Methods in Health Services Research I
HSMP 7607, Fall 2020

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Instructor:

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Office Hours: Available by appointment

Course Title:	**Methods in Health Services Research I**
Credit Hours:	Three Credit Hours
Meeting Time:	Tuesday and Thursday, 9am to 10:20am.
Meeting Place:	Zoom (link available on Canvas).

HSMP Course Competencies:

1. Accurately select, use, and interpret statistics commonly used in health services research
2. Apply and use appropriate study designs and methods to address research questions/hypotheses
3. Utilize healthcare databases and other information technologies used in research

Course Overview:

The first of a two-course sequence on empirical methods in health services research. This course introduces students to research designs for observational data. This course also covers Stata and advanced topics in regression modeling. Topics include:

- Causal inference and design of observational studies
- Maximum likelihood estimation
- Review of linear models (OLS), logistic, and Probit models
- Generalized Linear models (GLM) as a general framework
- Marginal effects to interpret models
- Analysis of cost data
- Introduction to longitudinal (aka panel data) methods
- Fixed and random effects models
- Difference-in-differences
- Propensity scores
- Regression discontinuity
- Instrumental variables

The course uses econometrics and statistics/biostatistics terms as health services research is an interdisciplinary field that uses methods originating from different disciplines.

Learning Objectives

1. Understand how to explore a dataset, including graphical techniques
2. Understand the statistical theory and assumptions underlying regression models (linear, logit, Probit, GLMs)
3. Understand how to interpret regression parameters and transformations
4. Understand how to perform hypothesis testing
5. Understand under which circumstances a regression model can have a causal interpretation
6. Understand when and how various methods should be used, including the different uses of regression analysis (causal, descriptive, predictive)
7. Understand how to correctly write a statistical model
8. Learn to "translate" econometrics to statistics terms (and vice versa)
9. Have a clear understanding of when to use, how to implement, and how to interpret methods for observational data analysis: difference-in-differences, regression discontinuity, instrumental variables, fixed-effects, interrupted time series.

IV. Evaluation

Grades are based on performance on:

- Homework 30%
- Midterm 25%
- Final exam 30%
- Study proposal 15%

Homework: Weekly homework assignments are usually due after a week of being posted. **No late homework allowed** unless you have a valid justification, which needs to be communicated *before* the due date. We will have regular check-ins during the semester about the study proposal.

Midterm: TBD.

Final Exam: TBD.

Required textbooks: **Note the editions**. Basic statistics/econometrics has not changed much in the last 20 years. **Save money; get a used textbook**. As a PhD student, you should own these textbooks. If

money is a concern, please let me know. I will buy any of the books for you. We will supplement textbooks with articles available on Canvas.

Angrist, Joshua D., and Jörn-Steffen Pischke. *Mostly Harmless Econometrics: An Empiricist's Companion*. 1 edition. Princeton: Princeton University Press, 2009.

Wooldridge, Jeffrey M. *Introductory Econometrics: A Modern Approach*. **5th edition**. Australia; Cincinnati, Ohio: South-Western College Pub, 2013.

Cameron, A. Colin, and Pravin K. Trivedi. *Microeconometrics Using Stata: **Revised Edition*.** **2nd edition**. College Station, Texas: Stata Press, 2010.

Helpful textbooks (some chapters will be assigned):

Rosenbaum, Paul R. Design of observational studies. Vol. 10. New York: Springer, 2020.

Wooldridge, J. (2010). Econometric Analysis of Cross Section and Panel Data, MIT Press.

Hardin, James W., Joseph M. Hilbe, *Generalized linear models and extensions*. Stata press, 2018 (Fourth Edition).

Guo, Shenyang, and Mark W. Fraser. *Propensity score analysis: Statistical methods and applications*. Vol. 11. SAGE publications, 2014.

Gelman, Andrew, and Jennifer Hill. *Data analysis using regression and multilevel/hierarchical models*. Vol. 1. New York, NY, USA: Cambridge University Press, 2007. (**Note**: The R code is out of date, but it's a fantastic introduction to many statistical concepts).

Gelman, Andrew, Jennifer Hill, and Aki Vehtari. Regression and other stories. Cambridge University Press, 2020. (The updated version of the one above, although this version omits multilevel models and is not as succinct, but still very good).

Imbens, Guido W., and Donald B. Rubin. Causal inference in statistics, social, and biomedical sciences. Cambridge University Press, 2015.

Fitzmaurice, Garrett M., Nan M. Laird, and James H. Ware. *Applied longitudinal analysis*. Vol. 998. John Wiley & Sons, 2012.

