

Causal Inference in Public Health

Faculty Information

Instructor	E. Michael Foster*
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Course Information

Course	759	Location	McGavran-Greenberg 2306
Section	001	Meetings	Tuesdays and Thursdays 8:00am – 9:30am

Texts

There are no longer any required texts for the course. However, you may find these books quite useful as references:

Lee, M. (2005). *Micro-econometrics for policy, program, and treatment effects*: Oxford University Press Oxford.

Morgan, S. L., & Winship, C. (2007). *Counterfactuals and Causal Inference: Methods and Principles for Social Research*: Cambridge University Press.

Rosenbaum, P. R. (2002). *Observational studies* (2nd ed.). New York: Springer.

Pearl, J. (2000). *Causality : models, reasoning, and inference*. Cambridge, U.K. ; New York: Cambridge University Press.

Note about office hours:

Formal office hours occur in the hour following class.

Because of the enormous volume of material in the class, you can expect to have to visit office hours multiple times.

* Students often wonder what to call me. I'm not keen on Dr. Foster. You may call me Michael or Mike but definitely not Edward, Ned or Ready Eddie. "My Captain" is satisfactory. However, when referring to me in front of other faculty members, you might identify me as "Dr. Foster" in order neither to violate social norms nor to confuse them.

In addition, I welcome students to stop by my office any time. Please e-mail me first, however, so I can be sure to be there (and sure to give you at least the majority of my attention).

Course Description

This course provides an introduction to causal inference in public health. The course combines methodological research in economics and statistics as well as substantive research in important areas of public health.

Course Objectives

- * To appreciate the importance of causal issues in public health
- * To raise your expectations of the steps required to identify the effect of one variable on another
- * To begin to understand the various tools available for improved causal inference
- * To empower you to use those tools and explain them correctly
- * To be able to write down the model underlying your research question in both simple mathematical terms and a directed acyclic graph (DAG).
- * To convince you not to contribute to the immense pool of inane studies that find causal effects when none exist
- * To teach you material for which you can identify no apparent purpose at this time
- * To assist me in identifying and ridiculing such studies and placing them on my blog, Casual_Inference.com
- * To assist me in refining the course for future students

Expectations

My expectations are that you will begin a long-term journey in understanding causal inference. I do not expect you to completely master the material. These ideas have kept philosophers and statisticians busy for hundreds of years. The enterprise will require substantive knowledge of relevant behaviors and choices and statistical knowledge necessary to understand key technical issues. My guess is that students will struggle with one of these themes or the other. I hope so.

How much math will we use? *Not much, but what do we need is essential.*

I will bear in mind that the course is not a biostatistics or econometrics course (nor is your humble instructor a statistician). At the same time, you need to bear in mind that this material may require multiple readings. I find that each time I read it, I understand some of this material more

myself.

The course also requires a graduate-level course in statistics as a prerequisite. You can try the course without it, but you will indeed have to do more work.

Course Schedule

See below.

FREE COFFEE GUARANTEE: IF I DON'T SPECIFY LEARNING OBJECTIVES AT THE START OF THE CLASS OR ASK FOR QUESTIONS AT THE END OF EACH CLASS, I'LL BRING COFFEE FOR THE NEXT CLASS.

Course Requirements

This course is a lecture and discussion course with active participation presumed on the part of each enrolled student. Lectures are limited and used primarily to establish a common foundation for or to summarize the discussions. Course grades will be determined as follows:

Assignment	Percentage of Grade
Take-home mid-term	20%
Class participation (including lab)	30%
Final paper	50%

The mid-term (20%) will be distributed in class on March 5 and due March 17.

Stupid Article Extra Credit: Students can add 10 points to their grade on the mid-term by bringing in a bad example of causal inference for use on my web site. Students can bring in as many as two. When submitting a stupid article, a brief critique (1 paragraph) will need to be provided. I will provide a few examples early in the semester.

Class participation is an essential component of making the class tolerable. I can drone on for 90 minutes bi-weekly, but such a class would be boring for both of us. You'll benefit from and enjoy the class to the degree you prepare for class and participate.

Students also are expected to arrive at class with questions for discussion. If students don't arrive with those questions, then we will move to a more formal system, such as quizzes.

