**Soc 952: Causality**
**Mathematical and Statistical Applications in Sociology**
Spring 2014
Sewell Social Science Bldg. 4322
Time: Wed 2:30-5:30

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**The Counterfactual Framework to Causal Inference**
Social scientists routinely ask causal questions. "Does job training cause higher earnings?" "Does divorce impede children's academic progress?" "Does the death of a husband raise the mortality of a surviving wife?" Questions such as these are as old as the discipline. And yet, social scientist used to retreat behind the dictum "correlation does not equal causation" (true as it is) to disavow the causal ambition of their empirical analyses.

Building on seminal work by statistician Donald Rubin in the 1970s, researchers today have at their disposal a powerful framework to conceptualize and implement causal inference. This *potential-outcomes framework of causal inference* (often called the *counterfactual approach*) is the dominant model of causal inference in the social and health sciences. It assimilates parallel developments in statistics, econometrics, and computer science unites them under a common roof.

A central appeal of the counterfactual framework is its simplicity and generality. In keeping with common intuition, it conceptualizes causal questions as "what-would-happen-if" questions, and causal effects as the difference between potential outcomes associated with alternative treatments.

In this course, we will use the counterfactual framework to investigate the conditions under which causal inference is possible and provide guidance for estimating causal effects in practice.

The counterfactual framework does not specialize in any particular data structure, but in a particular type of question—causal questions—that cuts across data structures (e.g., time-to-event data, or nested data) and techniques (e.g., survival analysis, or hierarchical linear models). Indeed, the counterfactual framework is credited with inventing relatively few genuinely new statistical techniques. Instead, it is appreciated for improving our understanding of existing techniques—such as matching, regression, or instrumental variables analysis—and advancing their use for new, causal, purposes. (That being said, the counterfactual approach is indeed credited with some important new techniques, such as propensity score estimation, principal stratum analysis, g-estimation, and inverse-probability-of-treatment weighting, some of which we will encounter in this course.)

**This Course**

This course provides a practical introduction to the potential outcomes (counterfactual) framework of causal inference. We will understand the general framework in some detail and then deal with selected estimation topics that either are or should be central to the social sciences.

Topics include causal inference for point treatments using matching, propensity scores, regression, instrumental variables; and causal inference for time-varying treatments using inverse probability weighting in marginal structural models. We will consider complementary approaches to the problem of unobserved heterogeneity such as instrumental variables estimation and sensitivity analysis. And we will consider the identification of causal effects in complex causal systems using directed acyclic graphs.

Throughout, we will focus on the *conceptual logic* of these methods by developing solid substantive intuition and studying empirical applications. We will focus first on the difficulty of formulating and articulating coherent causal questions, and then consider suitable methods for answering them.

**A word of warning:** A central contribution of the counterfactual framework of causality is to spotlight implicit assumptions and inherent limitations in existing techniques. Consequently, many methodologists embrace the lessons of the new literature on causality as a call for analytic modesty. This may be discouraging to you at first. Yet an improved understanding of current limitations also prepares the way for novel solutions that stand on firmer ground than previous practice. We will encounter numerous such solutions in this course. Nevertheless, *this course does not focus on hands-on practice* with canned software routines. Rather, the goal is to sensitize students to conceptual issues in applied work, and to develop guiding intuitions that may empower the independent study of appropriate techniques for own empirical research projects.

**A note on reading statistics**

There is real pleasure in reading statistics—but reading statistics is a different beast from reading applied work in sociology. This material is best read *slowly* with pencil and paper. Note the definitions of all symbols as they first appear in the text for your reading reference. Then identify the central insight explained in the text. Then understand how the accompanying equations cement the insight. Then figure out how the author arrives at the insight. Lastly, attempt to transfer the abstract insights of the readings to concrete applications in your own research by searching for a homologous problem in a substantive area that you understand well.

Don't be tricked by low page counts. A fruitful reading of 10 pages of introductory statistics may require anywhere between 2-10 hours of work. You'll often skip back and forth in an article to remind yourself of previous steps in a deductive chain, and you'll find yourself wanting to reread the entire thing once you've finally made it through for the first time.

It’s impossible to skim the assigned readings an hour before class.

**Class structure**
Class meetings will divide into lecture presentations of the technical material and student discussions of the empirical applications from the required readings.

