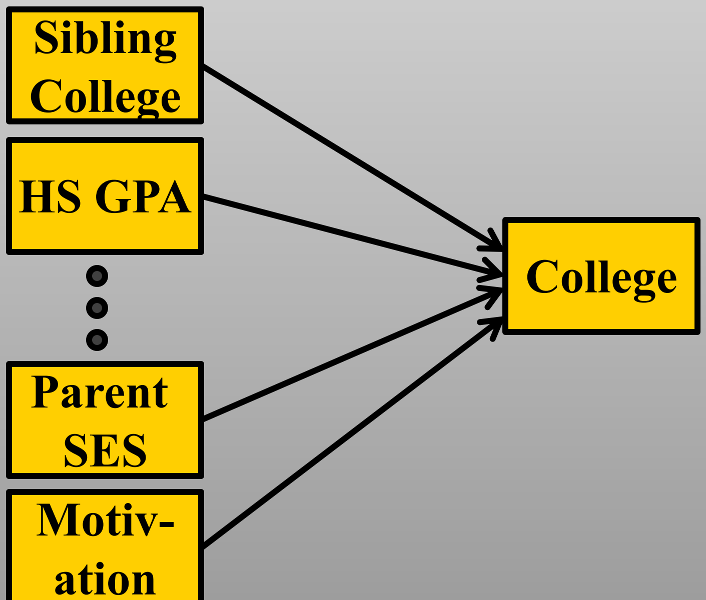

The treatment effect estimates are combined across the strata, weighted by number in treatment in each stratum

This approach removes the requirement that we know the functional form of the relation between covariates and outcome

**Provides us with the ATT – the average treatment effect on the treated**

# Propensity Scores

- What if we have more than two variables that theoretically determine membership into treatment groups?
- Estimate a <u>propensity</u> to be in the treatment group:

