MLDS Center
Maryland Longitudinal Data System
Better Data • Informed Choices • Improved Results

Value-Added Modeling and Alternate Approaches for Ranking Institutions

Laura M. Stapleton and Yating Zheng
MLDSC
and the University of Maryland, College Park

MLDS Center
Maryland Longitudinal Data System

Outline

- MLDS Center's research agenda
- Discuss alternate methods to address Question 12
  - Value-added modeling
  - Utilizing propensity scores
- Obtain ideas and feedback from you about important variables and considerations for use of the methods

MLDS CENTER
Maryland Longitudinal Data System

Research agenda

- Approved by the MLDS Governing Board
- https://mldscenter.maryland.gov/ResearchAgenda.html

- Centered on topical areas:
  - K-12 Readiness
  - Postsecondary Readiness and Access
  - Postsecondary Completion
  - Workforce Outcomes

- 21 broad questions

MLDS CENTER
Maryland Longitudinal Data System

Question #12

Which 4-year institutions are graduating students most effectively and in the timeliest fashion?

- ***Sounds like a classic "value-added" analysis!***

Value-added modeling

Key idea:

To isolate the contributions of cluster (teachers/schools) to student outcomes from factors outside the control of teachers/schools (e.g., students' initial abilities, resources/poverty, parental involvement)

Value-added modeling

Examples:

1. 2010, Louisiana State Senate passed a bill authorizing the use of value-added models in the state's public schools to reward strong ***teachers***
2. Texas used a value-added model to evaluate the effectiveness of ***principals*** on student achievement
3. Value-added models were used to evaluate ***school*** performance in a very large school district in the United Kingdom
4. In 2014, value-added models were used to evaluate 30 public ***postsecondary institutions*** in Texas

Value-added modeling

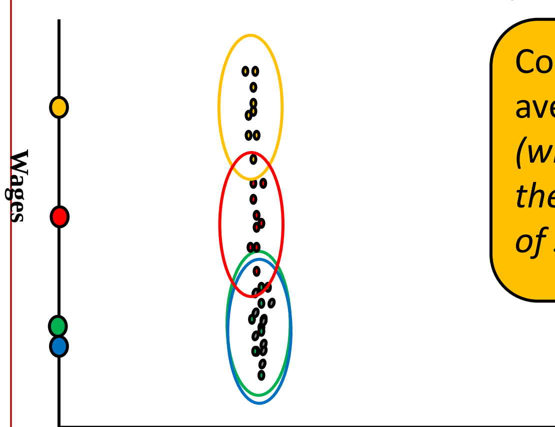
How does it work?

1. Use statistical models (e.g., multivariate regression, multilevel modeling) to predict students’ outcomes from their past performance and possibly other variables (e.g, SES, past experience, etc.)

2. Compare the predicted scores with observed scores

3. The difference between the predicted and actual scores is attributed to the cluster membership (e.g., teacher/school/institution)

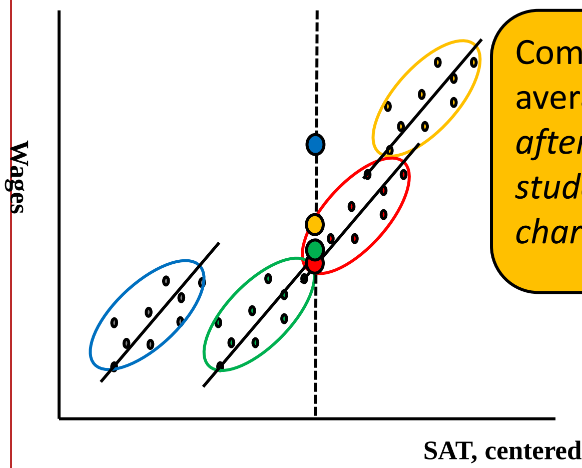
Value-added models, conceptually



Comparing the average outcomes *(without considering the “market basket” of students)…*

MLDS CENTER
Maryland Longitudinal Data System

Value-added models, conceptually



Comparing the average outcomes *after conditioning on students' characteristics…*