**Enrollment**
This course is limited to regularly enrolled students. Auditors must demonstrate a compelling reason against formal enrollment. Non-enrolled participants must contribute in the same manner as enrolled students, and fulfill the same requirements.

**Email communication:** I mostly communicate via email and use a sorting script to keep track. Please put “Soc952” in the subject line of all emails to me. If you don’t put “Soc952” in the subject line, I may not receive your email. That’s “Soc952” without spaces—not “Soc_952”, not “SOC952.” Thank you.

**Requirements**
*Readings:* You commit to carefully completing all required readings prior to the class meeting, and will make an effort to look at some of the optional readings as well.

*Abstracts:* Every week, you will submit a one-page (single-spaced) abstract of one or two assigned readings of your choice. Every abstract has two parts. First, you will highlight the key methodological insight from your readings and explain it in your own words. Second, you will offer reflections on the implications of this insight for some substantive topic in your area of interest, ideally relating to your own research. Please proof your abstracts for content, style, spelling, and grammar. Abstracts are due as pdf or .docx email attachments on Tuesday night (8PM).

*Presentations:* All participants will present assigned articles in class at various points throughout the semester. Schedule TBA.

*Assignments:* Students will complete 5 homework assignments, which I will tailor to the difficulties students may have with the material. We will discuss results in class. Assignments are worth 10-30 points each, for a total of 100 points.

*Paper:* You will write a term paper on a causal topic. The paper may be empirical or conceptual and should relate to the concerns of this class. I encourage you to develop an existing project, or thesis chapter, in a causal direction, but ask that you disclose the amount of previous work on the topic and elaborate on the specific revisions generated for this class. The paper must begin with posing a well-defined question, or struggle to render an existing question causally precise. A one-page proposal for the paper is due by the 6$^{th}$ week of class. Please submit your papers as pdf files, not exceeding 20 double-spaced pages, 12 point font, one-inch margin, including tables, figures, and references. I will stop reading after 20 pages. Papers are due on May 16 (absolutely no extensions).

**Grading**

20% participation, 10% abstracts, 30% homework assignments, 40% final paper.

**Prerequisites**
Students should bring a solid understanding of standard regression methods for continuous and categorical outcomes at the level of Soc 361 and Soc 362 or above. Knowledge of basic probability theory is helpful but not strictly required. You don't need calculus.

**Required Text**
Morgan, Stephen L., and Christopher Winship. 2007. Counterfactuals and Causal Inference: Methods and Principles for Social Research. Cambridge: Cambridge University Press.

> This is the first comprehensive survey of the counterfactual approach to causal inference, written for a social science audience with a strong emphasis on causal thinking over mathematical derivations. This book provides the backbone for about two thirds of this course and constitutes the core of the required readings.
>
> A second edition is in the works. If it comes out during the semester, you should get it.

**More Books on Causal Inference**
Angrist, Joshua D., and Jörn-Steffen Pischke. 2009. Mostly Harmless Econometrics: An Empiricist's Companion. Princeton: Princeton University Press.

> An excellent and very accessible textbook exposition of the counterfactual interpretation of standard econometric tools (i.e. regression, IV, fixed effects, RD). You should probably buy this text and read it in parallel with Morgan and Winship.

Pearl, Judea. 2009. Causality, 2nd edition. Cambridge. Cambridge University Press.

> An emerging classic: a comprehensive advanced treatment of directed acyclic graphs and their relationship to the potential outcomes model and structural equation models. For what it does, this is a surprisingly accessible book, requiring only a moderate background in probability theory and formal logic.

Manksi, Charles F. 2007. Identification for Prediction and Decision. Cambridge: Harvard University Press.

> Similar material as Angrist and Pischke, somewhat more technical. Greater emphasis on prediction.

Rosenbaum, Paul R. 2000. Observational Studies (2nd ed.). Springer Press.

> The most thorough textbook on matching models for observational studies, written by one of the progenitors of counterfactualism. Densely written. Requires a solid working knowledge of intermediate probability theory.

Shadish, WR, TD Cook, and DT Campbell. 2001. Experimental and Quasi-Experimental Designs for Generalized Causal Inference. Houghton Mifflin.

Update on a classic text in psychology and sociology. Covers in detail situations in which completely randomized experiments are not feasible yet close substitutes are, given suitable assumptions. Introduced regression-discontinuity and interrupted-time-series designs to the field. Low tech style.