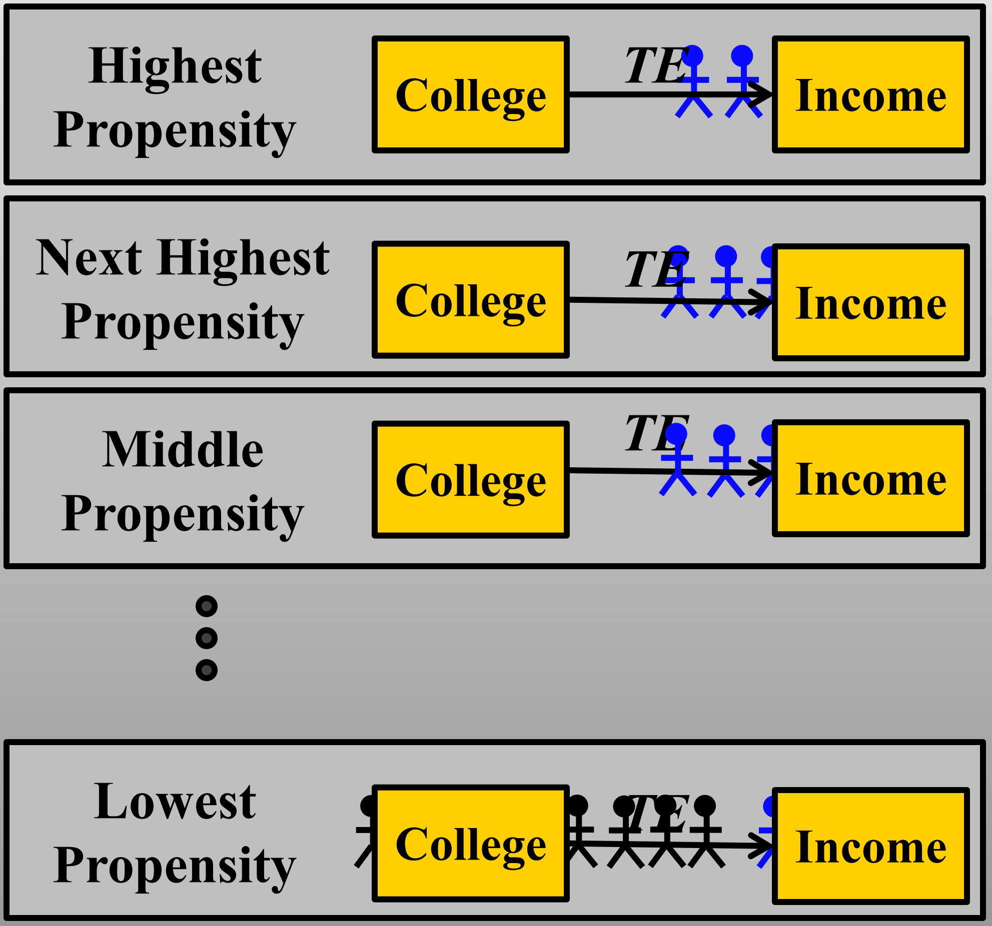



Using the observed membership, we create a prediction equation to determine a person's probability of being in treatment given covariates

Each person then receives a propensity score (ranging from 0 to 1)

This propensity score estimation process is done <u>without</u> knowledge of the value on the outcome

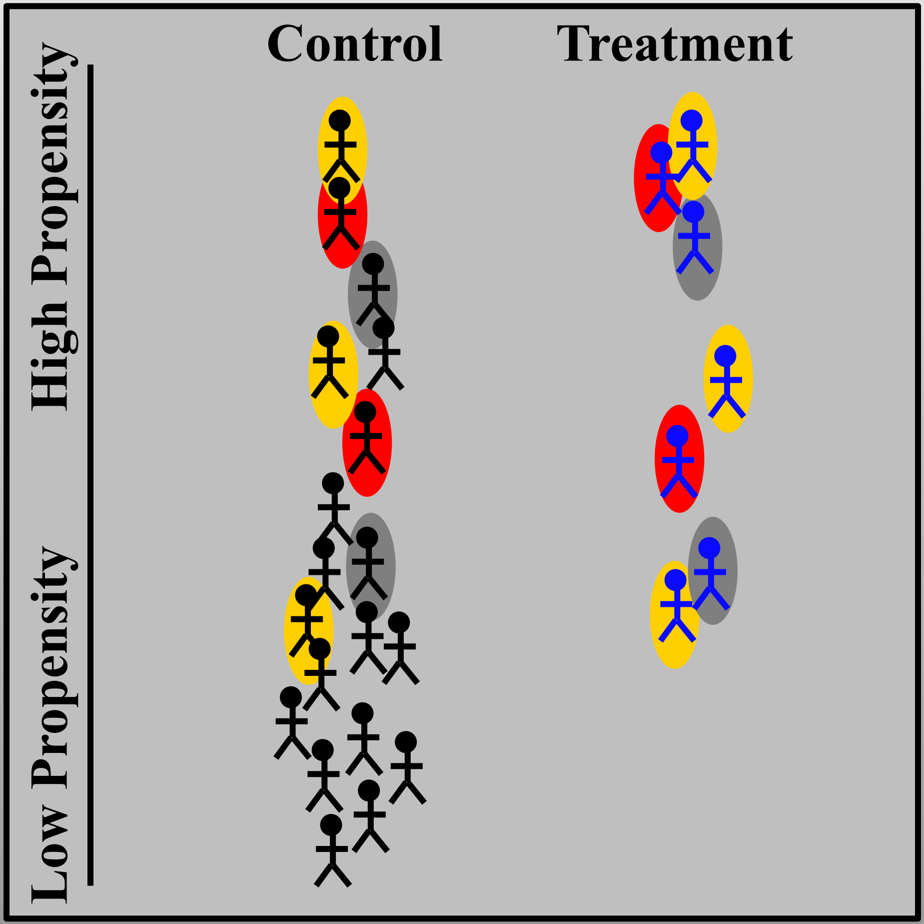
# Controlling for Covariates Using Propensity Score Stratification