Long, J. S., and J. Freese. Regression Models for Categorical Dependent Variables Using Stata, Second Edition. 2nd edition. College Station, Tex: Stata Press, 2005.

Hong, Guanglei. Causality in a social world: Moderation, mediation and spill-over. John Wiley & Sons, 2015.

Long, J. The workflow of data analysis using Stata. College Station, TX: Stata Press, 2009.

Deb P, Norton E, Manning WG, *Health Econometrics*, Stata Press, 2017.

Additional Reading Material: Posted on Canvas. **Starred articles are optional.**

Expectations:

I. Class attendance & Participation
   A. **Attendance is not required** but is highly recommended.

II. **Academic Conduct Policy**

All students are expected to abide the Honor Code of the Colorado School of Public Health. Unless otherwise instructed, all of your work in this course should represent completely independent work. Students are expected to familiarize themselves with the Student Honor Code that can be found at https://www.ucdenver.edu/docs/librariesprovider151/default-document-library/coloradosph-honor-code.pdf?sfvrsn=5d211eb9_4
or the Education – Calendar and Policies section of the ColoradoSPH website. Any student found to have committed acts of misconduct (including, but not limited to cheating, plagiarism, misconduct of research, breach of confidentiality, or illegal or unlawful acts) will be subject to the procedures outlined in the ColoradoSPH Honor Code.

Accommodations for Disabilities: Virtual and In-Class

University of Colorado Anschutz is committed to providing equitable access to learning opportunities to students with documented disabilities (e.g. mental health, attentional, learning, chronic health, sensory, or physical). To ensure access to this class, and program, please contact Sherry Holden (sherry.holden@cuanschutz.edu) for disability services to engage in a confidential conversation about the process for requesting reasonable accommodations in the classroom and clinical settings.

Accommodations are not provided retroactively Students are encouraged to register with Disability Resources and Services as soon as they begin their program. The Colorado School of Public Health encourages students to access all resources available through Disability Resources and Services for consistent support and access to their programs. More information can be found online at: http://www.ucdenver.edu/student-services/resources/disability-resources-services/CU%20ANSCHUTZ%20MEDICAL%20CAMPUS/CU%20Anschutz%20Disability%20Resources%20Contact%20Form/Pages/form.aspx.

Mental Health Services

https://www.ucdenver.edu/life/services/student-health/mental-wellness/Pages/default.aspx

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(Note: starred articles are optional)

Note: Syllabus will be updated during the semester to reflect readings, additional material.

Week 1: Overview of class and Stata

Review of required background for the class and introduction to Stata for linear and logit models.

Wooldridge, Appendix A to C.
Cameron and Trivedi (2010), Chapters 1 and 2.

*UCLA's Stata tutorials: https://stats.idre.ucla.edu/stata/modules/
*Stata tutorials https://www.stata.com/links/video-tutorials/
* Shmueli, G. "To Explain or Predict?", *Statistical Science*, 2010, Vol. 25, No 3, 289-310.

Week 2: Potential outcomes and causal effects

Overview of methods for framing causal inference, including the definition of causal effects. Estimating causal effects in the absence of randomization. Separating the design of a study from the statistical estimation of effects. Compare the Rubin counterfactual approach with the traditional introductory econometrics approach. Selection on observables, no unmeasured confounding, ignorability of treatment assignment, etc. Regression adjustment an overlap. Nonparametric methods.

Imbens and Rubin (2015), Chapter 2.
Angrist and Pischke, Chapter 2. "The Experimental Ideal."

*Imbens, Guido W., and Jeffrey M. Wooldridge. "Recent developments in the econometrics of program evaluation." *Journal of Economic Literature* 47, no. 1 (2009): 5-86.
*Heckman, James J., and Edward J. Vytlacil. "Econometric evaluation of social programs, part I: Causal models, structural models and econometric policy evaluation." *Handbook of econometrics* 6 (2007): 4779-4874.
*Heckman, James J., and Edward J. Vytlacil. "Econometric evaluation of social programs, part II: Using the marginal treatment effect to organize alternative econometric estimators to evaluate social programs, and to forecast their effects in new environments." *Handbook of econometrics* 6 (2007): 4875-5143.
*Abadie, Alberto, and Matias D. Cattaneo. "Econometric methods for program evaluation." *Annual Review of Economics* 10 (2018): 465-503.
*Wooldridge, J. (2010). Chapter 21.
*Guo and Fraser (2015), Chapter 2 (up to section 2.5).
*Gelman and Hill (2007), Chapters 9 and 10.