<u>General Statistics Texts for Social Scientists</u>

Gelman, Andrew, and Jennifer Hill. 2007. Data Analysis Using Regression and Multilevel/Hierarchical Models. Cambridge: Cambridge University Press.

This treatment of standard regression and multilevel techniques has the potential of becoming the new textbook of record for intermediate social science statistics courses. It is exceptionally well written, focuses on underlying ideas over mathematical details, and seamlessly integrates numerous line-by-line software examples (in R). This book presents the material from a statistical, rather than econometric, perspective (which are often equivalent, despite considerable differences in terminology). We'll occasionally draw on this book for expositions, examples, and some exercises. Additionally, you may find this book useful to brush up on techniques encountered but not explained in Morgan and Winship and the assigned journal articles. You should probably own this book.

Wooldrige, Jeffrey M. 2001. Econometric Analysis of Cross Section and Panel Data. Cambridge: MIT Press.

An excellent results-oriented treatment of modern applied econometrics, a current favorite of advanced survey courses in econometrics. This book focuses more on mathematical detail (but skips the outer reaches of econometric theory) and hence requires a solid working knowledge of multivariate calculus.

**Schedule**
(Subject to change!)

Note: Readings are arranged in the recommended order of reading (where possible)

**1. The Counterfactual Model**
*We introduce the counterfactual model. We learn about the fundamental problem of causal inference and how to solve it via randomized experiment and observational studies. We discuss some conceptual and practical issues, such as ignorability, manipulability, and SUTVA.*

*Recommended:*
Morgan, S. and C. Winship. 2007. Counterfactuals and Causal Inference: Methods and Principles for Social Research. Cambridge: Cambridge University Press. Read pp. 31-50.

Gelman, Andrew, and Jennifer Hill. 2007. *Data Analysis Using Regression and Multilevel/Hierarchical Models*. Cambridge: Cambridge University Press. Read Pp. 186-188.

Holland, P. 1986. "Statistics and Causal Inference." Journal of the American Statistical Association, 81(396): 945-960. Read: 945-949, 954-955, 959.

*Optional:*

Morgan, S. and C. Winship. 2007. Read 1-30.

Gangl, Markus. 2009. “Causal Inference in Sociological Research” *Forthcoming in* Annual Review of Sociology 2010. Read: 1-13.

Angrist, JD, and JS Pischke. 2009. Mostly Harmless Econometrics. Chapters 1 & 2.

Heckman, J. 2005. "The Scientific Model of Causality." Sociological Methodology 35(1): 1-98. Read Pp. 1-9.

Heckman, J, and JA Smith. (1995). "Assessing the Case for Social Experiments." Journal of Economic Perspectives 9: 85-110.

Bertrand, M., and S. Mullainathan. 2004. “Are Emily and Greg More Employable Than Lakisha and Jamal? A Field Experiment on Labor market Discrimination.” American Economic Review 94(4): 991-1013.

A great social experiment (audit study). Perhaps the greatest. Won’t cover much in lecture, but you should read/have read this.

**2. Directed Acyclic Graphs**
*We learn a graphical notation for causal models, called directed acyclic graphs (DAGs). DAGs represent the analyst's causal expert knowledge and assumptions. We use DAGs to derive non-parametric identification results—e.g., to determine if a treatment is conditionally ignorable. We focus on identification via "adjustment," i.e. confounder control.*

*Required:*
Morgan and Winship, Chapter 3.
An intuitive introduction to DAGs

Elwert, Felix. 2013. "Graphical Causal Models." Pp. 245-273 in S. Morgan (ed.), *Handbook of Causal Analysis for Social Research*. Dodrecht: Springer. Read: 245-61, 266, 270-1.
A fairly comprehensive treatment of DAGs for social research.

*Optional:*
Judea Pearl. 2010. "The Foundations of Causal Inference." Sociological Methodology. Vol. 40: 75-150.
Future lectures will draw on this, albeit less technically.

Pearl, J. 1995. "Causal Diagrams for Empirical Research." *Biometrika,* 82(4):669-710. Read: 669-688.
This is a classic. I've put an excerpt from Pearl's book on the course website that explains "d-separation without tears" (Pearl's title), which you may find helpful.