The treatment effect estimates are averaged across the strata

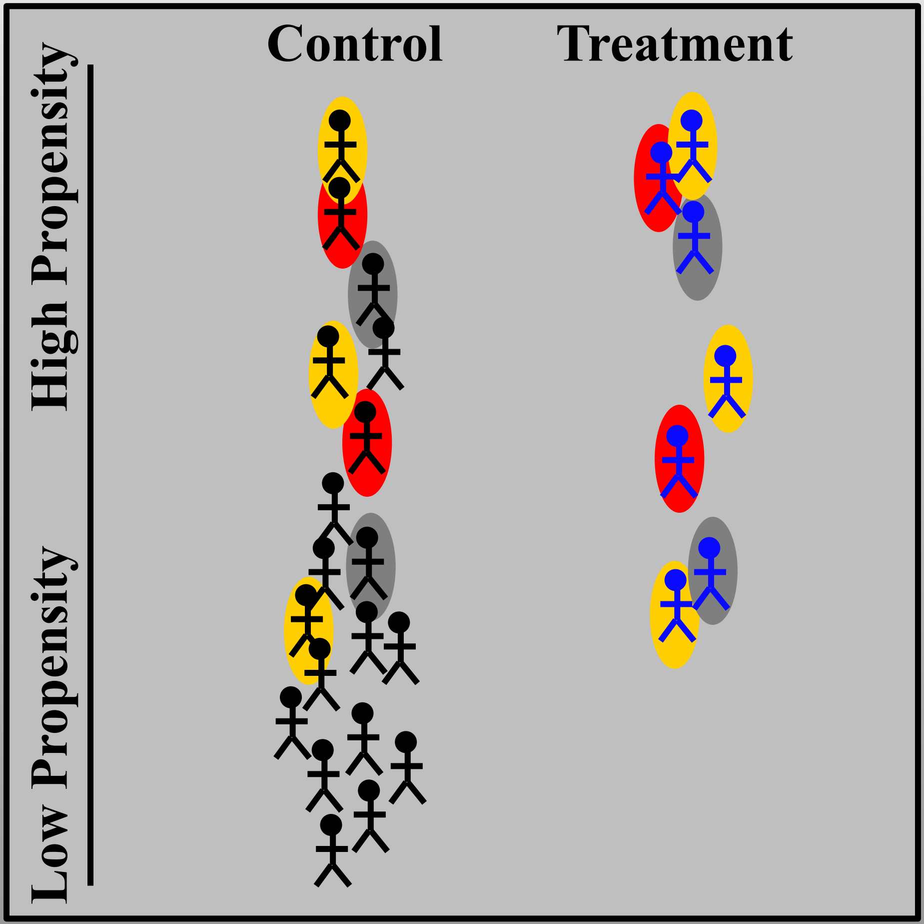
**Provides us with the ATT – the average treatment effect on the treated**

# Controlling for Covariates Using Propensity Score Matching




For each treatment person, a match is found in the control group based on propensity score