If you're not comfortable with asking questions, there will be the opportunity to present some of the papers in class, and you may prop up your participation grade by volunteering.

Lab: There will be two lab sessions each week:

Monday	9:30-11:00am	HSL 329
Tuesday*	9:30-11:00am	Rosenau 201

The lab is an essential part of the class. Attendance at the lab will count as part of class attendance. During the lab, we will work applied problems using actual data from current research.

NOTE: for the Monday sessions, we do not have the room for 2/2/09, 3/2/09, 4/6/09, and 4/13/09. We'll meet in alternative space

Final paper. The main assignment for the class will involve an analysis of observational data to examine a question of importance in public health. The paper will be graded on the skill with which the tools of this class are used and a thoughtful assessment of what those tools add above and beyond past research. In terms of formatting, the paper must conform to the submission guidelines of of the *American Journal of Public Health*.

The final paper is due on May 1 at 9:00am. No late papers will be accepted. You may turn in a preliminary draft on April 17 for my review.

Note to auditors: You are welcome to attend, but you should think of the class participation requirement as applying to you. If the auditors act like corpses and worse still deaden the classroom environment, auditing will be terminated.

Grading Policy

See discussion of class requirements.

Attendance Policy

See discussion of class requirements.

Academic Integrity Policy

Using the words of others without acknowledging their source is a form of theft (plagiarism), especially serious in a course such as this. Most new information you find belongs, in some sense, to others. Using the words of others is acceptable, as long as it is acknowledged as theirs, by proper citation. Presentation of another's work as one's own (i.e., w/o acknowledgment) will be penalized heavily.

Statement on Academic Integrity:

(taken from the Health Policy and Administration at Penn State, my former employer)
Health care is a field that will challenge an individual's personal and professional ethics and morals on a daily basis. From patient confidentiality to the balance between cost control and quality care, health professionals, health policy-makers, and health administrators face ethical dilemmas that must be handled in a responsible manner. This industry is one in which ethical compromises and shortcuts simply can have the worst

consequences imaginable.

MCH takes its responsibility to develop high ethical principles in its students seriously. We try to emphasize questions and issues in class that help students see all the ethical, legal, and moral implications of their decisions. We think that student ethical behavior in class and at the University reflects the way they will behave when confronted with ethical dilemmas in the workplace. As a consequence, we feel there is no room in this field for students who believe that it is acceptable to plagiarize, cheat, or otherwise violate standards of academic integrity at UNC-CH.

Plagiarism, or any other violation of UNC's honor code, will be dealt with as required by the University's rules. It is each student's responsibility to be familiar with the definition of plagiarism and the University's honor code. The University honor code may be viewed at the following web address: <http://instrument.unc.edu/>

Student Honor Code: The honor code will be in effect in this class. Students are encouraged to study together in preparation for exams and assignments, but written assignments should not involve aid from others. If you have questions about appropriate behavior regarding the honor code, check with the instructor.

Resources on Plagiarism:

Students who are unfamiliar with the University's academic honesty policy and policies regarding plagiarism and proper citation should consult the student handbook and other university documents outlining these policies. The University Writing Center is also a valuable resource for questions regarding appropriate citation. In addition, the following resources may be useful:

- [APA Writing & Citation Guidelines](http://karn.ohiolink.edu/~sg-ysu/apa2.html) (<http://karn.ohiolink.edu/~sg-ysu/apa2.html>)
- [Plagiarism materials at Purdue](http://owl.english.purdue.edu/owl/resource/589/01/) (<http://owl.english.purdue.edu/owl/resource/589/01/>)
- [Plagiarism.org](http://plagiarism.org/learning_center/what_is_plagiarism.html) (http://plagiarism.org/learning_center/what_is_plagiarism.html)

Examination Policy

See discussion of class requirements.

Learning and Other Disabilities

Services for students with learning and other disabilities are available through two offices.

