Week class in Econometrics

June 2023

Instructor: Magne Mogstad

TAs: Deniz Dutz (ddutz@uchicago.edu),

Santiago Lacouture (slacouture@uchicago.edu)

1 Overview

The main aim of this course is to develop a knowledge on the econometric methods that are useful to analyze individual level data (microdata).

2 Organization, teaching and Assessment

There will be lectures from 9:00-11:30 each day, Monday to Friday. After each lecture, I expect you to work on the relevant problem set (probably for most of the rest of the day). I attach the problem sets here.
You can work on the problem sets individually or in groups. I urge you to take the problem sets seriously, as they are essential to understand the material covered. The problem sets will include analytical problems and empirical problems that will require the use of statistical software (preferably R or STATA).
I will also distribute answer keys. By comparing these keys to your answers, you can learn what and why you failed or struggled with certain questions. I urge you to work hard on the problem set, before you start looking at the answer keys. Note that the problem sets will not be graded or count for your final mark. They are meant to help you understand the material.
Each day, from 16:00-17:00, a teaching assistant (Deniz Dutz or Santiago Lacouture) will be available (on zoom) to answer questions (about the problem set or the lecture). Zoom link for TA session will be provided.
On Friday after the lecture, I will give you a take-home exam. Exam due date is March 19th (3 weeks from the end of the class). The exam will be marked. The exam should be done independently (and not in groups).

3 Preliminary outline

Here is a preliminary course outline. * indicates that it would be very useful to read the paper prior to the class. Please note that the inclusion of a paper on the syllabus should not be considered an “endorsement” of that paper’s methods - read critically!

Topic 1:
<u>– Defining parameters and arguing their (policy) relevance</u>
Roy models, heteogeneity, and potential outcomes

– Edward Vytlacil & James J. Heckman (2001). Policy-Relevant Treatment Effects, American Economic Review

– Heckman, James J. 2010. Building Bridges between Structural and Program Evaluation Approaches to Evaluating Policy. Journal of Economic Literature, for now Sections 1 and 2.

– *Angrist and Pischke (2009): Mostly Harmless Econometrics, for now Chapters 1 and 2.

– Randomized controlled trials

– Heckman, James J., and Jeffrey A. Smith (1995): Assessing the Case for Social Experiments. Journal of Economic Perspectives

– Duflo, Esther, Glennerster, Rachel, and Kramer, Michael (2008): Using Randomization in Development Economics Research: A toolkit. Handbook of Handbook of Development Economics.

– Bitler, Marianne, P., Jonah B. Gelbach, and Hilary W. Hoynes (2006): "What Mean Impacts Miss: Distributional Effects of Welfare Reform Experiments." American Economic Review.

Topic 2: Controlling for observables

– Heckman, J., Ichimura, H., Smith, J. and Todd, P. (1998a). Characterizing Selection Bias Using Experimental Data. Econometrica

– Heckman, J. J., Ichimura, H. and Todd, P. (1998b). Matching as an Econometric Evaluation Estimator. The Review of Economic Studies

– Heckman, J. J., Ichimura, H. and Todd, P. E. (1997). Matching As An Econometric Evaluation Estimator: Evidence from Evaluating a Job Training Programme. The Review of Economic Studies

– Heckman, J. J. and Hotz, V. J. (1989). Choosing Among Alternative Nonexperimental Methods for Estimating the Impact of Social Programs: The Case of Manpower Training. Journal of the American Statistical Association 84: 408, 862-874

– *Angrist and Pischke (2009): Mostly Harmless Econometrics, Ch. 3.

– James Heckman & Salvador Navarro-Lozano, 2004. Using Matching, Instrumental Variables, and Control Functions to Estimate Economic Choice Models, The Review of Economics and Statistics. Discussion about choice of controls and controlling on too much.

– Neale and Johnsen (1996): The Role of Premarket Factors in Black-White Wage Differences. Journal of Political Economy, Vol. 104, No. 5 (Oct., 1996), pp. 869-895

– Reviews:

– Imbens, G. W. (2004). Nonparametric Estimation of Average Treatment Effects under Exogeneity: A Review. The Review of Economics and Statistics 86. This is a comprehensive review of selection on observables methods.

– *Imbens, G. W. (2015). Matching Methods in Practice: Three Examples. Journal of Human Resources 50: 373-419 This review covers more recent methods and implementation issues.

Much cited application where observables changes the conclusions drawn:

– Much cited application where observables changes the conclusions drawn:

– Dale, S. B. and Krueger, A. B. (2002). Estimating the Payoff to Attending a More Selective College: An Application of Selection on Observables and Unobservables. The Quarterly Journal of Economics 117.

– Analysis motivating selection on observables through knowledge of treatment assignment:

– Fagereng, A., M. Mogstad and M. Ronning (2021): Why do wealthy parents have wealthy children? Journal of Political Economy.

– Lalonde's paper and subsequent discussion of matching estimators:

– *Lalonde (1986): Evaluating the Econometric Evaluations of Training Programs with Experimental Data, American Economic Review

– 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. An influential and somewhat controversial application of selection on observables arguments.