# Controlling for Covariates Using Propensity Score Matching



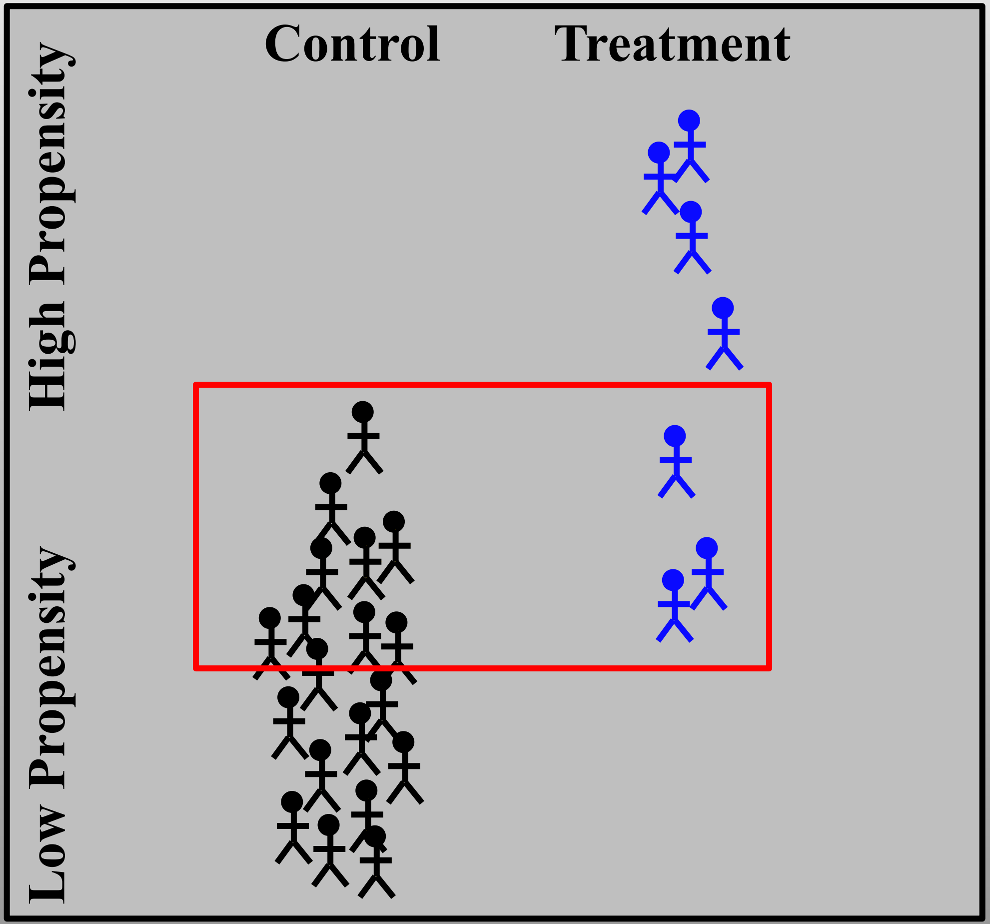

For each treatment person, a match is found in the control group based on propensity score

Unmatched control group members are not included in any analysis

The mean on the outcome for the treated group is then compared to the mean of the matched control group

**Provides us with the ATT – the average treatment effect on the treated**

# Controlling for Covariates Using Propensity Score Matching




What if there is minimal overlap?

Any comparison between the groups may be problematic

May need to compare only those persons with reasonable matches and confine generalization to just that population

# Instrumental Variable Estimator

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# Instrumental Variable Estimator

- We may not have access to the many covariates needed to "equate" our treatment and control groups
- It may be possible to locate and "carve out" an "exogenous" part of the variability in treatment assignment
- We then use this "exogenous" part only to estimate the causal effect
- The variable that is used to carve out exogeneity is referred to as an "instrumental" variable

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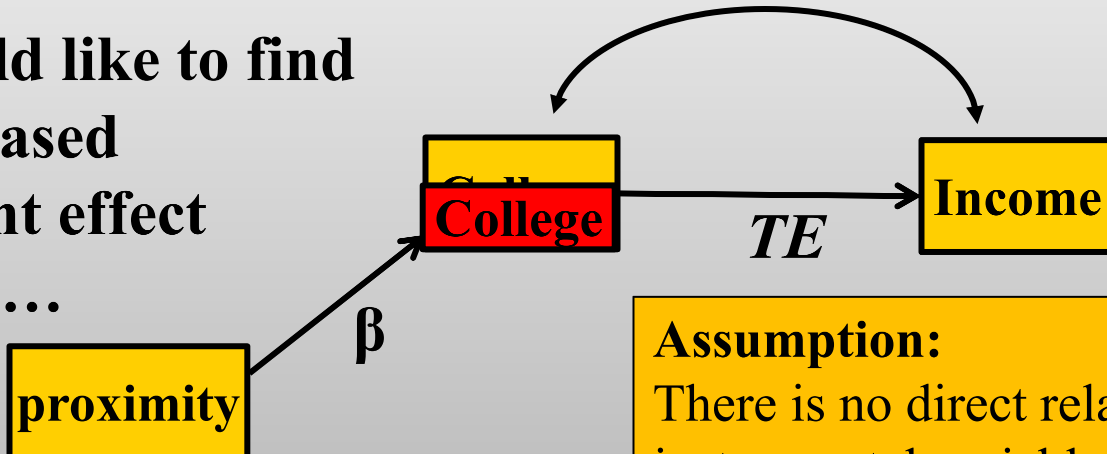
# Instrumental Variable Estimator