The *Department of Disability Services* (DDS) provides services and reasonable accommodations to currently enrolled undergraduate and graduate/professional students with disabilities other than LD an ADHD. The mission of DDS is to provide students with disabilities equal access to University services, programs, and activities. Because these disabilities have an impact on the varying demands of University life, in and out of the classroom, DDS works with faculty, departments, programs and offices throughout the University. It also provides training and consultation to instructors and administrators. DDS offices in the basement of Steele Building can be reached by telephone at (919) 962-8300 (V/TTY), by email at disabilityservices@unc.edu, or through

the web at <http://disabilityservices.unc.edu>. Jim Kessler is the Director.

Learning Disabilities Services (LDS) provides services and reasonable accommodations to currently enrolled undergraduate and graduate/professional students with documented learning disabilities (LD) and/or attention deficit hyperactivity disorder (ADHD). The mission of LDS is to assist students in achieving their academic potential within the regular, academically competitive University curriculum. In addition to providing reasonable accommodations, LDS provides strategies instruction and ADD coaching to students. LDS also provides training and consultation to instructors and administrators. The office, located at 137 East Franklin Street, Suite 602, can be reached by telephone at (919) 962-7227 or through the web at <http://www.unc.edu/depts/lds>. Jane Benson is the Director.

Class decorum

My expectation is that you will treat me and your fellow students courteously. This expectation requires that you arrive on time and that during class you not talk, sleep, answer the phone or read the newspaper. As a result, you should turn your phone/pager off when you arrive at class (or set them to silent mode).

Feel free to multi-task during class. Being a notorious multi-tasker myself, I would be a huge hypocrite if I set any other rule. However, you had better be as good at multi-tasking as I am—meaning, you need to know what the heck is going on in class and be able to talk about it intelligently.

Computing

You can use whatever program you want to do your paper. I will show you how to use R for many of the analyses in the computer lab. That lab will meet weekly at one of two times. Those times will be announced shortly.

We also will use Stata a bit. I haven't figured out how to calculate some of the sensitivity analyses in R.

Money Back Guarantee!

At the end of the course, if you don't agree that this topic is the most interesting one in public health, then I will donate \$50 per student to UNICEF.*

* Offer has no cash value and is void in Oklahoma, Bangladesh and Taiwan. Offer does not pertain to satisfaction with or competence of the instructor.