Week 3: Regression review

Applied review of regression analysis. Conditional expectation function. Model interpretation. Hypothesis testing and confidence intervals, simulations with a touch of Bayesian statistics. ANOVA and t-tests as linear models. Interactions and stratification.

Angrist and Pischke, Chapter 3
Cameron and Trivedi (2010), Chapters 3 and 12
*Wooldridge, Chapters 4 and 5

Weeks 4 and 5: Classic designs for observational studies

Review of methods traditional designs for observational studies, with an emphasis on design, not estimation. We will cover estimation after the midterm. ***Selection on observables (ignorability, CIA)***: regression adjustment, propensity scores, and matching. ***No selection on observables (no ignorability, no CIA)***: longitudinal data ("fixed-effects"), interrupted time series, difference-in-differences, instrumental variables, and regression discontinuity. Writing an Aims page and a sketch of methods as well as data sources.

Perraillon, MC, Oswley, KM, Welton JM, "Propensity Scores and Regression Adjustment," *Nursing Economics*, 2020.
Perraillon, MC, Lindrooth, R, Welton JM, "Difference-in-Difference Designs," *Nursing Economics*, Volume 7, Number 6, 2019.
Perraillon, MC., Hamer, M., Welton, JM, Myerson, RM, "Regression Discontinuity Designs," *Nursing Economics*, 2020.
Rubin, Donald B. "The design versus the analysis of observational studies for causal effects: parallels with the design of randomized trials." *Statistics in medicine* 26, no. 1 (2007): 20-36.
Rosenbaum, Paul R. "Design of observational studies." Vol. 10. New York: Springer, 2020, Chapter 2.
Angrist and Pischke, first sections of Chapters 3,4, 5 (skip section 5.1), and 6.

*Guo and Fraser Chapter 3.
*Gelman and Hill Chapter 10.
*Stata manual's `teffects` intro (teffects manual for Stata 16, pages 190-215).
*Wing, Coady, Kosali Simon, and Ricardo A. Bello-Gomez. "Designing difference in difference studies: best practices for public health policy research." Annual review of public health 39 (2018).

Weeks 6 and 7: Maximum likelihood estimation and marginal effects

Introduction to maximum likelihood estimation (MLE): linear, logit, and Probit models. MLE for Generalized Linear Models (GLM). Parameter interpretation using marginal effects.

Eliason, Scott R. Maximum likelihood estimation: Logic and practice. Vol. 96. *Sage Publications*, 1993. Pages 1-21.
*Greene, William. "Testing hypotheses about interaction terms in nonlinear models." *Economics Letters* 107, no. 2 (2010): 291-296.

*Norton, Edward C., and Bryan E. Dowd. "Log Odds and the Interpretation of Logit Models." *Health Services Research* 53, no. 2 (April 2018): 859–78.
*Karaca-Mandic, Pinar, Edward C. Norton, and Bryan Dowd. "Interaction terms in nonlinear models." Health services research 47, no. 1pt1 (2012): 255-274.

Week 8: GLM models and analysis of cost data

Medical cost data tend to be skewed and may have a large proportion of zeroes; therefore, these data do not distribute (conditionally) normal. Traditional methods: linear models (ignores problem), log-level models and "smearing," two-part models, Generalized Linear Models (GLM), and hurdle models. Choosing the best fitting model (BIC/AIC). Additional applications of GLM models (e.g. count data). GLM and marginal effects.

*Hardin and Hilbe, Chapters 2 and 4.
*Deb, Norton and Manning, Chapter 5 and 6.

Week 9: Midterm and propensity scores

Estimation and use of propensity scores. Propensity scores versus regression adjustment. Balance versus overlap. Matching, stratification, and inverse probability weighting (IPW). Interpretation of treatment effects.

Weeks 10 and 11: Matching estimators (and propensity scores)

Matching as a general framework for observational studies. Assumptions. Different distance metrics: Malahanobis, propensity score. Estimation and use of propensity scores. Propensity scores versus regression adjustment. Balance versus overlap. Stratification, and inverse probability weighting (IPW). Interpretation of treatment effects. ATE and ATET.

Stata's `teffects` documentation.
*Guo and Fraser, Chapter 5.

