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Learning About and From Variation in Treatment Effects

Sponsored by the Institute of Education Sciences
and the Stanford Center for Education Policy Analysis

July 18-21, 2016
CERAS 101 - Stanford Graduate School of Education

Day 1: Studying Cross-site Distributions of ITT Effects

Instructors: Howard Bloom, Michael Weiss, Steve Raudenbush

Time	Topic
8:30 – 9:00	Coffee and Breakfast Available
9:00 – 9:30	Introductions and Workshop Overview (Reardon)
	Framing the workshop. Heterogeneity, mediation, moderation (Reardon)
9:30 – 10:30	Estimating Parameters of a Cross-site Distribution of ITT Effects (Bloom)
10:30 – 10:45	Break
10:45 – 11:45	Statistical Precision/Power for Estimating Parameters of a Cross-site Distribution of ITT Effects (Bloom)
11:45 – 12:30	Small Group Activity (Bloom)
12:30 – 1:45	Lunch
1:45 – 2:45	Empirical Estimates of Parameters of Cross-site Distributions of ITT Effects and a Nascent Theory of Cross-site Impact Variation (Weiss)
2:45 – 3:00	Break
3:00 – 4:15	Alternative Estimands and Estimators for Parameters of a Cross-site Distribution of ITT Effects (Raudenbush)
4:15 – 5:00	Small group Activity (Weiss & Raudenbush)

Please read bolded readings prior to workshop. All readings can be found at https://cepa.stanford.edu/workshops/stanford-workshop-learning-about-and-variation-program-impacts.

Background Readings for Day 1:

- **Bloom, H.S., S.W. Raudenbush, M. J. Weiss and K. Porter (conditional acceptance) "Using Multisite Experiments to Study Cross-site Variation in Effects of Program Assignment," *Journal of Research on Educational Effectiveness*.**
- **Bloom, H.S. and J. Spybrook (under review) "Assessing the Precision of Multisite Trials for Estimating Parameters of Cross-site Distributions of Program Effects."**
- **Weiss, M.J., H.S. Bloom, N. Verbitsky Savitz, H. Gupta, A. Vigil and D. Cullinan (under review) "How Much Do the Effects of Education and Training Programs Vary Across Sites? Evidence from Existing Multisite Randomized Control Trials."**
- Raudenbush, S.W. and H.S. Bloom (2015) "Learning About and From a Distribution of Program Impacts Using Multisite Trials," *American Journal of Evaluation*.
- Weiss M.J, H.S. Bloom and T. Brock (2014) "A Conceptual Framework for Studying the Sources of Variation in Program Effects," *Journal of Policy Analysis and Management*.
- Raudenbush, S.W. and D. Schwartz (in progress) "Estimation of Means and Covariance Components in Multi-site Randomized Trials."

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Day 2: Studying Mediation of Treatment Effects Using Instrumental Variables Approaches

Instructors: Steve Raudenbush, Sean Reardon

Time	Topic
8:30 – 9:00	Coffee and Breakfast Available
9:00 – 9:15	A Framework for Studying Mediation (Reardon)
9:15 – 11:15	Complier Average Effects in Multisite Trials (Raudenbush)
11:15 – 12:00	Small Group Activity (Raudenbush)
12:00 – 1:30	Lunch
1:30 – 2:30	The MSMM-IV Model: Conceptual Model and Assumptions
2:30 – 2:45	Break
2:45 – 4:00	Using the MSMM-IV Model when the Exclusion Restriction is Invalid (Reardon)
4:00 – 4:45	Small group Activity (Reardon and Fox)

Background Readings for Day 2:

- **Reardon, S.F., and Raudenbush, S.W. (2013). "Under What Assumptions do Site-by-Treatment Instruments Identify Average Causal Effects?" *Sociological Methods and Research* 42(2): 143-163.**
- Reardon, S.F., Unlu, F., Zhu, P., & Bloom, H. (2014). "Bias and Bias Correction in Multi-Site Instrumental Variables Analysis of Heterogeneous Mediator Effects." *Journal of Educational and Behavioral Statistics* 39(1): 53-86.
- Reardon, S.F., Unlu, F., Zhu, P., & Bloom, H. (2016). "Using the MSMM-IV Model to Estimate Mediator Effects When the Exclusion Restriction is Invalid." Working Paper.
- Raudenbush, S.W., Reardon, S.F., & Nomi, T. (2012). "Statistical Analysis for Multi-site Trials Using Instrumental Variables with Random Coefficients" *Journal of Research on Educational Effectiveness* 5: 303-332.
- Duncan, G. J., Morris, P., and Rodrigues, C.(2011). Does money really matter? Estimating impacts of family income on young children's achievement with data from random-assignment Experiments. *Developmental Psychology*, 47(5): 1263-1279.
- Kling, J. R., Liebman, J. B., & Katz, L. F. (2007). Experimental analysis of neighborhood effects. *Econometrica, 75*(1), 83-119.