MLDS CENTER
Maryland Longitudinal Data System

Value-added model assumptions

Two key assumptions (among others)
Reardon and Raudenbush (2009)

1) Manipulability

"It is theoretically meaningful to define the potential outcome of each student if assigned to each of the *J* schools, ensuring that each student has at least one potential outcome per school"

Value-added model assumptions

Two key assumptions (among others)

Reardon and Raudenbush (2009)

1) **Manipulability**
2) **Functional form**

"The functional form of the model correctly specifies the potential outcomes even for types of students who are not present in a given school"

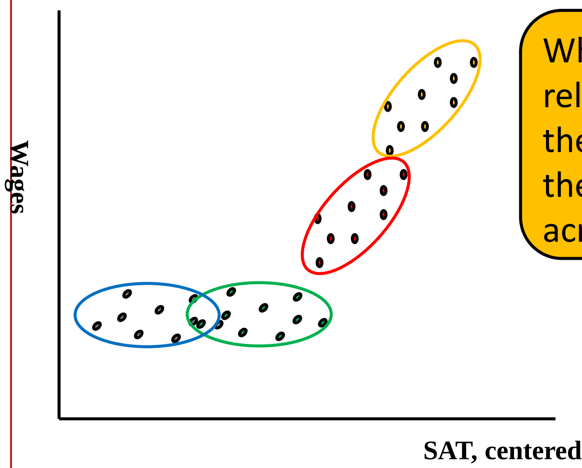
Value-added model assumptions

"..if groups look very different on background characteristics the results are likely to be based on untestable modeling assumptions and extrapolation…"

"…impossible to estimate the effect without making heroic assumptions…"

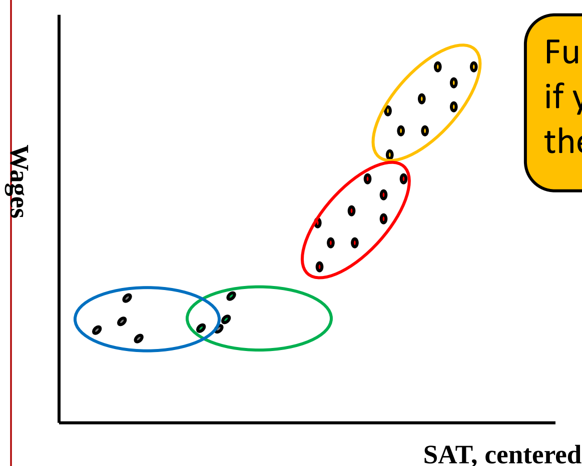
(Rubin, Stuart & Zanutto, 2004)

Concerns about value-added model assumptions



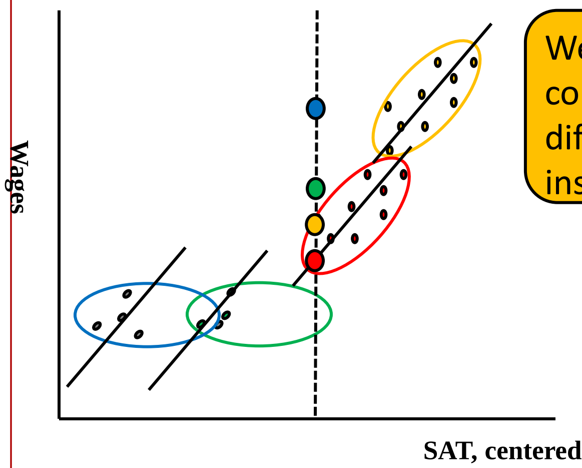
What if the relation between the covariates and the outcome differ across clusters?

Concerns about value-added model assumptions



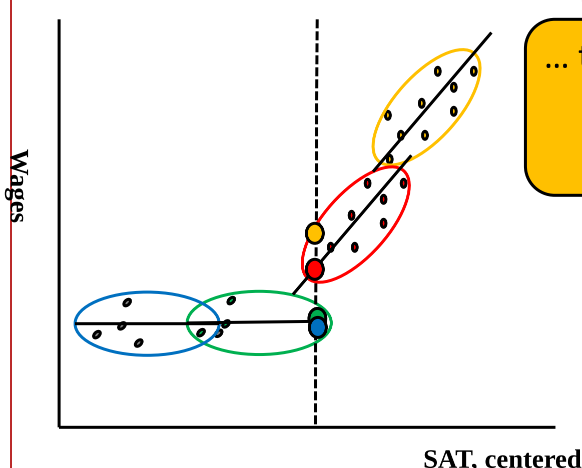
Furthermore, what if you do not have the data to see it?