		Key Readings	Learning Objectives	Week of	Lab Topic
1a	13-Jan	Rothman, K. J., & Greenland, S. (2005). Causation and Causal Inference in Epidemiology. American Journal of Public Health, 95(S 1), 144-150.	I) What do we want to know? Sufficient Component Cause Framework 1) Define causal inference 2) Learn why it's so darned interesting 3) Identify the key questions of interest		Introduction to R Alternative: the R course on 20Jan-22Jan at Odum
1b 2a	15-Jan 20-Jan	+ Rubin. (2005). Causal Inference Using Potential Outcomes: Design, Modeling, Decisions. Journal of the American Statistical Association, 100(469), 322-331.[#3151] [1] Rubin, D. B. (2008). For objective causal inference, design trumps analysis. Annals of Applied Statistics, 2(3), 808-840.	II) Basic Statistical Framework: Potential Outcomes Model 1) What is the PO causal model and what are its components? 2) What is the fundamental problem of causal inference? 3) What do we mean by an effect? 4) How are the ATT, ATE and ATU related to each other? 5) What can go wrong with an observational study? The problems of bias. 6) What are we assuming when we use regression to assess causality?	1/26, 1/27	Causality Lab @ Carnegie Mellon
2b 3a 3b	22-Jan 27-Jan	+ Hernan, Hernandez-Diaz, & Robins. (2004). A structural approach to selection bias. Epidemiology, 15(5), 615-625.[#2443] Shrier, I., & Platt, R. W. (2008). Reducing bias through directed acyclic graphs. BMC Medical Research Methodology, 8(1), 70. Greenland, S., & Pearl, J. (2008). Causal Diagrams. In S. Boslaugh & L.-A. McNutt (Eds.), Encyclopedia of epidemiology (Vol. 1, pp. 149-156). Los Angeles: Sage Publications. Greenland, S., Pearl, J., & Robins, J. M. (1999). Causal Diagrams for Epidemiologic Research. Epidemiology, 10(1), 37-48. Greenland, S., & Morgenstern, H. (2001). Confounding In Health Research. Annual Review of Public Health, 22(1), 189-212. Liker, J. K., Augustyniak, S., & Duncan, G. J. (1985). Panel data and models of change: A comparison of first difference and conventional two-wave models. Social Science Research, 14, 80-101. Hernandez-Diaz, S., Schisterman, E. F., & Hernan, M. A. (2006). The Birth Weight" Paradox" Uncovered? American Journal of Epidemiology, 164(11), 1115. Wilcox, A. J. (2006). Invited Commentary: The Perils of Birth Weight-A Lesson from Directed Acyclic Graphs. American Journal of Epidemiology, 164(11), 1121.	III) On What Should We Condition? The Directed Acyclic Grapt 1) Learn to draw a DAG 2) Understand what the DAG adds to our math 3) Learn to identify colliders 4) Learn when we should not control for a variable 5) Learn that weird samples produce not only poor external but also internal validity 5) Learn that (sadly) one can indeed control for too much (!) 6) Learn what to do with key baseline measures of outcomes	1/19, 1/20	Matchit Demo
29-Jan		+ Manski, Sandefur, McLanahan, & Powers. (1992). Alternative Estimates of the Effect of Family Structure during Adolescence on High School Graduation. Journal of Human Resources, 7(2), 143-174. Manski, C. F. (1989). Anatomy of the selection problem. The Journal of Human Resources, 24(3), 343-360.	IV) How Far Can We Go without Further Assumptions? Bounding 1) Learn why we have to make some assumption if we want point estimates 2) Learn what we can estimate without further assumptions	2/2, 2/3	Calculating Manski bounds (Alternative room on Monday) MAY DO THIS IN CLASS ON 5 FEB
3-Feb, 5-Feb		Chapters 4 and 5 of Wasserman, L. (2006). All of nonparametric statistics. New York: Springer.	V) Business as Usual: The Good News and Bad News about Regression 1) Learning the meaning and value of the ignorability assumption 2) Learn the assumptions underlying regression 3) Identify the potential problems with regression as used in causal inference		
10-Feb		Breslow, N. (1982). Design and analysis of case-control studies. Annu Rev Public Health, 3, 29-54.	VI) Matching as an Alternative 1) Identify the difficulties involved in matching estimators		
12-Feb 17-Feb		Rosenbaum, P. R. (1987). Model-based direct adjustment. Journal of the American Statistical Association, 82(398), 387-394.	VII) The Propensity Score Ain't Magic but it Is Useful 1) Learn the information provided by the propensity score 2) Learn the various ways in which propensity score can be used to the treatment effects of interest	2/9, 2/10	Applying Psmatch2 in Stata
19-Feb		Frangakis, C. E., & Rubin, D. B. (2002). Principal Stratification in Causal Inference. Biometrics, 58(1), 21-29. Hill, J., Waldfogel, J., & Brooks-Gunn, J. (2002). Differential Effects of High-Quality Child Care. Journal of Policy Analysis and Management, 27.	IV) What about indirect/direct effects and things that go bump in our experiments? 1) Learn how to adjust for post-treatment outcomes	2/16, 2/17	Stratification and alternative treatment estimates