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Day 3: Principal Stratification

Instructor: Lindsay Page

Time	Topic
8:30 – 9:00	Coffee and Breakfast Available
9:00 – 10:15	Conceptual framework and key assumptions (Page)
10:15 – 10:30	Break
10:30 – 12:00	Examples: principal stratification set up and defining estimands of interest (Page) • Small group exercise • Discussion
12:00 – 1:30	Lunch
1:30 – 3:30	Bounds Application and Guided Exercise (Page)
3:30 – 3:45	Break
3:45 – 4:30	Wrap Up (Nod to Principal Scores / Model-Based Estimation) (Page)

Background Readings for Day 3:

- **Page, L. C., Feller, A., Grindal, T., Miratrix, L. & Somers, M-A. (2015). Principal stratification: A tool for understanding variation in program effects across endogenous subgroups. American Journal of Evaluation, 36(4), 514-531.**
- **Long, D. M., & Hudgens, M. G. (2013). Sharpening bounds on principal effects with covariates. Biometrics, 69(4), 812-819.**
- Feller, A., Grindal, T., Miratrix, L. & Page, L. C. (forthcoming). Compared to what? Variation in the impacts of Head Start by alternative child care setting. Annals of Applied Statistics.
- Feller, A., Mealli, F., & Miratrix, L. (2016). Principal Score Methods: Assumptions and Extensions. arXiv preprint arXiv:1606.02682.
- Feller, A., Greif, E., Miratrix, L., & Pillai, N. (2016). Principal stratification in the Twilight Zone: Weakly separated components in finite mixture models. arXiv preprint arXiv:1602.06595.

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Day 4: Weighting Methods for Causal Mediation Analysis

Instructors: Guanglei Hong, Xu Qin, Lindsay Page, Sean Reardon

Time	Topic
8:45 – 9:00	Coffee and Breakfast Available
9:00 – 10:30	Concepts of causal mediation (Hong)
	Brief review of existing methods for causal mediation analysis (Hong)
10:30 – 10:45	Break
10:45 – 12:00	Rationale of the RMPW strategy (Hong)
12:00 – 1:00	Lunch
1:00 – 2:30	Parametric and nonparametric analytic procedures and simulation results (Hong)
	Hands-on exercise with the RMPW software (Hong, Qin)
	RMPW extensions: Stata, SAS, and R code (Hong, Qin)
2:30 – 2:45	Break
2:45 – 3:30	Multisite causal mediation analysis (Qin)
3:30 – 4:30	Q & A wrt Causal Meditation Analysis and Its Distinctions from and Connection with Other Methods (Hong, Page, Reardon)

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<u>Background Readings for Day 4</u>:

- **Hong, G., Deutsch, J., & Hill, H. D. (2015). Ratio-of-mediator-probability weighting for causal mediation analysis in the presence of treatment-by-mediator interaction. *Journal of Educational and Behavioural Statistics*, *40*(3), 307-340.**
- **Hong, G., & Nomi, T. (2012). Weighting methods for assessing policy effects mediated by peer change. *Journal of Research on Educational Effectiveness* special issue on the statistical approaches to studying mediator effects in education research, *5*(3), 261-289.**
- Hong, G. (2015). *Causality in a social world: Moderation, mediation, and spill-over*. West Sussex, UK: John Wiley & Sons.
- Bein, E., Deutsch, J., Porter, K., Qin, X., Yang, C., & Hong, G. (2015). *Technical report on two-step estimation in RMPW analysis*. MDRC.
- Huber, M. (2014). Identifying causal mechanisms (primarily) based on inverse probability weighting. *Journal of Applied Econometrics*, *29*(6), 920-943.
- Lange, T., Rasmussen, M., & Thygesen, L. (2014). Assessing natural direct and indirect effects through multiple pathways. *American journal of epidemiology*, *179* (4), 513-518.
- Lange, T., Vansteelandt, S., & Bekaert, M. (2012). A simple unified approach for estimating natural direct and indirect effects. *American journal of epidemiology*, *176* (3), 190–195.
- Tchetgen Tchetgen, E. J., & Shpitser, I. (2012). Semiparametric theory for causal mediation analysis: Efficiency bounds, multiple robustness and sensitivity analysis. *The Annals of Statistics*, *40*(3), 1816-1845.
- Hong, G., Deutsch, J., & Hill, H. (2011). Parametric and non-parametric weighting methods for estimating mediation effects: An application to the National Evaluation of Welfare-to-Work Strategies. In *JSM Proceedings*, Social Statistics Section. Alexandria, VA: American Statistical Association, pp.3215-3229.
- Hong, G. (2010). Ratio of mediator probability weighting for estimating natural direct and indirect effects. In *JSM Proceedings*, Biometrics Section. Alexandria, VA: American Statistical Association, pp.2401-2415.

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