Concerns about value-added model assumptions



We would conclude a different ranking of institutions…

Concerns about value-added model assumptions



… than "truth"

Concerns about value-added model assumptions

"… none of these articles attempts to define precisely the quantity that is the target of estimation… Thus, there is a focus on the estimation techniques rather than the definition of the estimand, i.e. the target of estimation"

(Rubin, Stuart & Zanutto, 2004)

Can we consider a different approach?

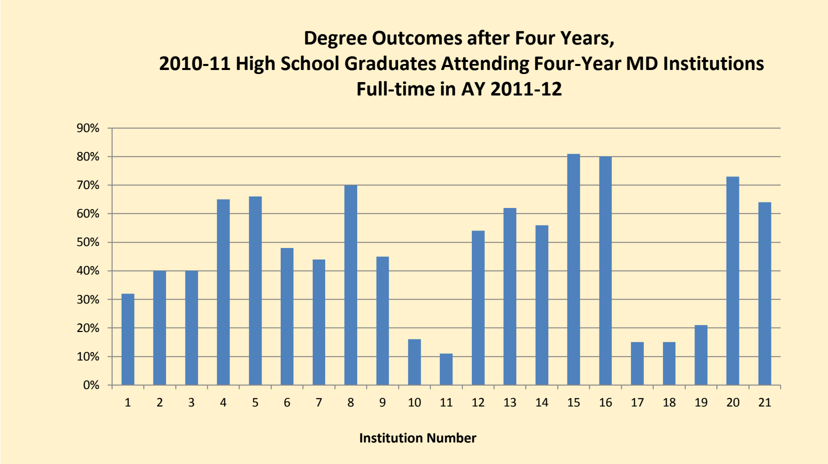
Which 4-year institutions are graduating students most effectively and in the timeliest fashion?

1) Initial stages of planning the analysis

2) Examples today are based on a selection of possible covariates and possible outcomes (*degree attainment and wages*)

3) At the end of the presentation, we will solicit feedback regarding variables you believe to be of interest

The naïve "treatment effect" estimates…



MLDSC Draft 5/4/17

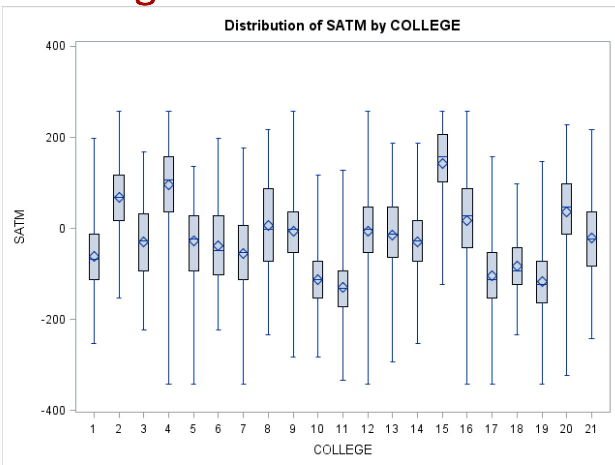
Do we satisfy the assumption of manipulability?

- Students selected into these 21 treatment conditions
- How comparable are they? Could we expect for each student to enroll at any of the 21 institutions?
- We utilized 20 conditioning variables, examples:
  - performance on college entrance exams
  - secondary school absenteeism, earnings during high school
  - successful advanced placement coursework
  - Receipt of aid/loan, family income (if available)
  - gender and race/ethnicity

MLDSC Draft 5/4/17

MLDS Center
Maryland Longitudinal Data System

Are we comparing apples and oranges?