**We would like to find the unbiased treatment effect estimate…**




**We can locate an instrumental variable to estimate…**

**Assumption:**
There is no direct relation between the instrumental variable and the outcome

True instrumental variables are difficult to find

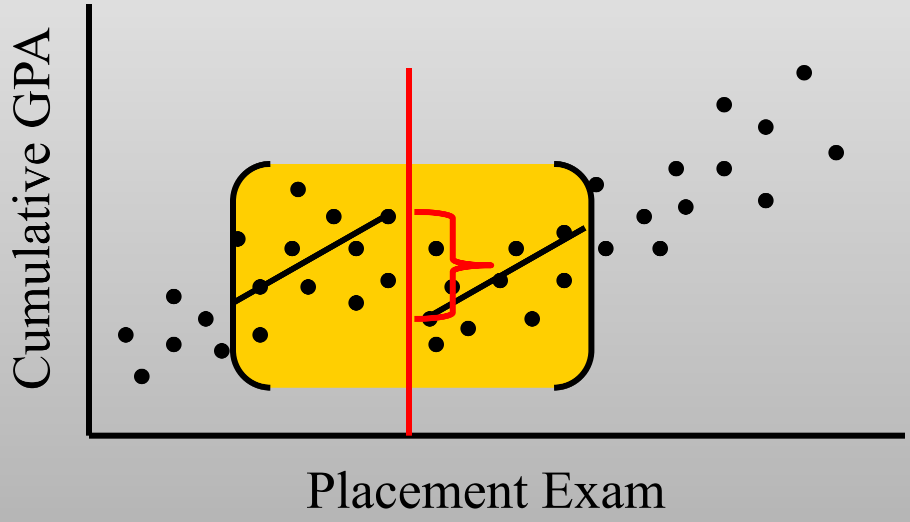
**This analysis provides the local average treatment effect (LATE), localized just to that part of the treatment variable that is "sensitive to" differences in the instrumental variable**
**(*that part of college that is a function of differences in geographic location*)**

# Regression Discontinuity Estimator

# Regression Discontinuity Estimator

- Sometimes in education, there is a “natural experiment” with what is referred to as a “discontinuity design”
  - Underlying continuum along which people are arrayed *(called the “forcing” variable)*
  - An exogenously determined cut-point on this continuum divides participants into levels of a treatment
- Goal is to limit the analysis to just those observations “at the cut-off” of this forcing variable
  - Compare the outcome for those just below the cut-off to those just above the cut-off

# Regression Discontinuity Estimator




**This analysis provides us with an estimate of the effect of the POLICY based on the cut-point and not of actually being exposed to the treatment**

The cut-point is determined and those just above and just below the cut-point are compared

The size of the comparison "bandwidth" is crucial

As the "bandwidth" is increased, the functional form between the forcing variable and outcome should be correctly specified

The treatment effect is the difference in predicted values at the location of the cut-point

# Recommendations and Issues for MLDS Center to Consider

- Use an appropriate analytic approach for the research or policy question
  - try not to take a quick or easy road
  - inform our various audiences over time
  - be leaders in analytic rigor
- Build models based on appropriate theory
  - need to partner with experts on each issue
  - examples: early education/childcare, financial aid, labor migration, etc.

# Recommendations and Issues for MLDS Center to Consider

- Data. These analytic techniques require that we need to capture those data elements that would allow us to:
  - make "matches"
  - identify instrumental variables
  - use a forcing variable in regression discontinuity
  - these variables may include those not typically considered of interest in analyses

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# Recommendations and Issues for MLDS Center to Consider

- Be responsive and efficient
  - Policy decisions are often made quickly
  - We need to be similarly quick (yet rigorous…a hard balancing act)
- Learn how to tell a story
  - These analyses can be very intricate -- our policy briefs need to mask that intricacy