24-Feb 26-Feb	Direct and Indirect Effects Revisited	Petersen, M. L., Sinisi, S. E., & van der Laan, M. J. (2006). Estimation of Direct Causal Effects. <i>Epidemiology</i> , 17(3), 276. Vanderweele, T. J. (2008). Simple relations between principal stratification and direct and indirect effects. <i>Statistics and Probability Letters</i> , 78(2957-2962). Blakely, T. (2002). Commentary: Estimating direct and indirect effects--fallible in theory, but in the real world? <i>Int. J. Epidemiol.</i> , 31(1), 166-167. Cole, S. R., & Hernan, M. A. (2002). Fallibility in estimating direct effects. <i>Int J Epidemiol</i> , 31(1), 163-165.	2) Learn how to link proper causal estimates to the standard ways researchers talk about direct and indirect effects.	2/23, 2/24	TBD
V) My problem just doesn't seem to fit. Extensions to the Basic Structure					
3-Mar 5-Mar	Interference	Hong, G., & Raudenbush, S. W. (2006). Evaluating Kindergarten Retention Policy: A Case Study of Causal Inference for Multilevel Observational Data. <i>Journal of the American Statistical Association</i> , 101(475), 901-910. Hudgens, M. G., & Halloran, M. E. (2008). Toward Causal Inference With Interference. <i>Journal of the American Statistical Association</i> , 103, 832-842.	3) Learn how to handle situations where the treatment status of one individuals affects other individuals	3/2, 3/3	Application of MSM to Special Education (Alternative room on Monday)
17-Mar 19-Mar	Dynamic treatments	Hong, G., & Raudenbush, S. W. (2008). Causal inference for time-varying instructional treatments. <i>Journal of Educational and Behavioral Statistics</i> , 33(3), 333-362. Chelsea and Mike's paper on special education Bodnar, L. M., Davidian, M., Siega-Riz, A. M., & Tsiatis, A. A. (2004). Marginal Structural Models for Analyzing Causal Effects of Time-dependent Treatments: An Application in Perinatal Epidemiology. <i>Am. J. Epidemiol.</i> , 159(10), 926-934. Cole, S. R., & Hernan, M. A. (2008). Constructing Inverse Probability Weights for Marginal Structural Models. <i>American Journal of Epidemiology</i> , 168(6), 656-664. Robins, J. M. (1999). Association, Causation, And Marginal Structural Models. <i>Synthese</i> , 121(1), 151-179. Robins, J. M., & Wasserman, L. (1997). Estimation of Effects of Sequential Treatments by Reparameterizing Directed Acyclic Graphs. In D. Geiger & P. Shenoy (Eds.), <i>Proceedings of the Thirteenth Conference on Uncertainty in Artificial Intelligence</i> (pp. 409-420). San Francisco.: Morgan Kaufmann.	4) Learn how to handle situations where treatment varies over time in response to outcomes	3/16, 3/17	
VI) What do we do about those pesky unobservables?					
24-Mar 26-Mar	Modelling as a solution (econometrics)	Briggs, D. C. (2004) Causal inference and the Heckman model. <i>Journal of Educational and Behavioral Statistics</i> . Vol 29(4), 397-420. Heckman, J. J., & Vytlacil, E. J. (2007). Econometric evaluation of social programs, part I: Causal models, structural models and econometric policy evaluation. <i>Handbook of Econometrics</i> , 6, 4779-4874.	1) Learn the basic selection model 2) Gain a taste of more complex models in econometrics 3) Identify the strengths and weaknesses of the econometric approach	3/23, 3/24	TBD
31-Mar	Instrumental Variables Estimation	+ Foster & McLanahan. (1996). An Illustration of the Use of Instrumental Variables: Do Neighborhood Conditions Affect a Young Person's Chance of Finishing High School? <i>Psychological Methods</i> , 3(1), 249-260.[#254] Angrist, J. D., & Krueger, A. B. (2001). Instrumental Variables and the Search for Identification: From Supply and Demand to Natural Experiments. <i>The Journal of Economic Perspectives</i> , 15(4), 69-85. + Carneiro, Heckman, & Vytlacil. (2003). Understanding What Instrumental Variables Estimate: Estimating Marginal and Average Returns to Education.[#1708] Angrist, J. D., & Krueger, A. B. (2001). Instrumental Variables and the Search for Identification: From Supply and Demand to Natural Experiments. <i>The Journal of Economic Perspectives</i> , 15(4), 69-85.	1) Learn the nuts and bolts of IVE 2) Learn the intuition behind IVE 3) Learn how IVE relates to the selection model	3/30, 3/31	TBD
2-Apr	Condition on unobservables	+ Glymour, Weuve, Berkman, Kawachi, & Robins. (2005). When Is Baseline Adjustment Useful in Analyses of Change? An Example with Education and Cognitive Change. <i>American Journal of Epidemiology</i> , 162(3), 267-278.[#3140] Foster, E. M., & Kalil, A. (2007). Living Arrangements and Children's Development in Low-Income White, Black, and Latino Families. <i>Child Development</i> , 78(6), 1657-1674.	4) Learn what economists mean by "fixed effects estimation" 5) Learn that random-effects models do not control for unobservables in a meaningful way.	LAB ENDS	
		+ Jacob & Lefgren. (2004). Remedial Education and Student Achievement: A Regression-Discontinuity Analysis. <i>Review of Economics and Statistics</i> , 86(1), 226-244.[#2908] Imbens, G. W., & Lemieux, T. (2008). Regression discontinuity designs: A guide to practice. <i>Journal of Econometrics</i> , 142(2), 615-635.	5) Learn the nuts and bolts of regression discontinuity		