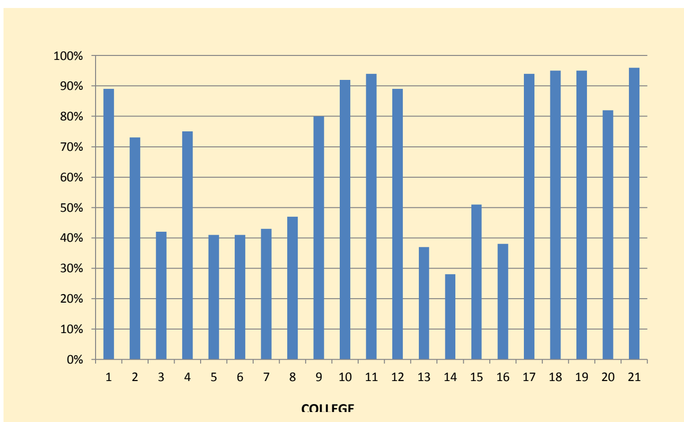


Mathematics Exam Score Centered

MLDSC Draft 5/4/17

MLDS Center
Maryland Longitudinal Data System

Are we comparing apples and oranges?



% Receiving Grant or Loan Aid

MLDSC Draft 5/4/17

MLDS CENTER
Maryland Longitudinal Data System

Perhaps we can just condition on covariates in a multilevel model?

- In a typical value added analysis, we would run a model wherein we condition on student (input) characteristics

For degree attainment:

$$\ln\left(\frac{P(y_{ij}=1\mid X)}{1-P(y_{ij}=1\mid X)}\right)=\beta_0+\sum\beta_p X_{pij}$$
$$\beta_0=\gamma_{00}+u_{0j}$$
$$\beta_p=\gamma_{p0}$$

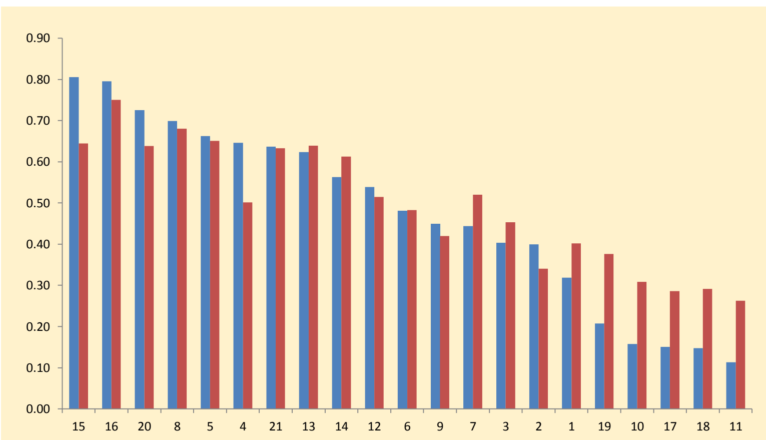
For wages:

$$Y_{ij}=\beta_0+\sum\beta_p X_{pij}+r_{ij}$$
$$\beta_0=\gamma_{00}+u_{0j}$$
$$\beta_p=\gamma_{p0}$$

MLDSC Draft 5/4/17

MLDS CENTER
Maryland Longitudinal Data System

Predicted 4-Year graduation rates, naïve and conditioned



MLDSC Draft 5/4/17

MLDS CENTER
Maryland Longitudinal Data System

Alternate approach: Separate the outcome model and conditioning model

What if we consider utilizing propensity score methods to condition pre-existing groups?

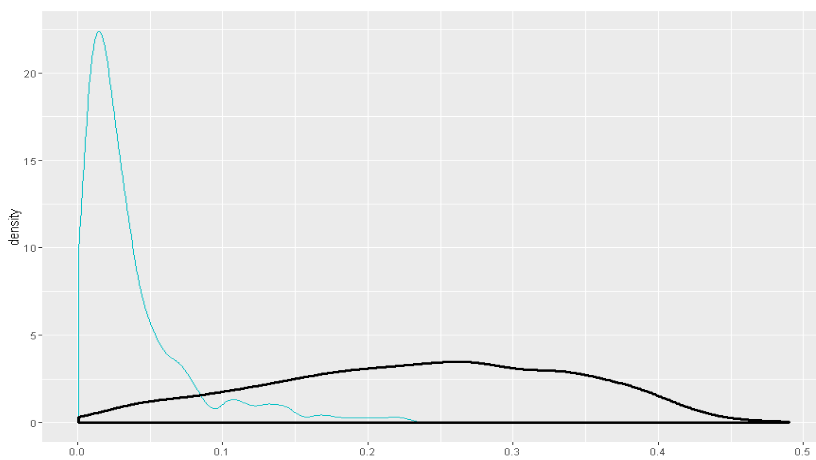
1) Calculate multinominal propensity scores