Shpitser, Ilya, Tyler J. VanderWeele and James M. Robins. 2010. "On the validity of covariate adjustment for estimating causal effects." Pp. 527-536 in Proceedings of the 26th Conference on Uncertainty and Artificial Intelligence. Corvallis, OR: AUAI Press. http://arxiv.org/pdf/1203.3515.pdf
Shows tat the graph-based adjustment criterion is equivalent to conditional ignorability criterion. Goes a long way toward showing that using graphs vs potential outcomes is equivalent for most of what social scientists do. Highly technical. Elwert (2013) translates.

**3. Endogenous Selection**
*In a certain sense, selection bias is the opposite of confounding bias. Analysts often have better intuition for confounding than for selection. Today, we will use DAGs to explain selection bias and go through a slew of examples.*

*Required:*
Elwert, Felix, and Christopher Winship. *Forthcoming*. "Endogenous Selection Bias: The Problem of Conditioning on a Collider Variable." *Annual Review of Sociology.* Read entire.
A systematic treatment of selection bias using DAGs, many sociological examples.

Elwert, Felix. “Graphical Causal Models.” Pp. 245-273 in S. Morgan (ed.), *Handbook of Causal Analysis for Social Research*. Dodrecht: Springer. Read: 262-6.
Same material as Elwert & Winship above, but some different substantive examples.

Morgan and Winship, Pp. 179-181 (on controlling for pretests)

*Optional:*
Gelman and Hill, 2007. Read: 188-194

Rosenbaum, Paul. 1984. “The Consequences of Adjustment for a Concomitant Variable that has been Affected by the Treatment.” Journal of the Royal Statistical Society, Series A, 147:656-666.
This is the canonic citation for selection bias in the counterfactual literature.

***4. Matching I***
*Matching, as a statistical technique, is most closely associated with the potential outcomes framework for historical reasons—so much so, in fact, that some people (falsely) believe the two are one and the same. One of the greatest virtues of matching estimators is that they are transparent; hence, it is better possible to understand when they are appropriate and when they are not. In this and the next lecture, we discuss exact matching, propensity score matching, their variants, and specification checks as centrally important techniques for recovering causal effects from observational data.*

*Required:*
Morgan and Winship, Chapter 4.

Stuart, E.A. (2010). Matching Methods for Causal Inference: A review and a look forward. Statistical Science 25(1): 1-21.
A non-technical review of the field with special emphasis on balance testing.

Rosenbaum and Rubin. 1984. "Reducing Bias in Observational Studies Using Subclassification on the Propensity Score." Journal of the American Statistical Association 79: 516-24.
Hard—try your best. We will review only the central proof in lecture.

*Recommended:*
Dehejia and Wahba. (1999). "Causal Effects in Nonexperimental Studies: Reevaluating the Evaluation of Training Programs." Journal of the American Statistical Association 1053-62.
This application, perhaps more than any other, popularized propensity score matching in the social sciences.

Rosenbaum and Rubin. 1983. “The Central Role of the Propensity Score in Observational Studies for Causal Effects.” Biometrika 70: 41-55.
The classic.

**5. Matching II**

*Required:*
Imai, K, G King, and EA Stuart. 2008. “Misunderstandings Between Experimentalists and Observationalists about Causal Inference.” Journal of the Royal Statistical Society, Ser. A 171(2):481-502.

Ho, DE, K Imai, G King, EA Stuart. 2007. “Matching as Non-parametric Preprocessing for Reducing Model Dependence in Parametric Causal Inference.” Political Analysis 15: 199-236.

*Optional:*
Steiner PM, Cook TD, Shadish WR, Clark MH. 2010. The importance of covariate selection in controlling for selection bias in observational studies. Psychol. Methods 15(3):250—67.

Iacus, Stefano M, Gary King, and Giuseppe Porro. 2011. Causal Inference Without Balance Checking: Coarsened Exact Matching. Political Analysis

Abadie, Alberto, David Drukker, Jane Leber Herr, and Guido W. Imbens. 2004. "Implementing Matching Estimators for Average Treatment Effects in Stata." Stata Journal 4(3): 290-311.

> If you have Stata 13, you should also review the psmatch entry in the manual, or better, yet, read about the entire new “treatment effects” suite of commands in the pdf documentation that comes with the software.