7-Apr	Regression Discontinuity	<p>Battistin, E., & Rettore, E. (2002). Testing for programme effects in a regression discontinuity design with imperfect compliance. <i>Journal of the Royal Statistical Society: Series A (Statistics in Society)</i>, 165(1), 39-57.</p> <p>Ludwig, J., & Miller, D. L. (2007). Does Head Start Improve Children's Life Chances? Evidence from a Regression Discontinuity Design*. <i>The Quarterly Journal of Economics</i>, 122(1), 159-208.</p> <p>Lee, D. S., & Card, D. (2008). Regression discontinuity inference with specification error. <i>Journal of Econometrics</i>, 142(2), 655-674.</p> <p>Van Der Klaauw, W. (2002). Estimating the Effect of Financial Aid Offers on College Enrollment: A Regression–Discontinuity Approach. <i>International Economic Review</i>, 43(4), 1249-1287.</p>	6) Learn how regression discontinuity relates to other common methods, such as interrupted time-series and IVE
9-Apr 14-Apr	Bounding	<p>Handout from Rosenbaum, P. R. (2002). <i>Observational studies</i> (2nd ed.). New York: Springer.</p> <p>+ G. W. Imbens. (2003). Sensitivity to Exogeneity Assumptions in Program Evaluation. <i>The American Economic Review</i>, 93(1), 126-132. [#2889]</p> <p>+Rosenbaum, P. R. (2004). Design sensitivity in observational studies. <i>Biometrika</i>, 91(1), 153-164.</p>	7) Learn how to assess the potential trouble caused by unobservables
16-Apr		<p style="text-align: center;">V) A Case Study</p> <p>+ Doob & Webster. (2003). Sentence severity and crime: accepting the null hypothesis. <i>Crime and Justice: a Review of Research</i>, 30(1), 143-195. [#3090]</p> <p>+ Kessler & Levitt. (1999). Using Sentence Enhancements to Distinguish between Deterrence and Incapacitation. <i>Journal of Law and Economics</i>, 42(1), 343-363. [#3091]</p> <p>+ Lee & McCrary. (2005). Crime, Punishment, and Myopia. [#3092] Cambridge, MA: National Bureau of Economic Research.</p> <p>+ Levitt. (2006). The Case Of The Critics Who Missed The Point: A Reply To Webster Et Al. <i>Criminology & Public Policy</i>, 5(3), 449-460. [#3093]</p> <p>+ Levitt & Journals. (1998). Why Do Increased Arrest Rates Appear To Reduce Crime: Deterrence, Incapacitation, Or Measurement Error? <i>Economic Inquiry</i>, 36(3), 353-372. [#3094]</p> <p>+ Webster, Doob, & Zimring. (2005). Proposition 8 And Crime Rates In California: The Case Of The Disappearing Deterrent. <i>Criminology & Public Policy</i>, 5(3), 317-340. [#3095]</p>	
21-Apr 23-Apr		<p style="text-align: center;">VI) Does any of this stuff work??? Comparisons of Experiments and Non-experimental analyses</p> <p>Smith, J., & Todd, P. (2005). Does matching overcome LaLonde's critique of nonexperimental estimators? <i>Journal of Econometrics</i>, 125(1-2), 305-353.</p> <p>Cook, T. D., Shadish, W. R., & Wong, V. C. (Forthcoming). Three Conditions under which Experiments and Observational Studies Produce Comparable Causal Estimates: New findings from within-study comparisons. <i>Journal of Policy Analysis and Management</i>.</p> <p>Buddelmeyer, H., & Skoufias, E. (2004). An Evaluation of the Performance of Regression Discontinuity Design on PROGRESA. Bonn, Germany: IZA.</p> <p style="text-align: center;">Spillover</p>	