$$logit\left(\frac{P(COLLEGE_i = z \mid X)}{P(COLLEGE_i = Z \mid X)}\right) = \beta_{0z} + \sum \beta_{pz} X_{pi}$$

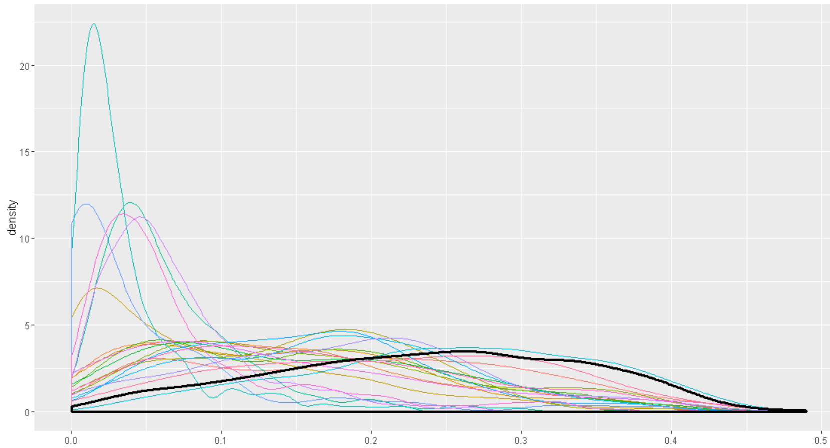
2) Examine common support
3) Select a conditioning method and evaluate balance
4) Examine outcomes across (multiple) conditioned samples

MLDS CENTER
Maryland Longitudinal Data System

Propensity density for one target college (z) – *College 9*



Propensity density for one target college (z) – *College 9*

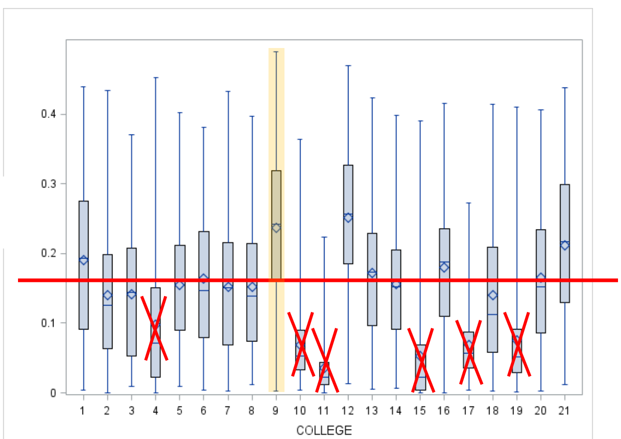


Propensity distributions for one target college (z) – *College 9*

Another view…

Are they similar enough to compare?

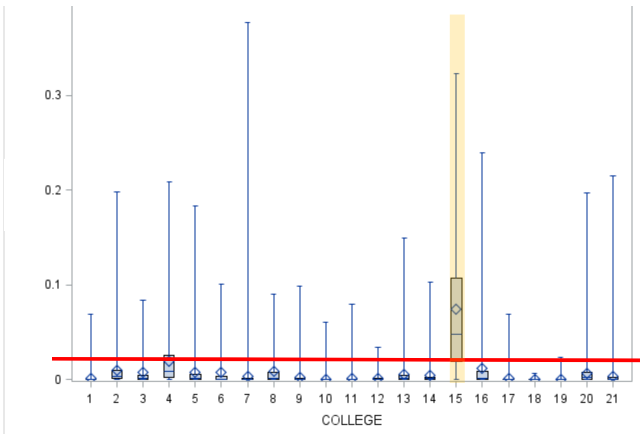
Is there "common support?"