**6. Regression**
*Regression is the workhorse of empirical data analysis. We will analyze regression from two perspectives. First, we will ask under what conditions regression can recover various types of causal effects from observational data. Second, we will use elementary path analysis to understand some central (and difficult) problems of causal inference in a straightforward parametric context.*

Paper proposals due in class!

*Required:*
Morgan and Winship: Chapter 5.

Pearl, J. 2013. “Linear models: A useful “microscope” for causal analysis.” *Journal of Causal Inference* 1:155–170.

*Optional:*
Freedman, DA. 1983. “A Note on Screening Regression Equations.” American Statistician 37:152-5.

One of the most frightening articles on regression ever written.

Elwert, Felix, and Christopher Winship. "Effect Heterogeneity and Bias in Main-Effects-Only Regression Models." Pp. 327–336 in *Heuristics, Probability and Causality: A Tribute to Judea Pearl*, Rina Dechter, Hector Geffner, and Joseph Y. Halpern (eds.). College Publications, UK.

On the consequences of unmodeled effect heterogeneity in linear regression, suing DAGs.

Angrist and Pischke. 2009. Mostly Harmless Econometrics. Chapter 3.

**7. Bounds and Sensitivity Analysis**

*Identification in observational studies is always iffy because one has to make strong assumptions. Sensitivity analysis formally investigates what would happen to estimates and inferences if certain assumptions were violated to varying degrees. IMO, every paper should be accompanied by a sensitivity analysis. Bounds investigate what happens to estimates and inferences if the analyst makes* *no* *assumptions.*

*Required:*

Morgan and Winship, Pp. 169-179 (on Manski bounds)

Rosenbaum. (1987). "The Role of a Second Control Group in an Observational Study (with Discussion)." Statistical Science 2: 292-316. Read pp292-302.

For substantially the same material, with less technical detail, read Rosenbaum, Paul (2002) *Observational Studies (second edition)*. Chapter 8.

Harding. (2003). "Counterfactual Models of Neighborhood Effects: The Effect of Neighborhood Poverty on Dropping out and Teenage Pregnancy." American Journal of Sociology 109: 676-719. Skim entire and carefully read 691-694 and 700-712.

One of the first (and still rare) applications of Rosenbaum & Rubin style sensitivity analyses in sociology.

*Optional:*

Sharkey, Patrick, and Felix Elwert. 2011. "The Legacy of Disadvantage: Multigenerational Neighborhood Effects on Cognitive Ability." *American Journal of Sociology* 116(6):1934–81. Especially pp.1954-8.

For a low-tech introduction to Robins (1999) style sensitivity analysis.

Greenland, S. 1996. "Basic Methods for Sensitivity Analysis of Biases." International Journal of Epidemiology. 25(6): 1107-1116.

Basic ideas presented with great clarity. Uses epi lingo. Read this, then try Rosenbaum and Rubin 1983.

Rosenbaum and Rubin. 1983. “Assessing Sensitivity to an Unobserved Binary Covariate in an Observational Study with Binary Outcome.” Journal of the Royal Statistical Society, Ser. B 45: 212-218.

The original R&R exposition of sensitivity analysis. Basis of Harding 2003. Warrants careful reading. Difficult. Give it a shot.

**8. Instrumental Variables I (Technical Introduction)**

*Instrumental variables (IV) analysis is one technique to get identification if the treatment is confounded in unobservables, i.e., when identification by adjustment fails. IV analysis is extremely popular in economics and increasingly so in epidemiology. I expect that IV analysis will become more important in sociology and hence devote three lectures to introducing and understanding the technique, the substantive content of its assumptions, and what can be done to test them.*

*Required:*

Morgan and Winship, Pp. 181-184 and Chapter 7

*Optional*

Angrist, J, G. Imbens, and D. Rubin. (1996). "Identification of Causal Effects Using Instrumental Variables." Journal of the American Statistical Association 91: 444-455.

The classic treatment of IV from a counterfactual perspective. Canonic treatment of LATE estimands.

Brito, C. (2010). Instrument sets. In Dechter, R., Geffner, H., and Halpern, J., editors, Heuristics, Probability and Causality: A Tribute to Judea Pearl, pages 295–307. College Publications.

A succinct introduction to basic and advanced IV models in linear models using DAGs. Fairly self-contained, give it a try.

Angrist and Pischke. 2009. Mostly Harmless Econometrics. Chapter 4.