– Dehejia, R. H. and Wahba, S. (2002). Propensity Score-Matching Methods for Nonexperimental Causal Studies. The Review of Economics and Statistics 84

– Smith, J. and Todd, P. (2005). Does matching overcome LaLonde's critique of nonexperimental estimators? Journal of Econometrics. This paper argues that the specications in Dehejia and Wahba (1999, 2002) papers are not robust, then there is a reply and a rejoinder. Altogether, these papers are well-known and form an important backdrop to the way that economists think about selection on observables approaches.

– Dehejia, R. (2005). Practical propensity score matching: a reply to Smith and Todd. Journal of Econometrics

– Bunching

– Blomquist, S., Newey, W. K., Kumar, A., and Liang, C. Y. (2021). On bunching and identification of the taxable income elasticity. Journal of Political Economy, 129(8), 2320-2343.

– Saez, E. (2010), Do Taxpayers Bunch at Kink Points, American Economic Journal: Economic Policy 2, 180-212

– Chetty et al. (2011), Adjustment Costs, Firm Responses, and Micro vs. Macro Labor Supply Elasticities: Evidence from Danish Tax Records, Quarterly Journal of Economics 126

Topic 3: Instrumental variables and heterogenous effects.

Part 1: Reverse engineering

– Local average treatment effects

– *Angrist and Pischke (2009): Mostly Harmless Econometrics, Ch. 4. This chapter covers the next few papers:

– Imbens, G. W. and Angrist, J. D. (1994). Identication and Estimation of Local Average Treatment Effects. Econometrica

– Angrist, J. D., Imbens, G. W. and Rubin, D. B. (1996). Identification of Causal Effects Using Instrumental Variables. Journal of the American Statistical Association. Further discussion of LATE from its proponents.

– Heckman, J. J. and Hotz, V. J. (1989). Choosing Among Alternative Nonexperimental Methods for Estimating the Impact of Social Programs: The Case of Manpower Training. Journal of the American Statistical Association 84: 408, 862-874

– Kitagawa, T. (2015). A Test for Instrument Validity. Econometrica 83: 2043-2063

– Interpreting Monotonicity and multiple distinct instruments

– Vytlacil, E. (2002). Independence, Monotonicity, and Latent Index Models: An Equivalence Result. Econometrica 70: 331-341

– Mogstad, M., Torgovitsky, A. and Walters, C. R. (2021). The Causal Interpreta- tion of Two-Stage Least Squares with Multiple Instrumental Variables. American Economic Review 111: 3663-3698.

– TSLS: Covariates, multiple instruments and multivalued treatments

– Angrist, J. D. and Imbens, G. W. (1995). Two-Stage Least Squares Estimation of Average Causal Effects in Models with Variable Treatment Intensity. Journal of the American Statistical Association 90:

431. LATE-type results for IV/TSLS estimands when the treatment takes multiple values.

– Blandhol, C., Bonney, J., Mogstad, M., and Torgovitsky, A. (2022). "When is TSLS Actually LATE?" NBER Working Paper 29709.

– Kirkeboen, L, Leuven, E. and Mogstad, M. (2016). "Field of Study, Earnings, and Self-Selection" Quarterly Journal of Economics, 131, 1057-1111

– Examples of studies applying and arguing the exogeneity (and sometimes policy relevance) of the instruments:

– Angrist, J. D. and Evans, W. N. (1998). Children and Their Parents' Labor Supply: Evidence from Exogenous Variation in Family Size. The American Economic Review.

– Dahl, G. B., Kostøl, A. R., and Mogstad, M. (2014). Family welfare cultures. The Quarterly Journal of Economics, 129(4), 1711-1752.

– Weak instruments

– Andrews I, Stock J, Sun L (2019): Weak Instruments in IV Regression: Theory and Practice. Annual Review of Economics.

Part 2: Forward engineering

– Observed heterogenity

– Angrist, J., and Fernandez-Val, I. (2010). ExtrapoLATE-ing: External validity and overidentification in the late framework (No. w16566). National Bureau of Economic Research.

– Unobserved heterogeneity without selection model

– Manski, C. F. (1990). Nonparametric Bounds on Treatment Effects. The American Economic Review 80: 319-323

– Horowitz, J. L., & Manski, C. F. (1998). Censoring of outcomes and regressors due to survey non-response: Identification and estimation using weights and imputations. Journal of Econometrics, 84(1), 37-58.

– Manski, C. and J. Pepper. (2000). Monotone Instrumental Variables: With an Application to the Returns to Schooling. Econometrica 68. pp. 997–1010.

– Manski, C. (2003). Partial Identification of Probability Distributions, New York: Springer-Verlag.

– *Manski, C. F. (2007). Identification for Prediction and Decision. Harvard University Press. Ch. 2

– *De Haan, M. (2017). The effect of additional funds for low-ability pupils: A nonparametric bounds analysis. Economic Journal 127(599), pp. 177–198

– Imbens, G. W., and Manski, C. F. (2004). Confidence intervals for partially identified parameters. Econometrica, 72(6), 1845-1857.