Propensity distributions for another target college (z) – *College 15*

Are they similar enough to compare?

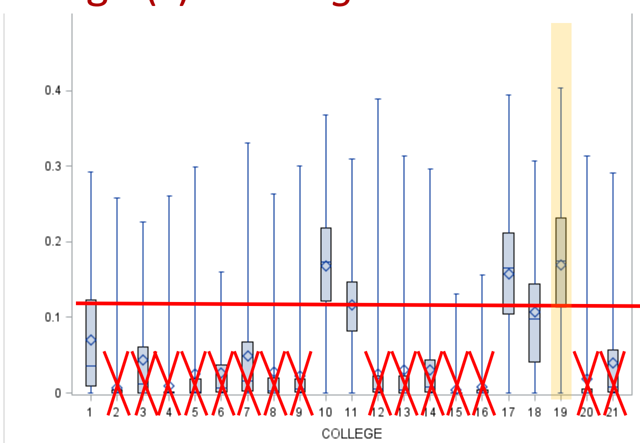
Is there "common support?"



Propensity distributions for another target college (z) – *College 19*

Are they similar enough to compare?

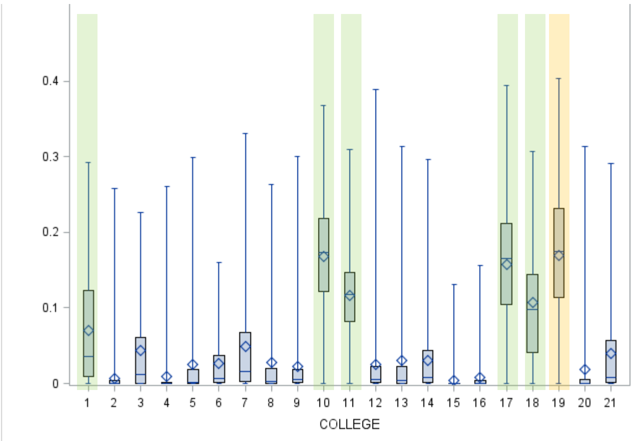
Is there "common support?"



Propensity distributions for another target college (z) – *College 19*

Are they similar enough to compare?

Is there "common support?"



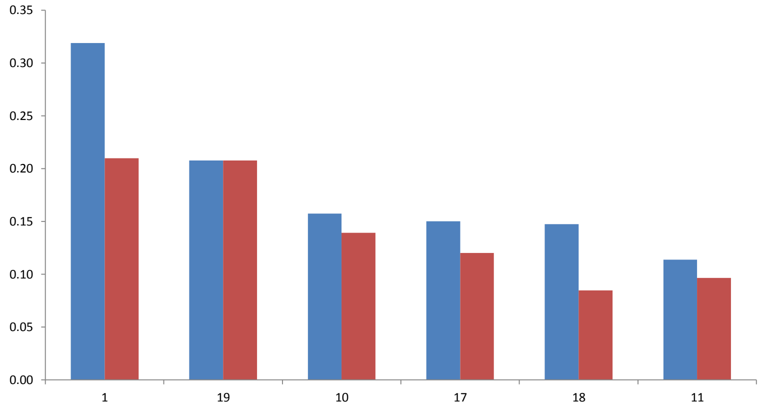
How can we examine conditioned "treatment effects" of colleges?

- For those institutions that demonstrate some degree of "common support" with the target institution, calculate a weight for each student that weights more heavily those who are more like the students at the target institution
- "Weighting by the Odds"