**9. Instrumental Variables II (Applications)**

Morgan and Winship, pp.219-230

*Required:*

Angrist, J. 1990. "Lifetime Earnings and the Vietnam Era Draft Lottery: Evidence from Social Security Administrative Records." American Economic Review 80(3): 313-336.

Angrist, J. 1990. “Errata: Lifetime Earnings and the Vietnam Era Draft Lottery: Evidence from Social Security Administrative Records.” The American Economic Review80(5): 1284-1286.

Perhaps the most famous IV application there is.

Angrist, JD, and Alan B. Krueger. 1991. Does Compulsory School Attendance Affect Schooling and Earnings? The Quarterly Journal of Economics, 106(4): 979-1014.

*Optional:*
Rosenzweig and Wolpin. 2000. "Natural 'Natural Experiments' in Economics." Journal of Economic Literature 38: 827-74.

Read sections 1-3, focusing on examples discussed in Morgan and Winship, Ch 8.

Altonji, JG, Todd E. Elder, Christopher R. Taber. 2005. "An Evaluation of Instrumental Variable Strategies for Estimating the Effects of Catholic Schooling." The Journal of Human Resources, 40(4): 791-821.

**10. Instrumental Variables III (Testing Assumptions)**

*Required:*
Glymour, M. Maria, Eric J. Tchetgen Tchetgen, and James M. Robins. 2012. "Credible Mendelian Randomization Studies: Approaches for Evaluating the Instrumental Variable Assumptions." American Journal of Epidemiology 175(4):332-339.

A fairly comprehensive overview of IV assumption checks, low tech, and very useful.

Davies, Neil, George Davey Smith, Frank Windmeijer, and Richard M. Martina. 2013. "COX-2 Selective Nonstereoidal Anti-inflammatory Drugs and Risk of Gastrointestinal Tract Complications and Myocardial Infarction: An Instrumental Variables Analysis." *Epidemiology* 24(3):352-62.

The most careful and comprehensive assessment of IV assumptions in any application. I know, it's not social science, but it's great methodologically.

Swanson, Sonja A. and Miguel A. Hernán. 2013. "How to Report Instrumental Variables Analyses (Suggestions Welcome" (Comment on Davies et al). *Epidemiology* 24(3):370-4.

Provides a normative checklist for executing IV analyses.

*Optional:*
Balke A, Pearl J. Bounds on treatment effects for studies with imperfect compliance. *J Am Statist Assoc*. 1997;92:1171–1176.

Shows that IVs nonparametrically justify bounds on the treatment effect. Need further assumptions for point identification.

Bonet, B. (2001). Instrumentality tests revisited. In *Pro- ceedings of the 17th Conference on Uncertainty in Artificial Intelligence* 48–55. Morgan Kaufmann, San Francisco, CA.

This discusses and develops Pearl's test for exclusion violations (something that's typically though impossible) with categorical instruments. Difficult.

**11. Regression Discontinuity Design and Interrupted Time Series**

*RDD and ITS are quasi-experimental techniques that are popular in policy research, parts of psychology, and economics. These designs, not unlike IV, cleverly exploit so-called "discontinuities' in the data generating mechanism.*

*Required:*
Morgan and Winship, pp. 243-251

Lee, D.S., and T Lemieux. 2010. "Regression Discontinuity Designs in Economics." Journal of Economic Literature 48:281-355.
An excellent comprehensive review.

Steiner et al. 2014. Paper on DAG and quasi-experimental tecniques TBD (in the works).

*Read one of the following two carefully, skim the other (we will discuss both):*
Angrist, JD, and Victor Lavy. 1999. "Using Maimonides' Rule to Estimate the Effect of Class Size on Scholastic Achievement." The Quarterly Journal of Economics, 114(2): 533-575.

Groger, J., and G. Ridgeway. 2006. "Testing for Racial Profiling in Traffic Stops From Behind a Veil of Darkness." JASA 101(475): 878-887.

*Optional:*
Angrist and Pischke. 2008. Chapter 6

**12. Inference for Time Varying Treatments**
*Many treatments in sociology are time-varying. Causal inference for time-varying treatments faces considerably higher hurdles than inference for point treatments. In this lecture, we introduce two classes of interesting estimands for time-varying treatments and learn about estimating one of them with marginal structural models.*

*Required:*
Robins, James M. 1999. "Association, Causation, and Marginal Structural Models." *Synthese* 121:151–79.
Canonic reference for marginal structural models. Less technical than others, but still quite difficult. Read pp. 151-163 (more if you are so inclined).