– Unobserved heterogeneity with selection model

– Heckman, J. J., Urzua, S. and Vytlacil, E. (2006). Understanding Instrumental Variables in Models with Essential Heterogeneity. Review of Economics and Statistics 88: 389-432.

– Carneiro, P., Heckman, J. J. and Vytlacil, E. (2010). Evaluating Marginal Policy Changes and the Average Effect of Treatment for Individuals at the Margin. Econometrica 78: 377-394.

– *Mogstad, M. and Torgovitsky, A. (2018). Identication and Extrapolation of Causal Effects with Instrumental Variables. Annual Review of Economics 10. This paper surveys the modern literature on instrumental variables with unobserved heterogeneity.

– Mogstad, M., Santos, A. and Torgovitsky, A. (2018). Using Instrumental Variables for Inference About Policy Relevant Treatment Parameters. Econometrica 86: 1589-1619. The application to the demand for bed nets is only in the 2017 NBER working paper version.

– Brinch, C. N., Mogstad, M. and Wiswall, M. (2017). Beyond LATE with a Discrete Instrument. Journal of Political Economy 125: 985-1039.

Topic 4: Regression Discontinuity

– Local average treatment effects (and its extensions)

– *Angrist and Pischke (2009): Mostly Harmless Econometrics, Ch. 6.

– *Lee, D. S. and Lemieux, T. (2010). Regression Discontinuity Designs in Economics. Journal of Economic Literature, which is a (lengthy) survey on RDD

– Examples of studies applying RDD:

– Angrist, J. D. and Lavy, V. (1999). Using Maimonides' Rule to Estimate the Effect of Class Size on Scholastic Achievement. The Quarterly Journal of Economics 114. An early and classic example of a fuzzy RDD as IV.

– Dahl, G. B., Loken, K. V. and Mogstad, M. (2014). Peer Effects in Program Participation. American Economic Review 104. Application of fuzzy RDD argument to study peer effects

– Kostol, A. R. and Mogstad, M. (2014). How Financial Incentives Induce Disability Insurance Recipients to Return to Work. American Economic Review. A straightforward application of a sharp RDD argument

Topic 5: Some approaches to analyze repeated cross-sections and panel data

– Difference in Differences

– Heckman and Robb (1986): Alternative Identifying Assumptoins in Econometrics Models of Selection Bias.

– Ashenfelter and Card (1985): Using the Longitudinal Structure of Earnings to Estimate the Effect of Training Program, The Review of Economics and Statistics. Much cited paper using difference-in-differences.

– *Lalonde (1986): Evaluating the Econometric Evaluations of Training Programs with Experimental Data, American Economi Review

– Heckman, J. J. and Hotz, V. J. (1989). Choosing Among Alternative Nonexperimental Methods for Estimating the Impact of Social Programs: The Case of Manpower Training. Journal of the American Statistical Association 84: 408, 862-874

– Meyer, Viscusi and Durbin (1995): Workers' Compensation and Injury Duration: Evidence from a Natural Experiment, American Economic Review. Simple application with available data.

– Cameron, A. C. and Miller, D. L. (2015). A Practitioner's Guide to Cluster- Robust Inference. Journal of Human Resources 50: 317-372. A survey that discusses problems and solutions to clustered standard errors. Section VI is especially relevant for difference-in-differences designs using repeated cross sections.

– Heckman, J., Ichimura, H., Smith, J. and Todd, P. (1998a). Characterizing Selection Bias Using Experimental Data. Econometrica

– Athey, S. and Imbens, G. W. (2006). Identification and Inference in Nonlinear Difference-in-Differences Models. Econometrica

– Event studies

– *Callaway and Sant'Anna (2020): "Difference-in-Differences with Multiple Time Periods". Journal of Econometrics.

– Abraham and Sun (2020). Estimating Dynamic Treatment Effects in Event Studies with Heterogeneous Treatment Effects. Working paper.

– Goodman-Bacon, A (2020). Difference-in-Differences with Variation in Treatment Timing. Working paper.

– de Chaisemartin and D'Haultfoeuille (2020). Two-Way Fixed Effects Estimators with Heterogeneous Treatment Effects. American Economic Review 110.

– Synthethic control

– Abadie, A., Diamond, A. and Hainmueller, J. (2010). Synthetic Control Methods for Comparative Case Studies: Estimating the Effect of Californias Tobacco Control Program. Journal of the American Statistical Association.

– Kellogg, M., Mogstad, M., Pouliot, G. and Torgovitsky, A. (2021). Combining Matching and Synthetic Controls to Trade off Biases from Extrapolation and Interpolation. Working Paper

– More on panel data:

– Heckman and Robb (1986): Alternative Identifying Assumptoins in Econometrics Models of Selection Bias. This paper discussion how one can use repeated cross-sections and panel data for identification. Contains fixed effects, difference-in-differences, etc.

– *Angrist and Pischke (2009): Mostly Harmless Econometrics, Ch. 5.