$$w_{zij} = 1(T_{zij}) + (1 - T_{zij})\frac{e_{zij}}{(1 - e_{zij})}$$

- We can then calculate weighted outcomes

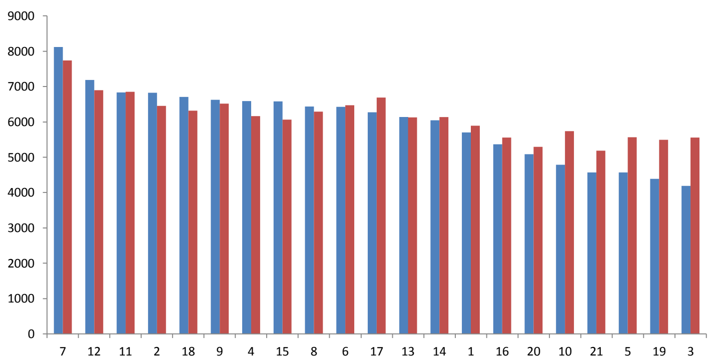
Naïve and WBO predicted graduation rates for colleges with common support of college 19



MLDSC Draft 5/4/17

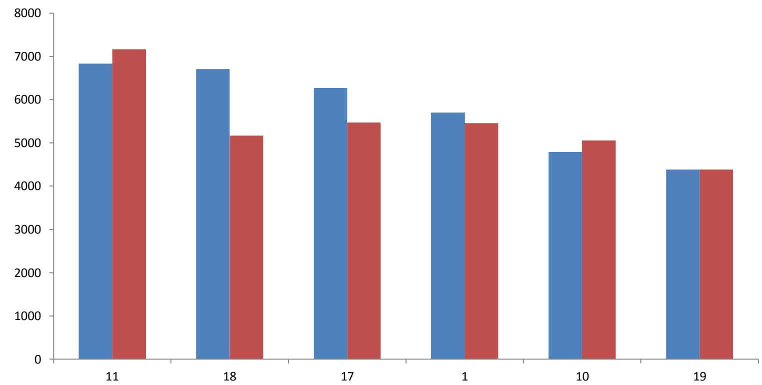
A different outcome: Value-added results

Predicted Quarterly Wage (for those with 4-year degree), Naïve and Conditioned



MLDSC Draft 5/4/17

WBO predicted quarterly wage for colleges with common support of college 19



Summary

The propensity score approach allows us to more precisely define the estimand:

How well does institution z perform relative to a “case mix” weighted estimate from other institutions that enroll some similar students?

MLDS CENTER
Maryland Longitudinal Data System

Summary

This approach has some advantages:

1) examine common support / overlap
2) stakeholder concerns of being compared with non-comparable institutions may be addressed
3) conditioning model is the same for all outcomes

MLDS CENTER
Maryland Longitudinal Data System

Summary

This approach needs some work:

1) how does one determine common support?
2) is weighting or matching a better approach?
3) is there a parsimonious index that can be defined across the many target institutions?

MLDS Center
Maryland Longitudinal Data System

Summary

Questions for the audience:
What student body characteristics would you want to "equate" institutions on?

What outcomes do you think reflect "effective" and "timely"?

What are the policy implications of providing such information to stakeholders?

MLDS Center
Maryland Longitudinal Data System

References

Cunha, J. M., & Miller, T. (2014). Measuring value-added in higher education: possibilities and limitations in the use of administrative data. *Economics of Education Review, 42*, 64-77.

McCaffrey, D. F., Koretz, D., Louis, T. A., & Hamilton, L. (2004). Models for value-added modeling of teacher effects. *Journal of Educational and Behavioral Statistics, 29*(1), 67-101.

Reardon, S. F., & Raudenbush, S. W. (2009). Assumptions of value-added models for estimating school effects. *Education Finance and Policy, 4*(4), 492-519.

References

Rubin, D. B., Stuart, E. A., & Zanutto, E. L. (2004). A potential outcomes view of value-added assessment in education. *Journal of Educational and Behavioral Statistics, 29*(1), 103-116.

Tekwe, C. D., Carter, R. L., Ma, C. X., Algina, J., Roth, J., & Ariet, M. (2004). An empirical comparison of statistical models for value-added assessment of school performance. *Journal of Educational and Behavioral Statistics, 29*(1), 11-36.

Thoma, S., Peng. W. J., & Gray, J. (2007). Modeling patterns of improvement over time: value added trends in English secondary school performance across ten cohorts. *Oxford Review of Education, 33*(3), 261-295.

Thank you!

Laura.Stapleton1@maryland.gov

Lstaplet@umd.edu