*Abadie, A. and Imbens, G.W., 2011. Bias-corrected matching estimators for average treatment effects. Journal of Business & Economic Statistics, 29(1), pp.1-11.
* Dehejia, R.H. and Wahba, S., 1999. Causal effects in nonexperimental studies: Reevaluating the evaluation of training programs. Journal of the American statistical Association, 94(448), pp.1053-1062.
*Smith, J.A. and Todd, P.E., 2005. Does matching overcome LaLonde's critique of nonexperimental estimators?. Journal of econometrics, 125(1-2), pp.305-353.
*Abadie, A. and Imbens, G.W., 2006. Large sample properties of matching estimators for average treatment effects. econometrica, 74(1), pp.235-267.
*Abadie, A., Drukker, D., Herr, J.L. and Imbens, G.W., 2004. Implementing matching estimators for average treatment effects in Stata. The stata journal, 4(3), pp.290-311.

Weeks 12 and 13: Difference-in-differences

Estimation of treatment effects using difference-in-difference design (DiD)**.** Testing the parallel trends assumption. Adjusted and unadjusted trends. Estimating correct standard errors. DiD and propensity scores. Interpretation of treatment effects. Overview of other developments.

Angrist and Pischke Chapter 2.

Lechner, M. The Estimation of Causal Effects by Difference-in-Difference Methods, Foundations and Trends in Econometrics, Vol 4. No. 3 (2010) 165-224.

*Lindrooth R, Perraillon MC, Hardy R, Tung GJ, "Understanding the Relationship Between Medicaid Expansion and Hospital Closures," *Health Affairs*, January 2018.

*Brandt, Myerson, Perraillon, Polonsky. "Hospital Admissions for Myocardial Infarction and Stroke before and after the Trans Fatty Acid Restriction Bans in New York", April 27th,2017. *JAMA Cardiology*.

*Ryan, A.M., Burgess Jr, J.F. and Dimick, J.B., 2015. Why we should not be indifferent to specification choices for difference-in-differences. Health services research, 50(4), pp.1211-1235.

*Wing, C., Simon, K. and Bello-Gomez, R.A., 2018. Designing difference in difference studies: best practices for public health policy research. Annual review of public health, 39.

*Card, D. and Krueger, A.B., 2000. Minimum wages and employment: a case study of the fast-food industry in New Jersey and Pennsylvania: reply. American Economic Review, 90(5), pp.1397-1420.

Week 14: Regression discontinuity

Sharp and fuzzy regression discontinuity estimation**.** Parametric and non-parametric estimation. Optimal bandwidth.

Angrist and Pischke Chapter 6.

Lee, D.S., and T. Lemieux. "Regression discontinuity designs in economics." *Journal of economic literature* 48, no. 2 (2010): 281-355.

*Perraillon MC, Konetzka RT, He D, Werner RM, "Consumer Response to Composite Ratings of Nursing Home Quality," *American Journal of Health Economics*, December 2017.

*Card, D., Dobkin, C. and Maestas, N., 2009. Does Medicare save lives?. The quarterly journal of economics, 124(2), pp.597-636.

*Gelman, A. and Imbens, G., 2019. Why high-order polynomials should not be used in regression discontinuity designs. Journal of Business & Economic Statistics, 37(3), pp.447-456.

*Calonico, S., Cattaneo, M.D., Farrell, M.H. and Titiunik, R., 2017. rdrobust: Software for regression-discontinuity designs. The Stata Journal, 17(2), pp.372-404.

*Calonico, S., Cattaneo, M.D. and Titiunik, R., 2014. Robust nonparametric confidence intervals for regression-discontinuity designs. Econometrica, 82(6), pp.2295-2326.

*Cattaneo, M.D., Titiunik, R. and Vazquez-Bare, G., 2019. Power calculations for regression-discontinuity designs. The Stata Journal, 19(1), pp.210-245.

*Cattaneo, M.D., Titiunik, R. and Vazquez-Bare, G., 2017. Comparing inference approaches for RD designs: A reexamination of the effect of head start on child mortality. Journal of Policy Analysis and Management, 36(3), pp.643-681.

Week 15: Instrumental variables (maybe)

Estimation of treatment effects with instrumental variables. Assumptions (emphasis on the exclusion restriction). Instrumental variables and encouragement designs. Interpretation of treatment effects, LATE.

Angrist and Pischke Chapter 4.

Baicker, Katherine, Sarah L. Taubman, Heidi L. Allen, Mira Bernstein, Jonathan H. Gruber, Joseph P. Newhouse, Eric C. Schneider, Bill J. Wright, Alan M. Zaslavsky, and Amy N. Finkelstein. "The Oregon experiment—effects of Medicaid on clinical outcomes." *New England Journal of Medicine* 368, no. 18 (2013): 1713-1722.

*Lind K, Lindrooth RM, Perraillon. "The Effect of Direct Cognitive Assessment in the Medicare Annual Wellness Visit on Dementia Diagnosis Rates."