**"Any fool can make something complicated.**
**It takes a genius to make it simple."**
*(Woody Guthrie)*

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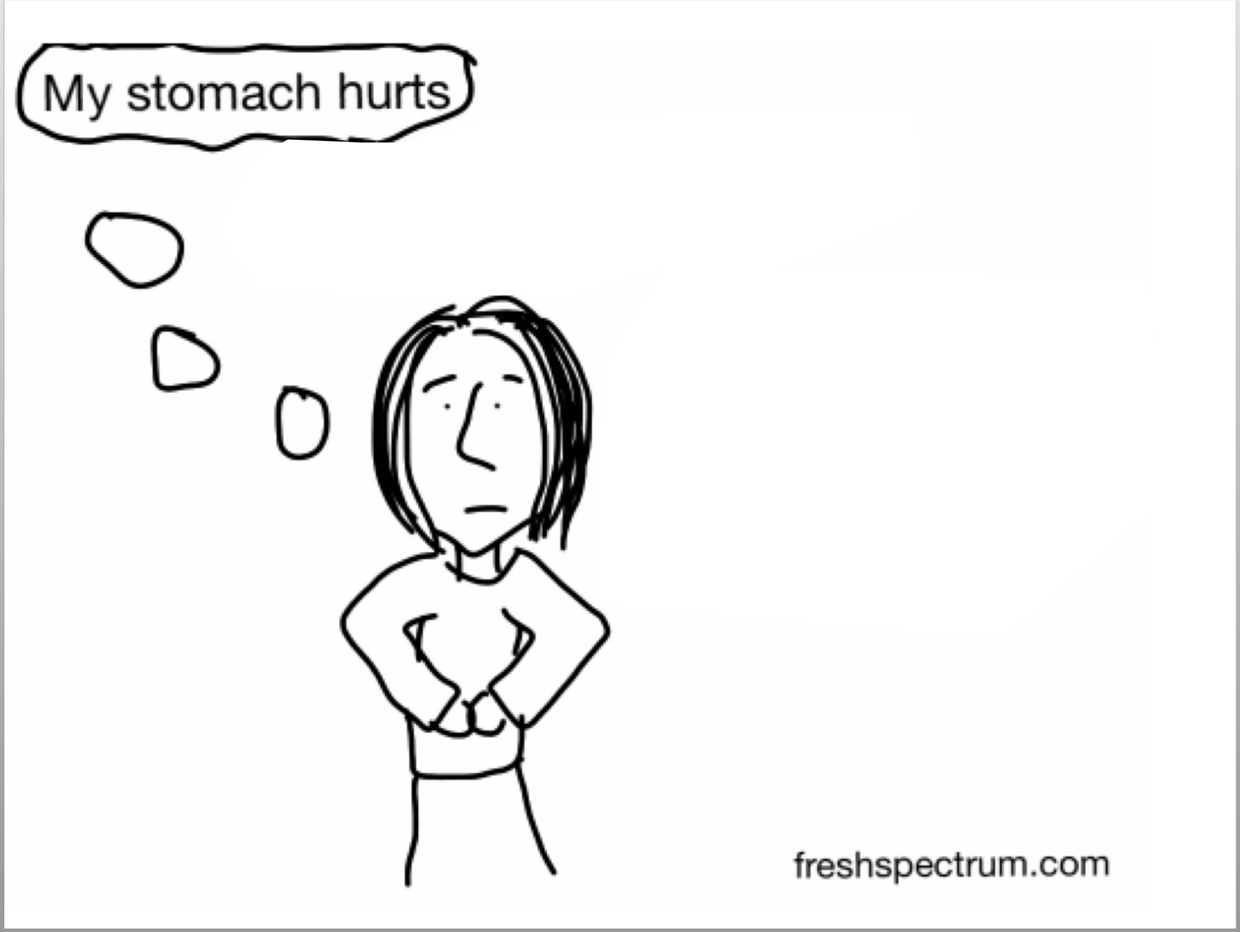
# References for More Information

- **Methodological resources:**
  - Murnane, R. J., & Willett, J. B. (2010). *Methods matter: Improving causal inference in educational and social science research*. New York, NY: Oxford University Press.
  - Stuart, E. A. (2010). Matching methods for causal inference: A review and a look forward. *Statistical Science*, *25*, 1-21.
- **Empirical examples of methods:**
  - Jacob, B. A., & Lefgren, L. (2004). Remedial education and student achievement: A regression-discontinuity analysis. *Review of Economics and Statistics*, *86*, 226-244.
  - Long, B. T., & Kurlaender, M. (2009). Do community colleges provide a viable pathway to a baccalaureate degree? *Educational Evaluation and Policy Analysis*, *31*, 30-53.
  - Titus, M. A. (2007). Detecting selection bias, using propensity score matching, and estimating treatment effects: An application to the private returns to a Master's degree. *Research in Higher Education*, *48*, 487-521.


My stomach hurts
freshspectrum.com

# Questions?

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