Cole, SR, and MA Hernan. 2008. "Constructing Inverse Probability Weights for Marginal Structural Models." American Journal of Epidemiology.
A How-To for marginal structural models.

Wodtke, Geoffrey, David Harding, and Felix Elwert. 2011. "Neighborhood Effects in Temporal Perspective: The Impact of Long-Term Exposure to Concentrated Disadvantage on High School Graduation." *American Sociological Review* 76(5):713–36.
Marginal structural models in sociology.

*Optional:*
Fewell, Z, MA Hernan, F Wolfe, K Tilling, H Choi, and JAC Sterne. (2004). "Controlling for time-dependent confounding using marginal structural models." The Stata Journal 4(4):402-420.

A How-To for marginal structural models in Stata.

**13. Direct and Indirect Effects**
*This is one of the hottest areas in causal inference right now: causal mediation analysis. We will review new estimands and identification strategies.*

*Required:*
Pearl, J.. 2005. "Direct and Indirect Effects." JSM Proceedings: 1572-1581.

*Optional:*
VanderWeele, T.J. (2009). Marginal structural models for the estimation of direct and indirect effects. Epidemiology, 20:18-26.

Imai, K., Keele, L., Tingley D., & Yamamoto, T. (2011). Unpacking the Black Box of Causality: Learning about Causal Mechanisms from Experimental and Observational Studies. American Political Science Review, Vol. 105, No. 4, pp. 765-789.

Pearl, J. (2012). "Interpretable Conditions for Identifying Direct and Indirect Effects. Technical Report (R-389). UCLA Cognitive Systems Laboratory.

Imai, K., Tingley, D., & Yamamoto, T. (2013). Experimental Designs for Identifying Causal Mechanisms. (with discussions) Journal of the Royal Statistical Society, Series A (Statistics in Society), Vol. 176, No. 1, pp. 5-51.

J. Pearl. (2012). "The Causal Mediation Formula—A Guide to the Assessment of Pathways and Mechanisms." UCLA Cognitive Systems Laboratory, Technical Report (R-379), October 2011. Prevention Science, 13:426-436, DOI: 10.1007/s11121-011-0270-1, March 2012. http://ftp.cs.ucla.edu/pub/stat_ser/r379.pdf

**12. Interference (Spillover) and Contagion: Causal Inference in Social Networks**
*So far, we have assumed SUTVA. When units of analysis interact—e.g. in social networks—SUTVA is generally not credible. Here we review some challenges and solutions of causal inference with spillover and contagion between units.*

*Required:*
Shalizi, C. R., & Thomas, A. C. (2011). Homophily and contagion are generically confounded in observational social network studies. *Sociological Methods and Research, 40*, 211–239.

A terrific exposition of the problem of latent homophily for inference about contagion.

VanderWeele, T.J, and E. Techtgen Tchetgen. 2011. "Estimation of Spillover effects in the presence of interference: causal inference when SUTVA does not hold." UMich. Powerpoint presentation.

http://www.sph.umich.edu/biostat/2011acic/acic_abstracts/Slides_VanderWeele_Tchetgen.pdf

VanderWeele, T.J., Hong, G., Jones, S. and Brown, J. (2013). Mediation and spillover effects in group-randomized trials: a case study of the 4R's educational intervention. *Journal of the American Statistical Association*, 108:469-482.

A leading application. Read this for the intuition. Try to understand the estimands. Don't worry too much about identification. Difficult.

*Optional:*

Tchetgen Tchetgen, E.J. and VanderWeele, T.J. (2012). On causal inference in the presence of interference. *Statistical Methods in Medical Research - Special Issue on Causal Inference*, 21:55-75.

Long and more technical version of the ppt presentation.

**15. Student Paper Presentations**

10-15 minute presentations on each student final paper project.

- Clearly present the question or problem that you are working on.
- Explain the statistical means by which you will address the problem, or the theoretical or conceptual insight that you intend to exploit.
- State the definition of your population, your treatment, and your estimand (but do not dwell on data preparation issues).
- All presentations should be accompanied by a one-page handout listing the key points of your presentation. Pictures are often helpful.