Week course in Econometrics

Monday-Friday, 9:00-12:00 each day

Instructor: Magne Mogstad

TA: Deniz Dutz (ddutz@uchicago.edu)

1 Overview

The goal of this course is to develop a knowledge of the econometric methods that are useful to analyze individual level data (microdata). Special focus is given to analyzing data with (conditionally) randomly assigned treatment or using instrumental variables (IV). The course develops IV by first discussing frequently (ab)used linear IV estimators (such as 2SLS) to analyze various settings and data, including binary, ordered, and unordered treatments, as well as single, multi-valued, and multiple instruments. The course then shows how methods other than linear IV estimators can be used for causal inference. These methods include partial identification approaches and marginal treatment effects. Real-life applications are given throughout the class.

Introduction

1. Defining parameters and arguing their policy relevance
2. Potential outcome notation and choices

Random assignment and selection on observables

1. Random assignment
2. Selection on observables

IV Part I. Reverse Engineering: Interpreting Linear Estimators

1. LATE result
   - Complier distributions and characteristics
   - Understanding the biases in IV when different assumptions fail
2. Importance of the monotonicity condition
   - Connection to choice models, with a single or multiple instruments
3. When is 2SLS actually LATE?
   - Accounting for covariates
   - Multivalued and multiple instruments
   - Unordered/ordered treatments
4. Practical advice when doing IV with applications to regression discontinuity designs and judge IVs

IV Part II. Forward Engineering: Inference on Target Parameters

1. Only observed heterogeneity in treatment effects
2. Unobserved heterogeneity in treatment effects but no explicit choice model
   - Missing data problem and partial identification
   - Manski bounds and extensions
3. Unobserved heterogeneity in treatment effects with choice models
   - Marginal treatment effects and policy relevant target parameters
   - (Semi)parametric approaches
   - A general framework
   - Missing data with application to survey non-response

2 Teaching and Assessment

There will be a lectures every day that you are expected to attend. Course material will be uploaded at the beginning of the course. Do not share any course material without permission. After each lecture, I expect you to work on the relevant problem set (probably for most of the rest of the day). 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 nal mark. They are meant to help you understand the material.

There will also be TA sessions every day 16:00-17:00 on Zoom (link here). Deniz will be the TA in the class. The TA sessions are for you to learn; I encourage you to ask Deniz questions about things you struggle to understand with regards to both the class material and the problem sets. On Friday after the lecture, I will give you a take-home exam. Exam due date is 5weeks from the end of the class. The exam will be marked. The exam should be done independently (and not in groups).

3 References list

Here is a reference list, following the outline of the course. * 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!

Introduction

– Defining parameters and arguing their (policy) relevance

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.

Random assignment and selection on observables

– 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.

– 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.

– 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

Instrumental variables – Part I

– *Mogstad, M., & Torgovitsky, A. (2024). Instrumental variables with unobserved heterogeneity in treatment effects. In Handbook of Labor Economics (Vol. 5, pp. 1-114). Elsevier. This handbook chapter covers most of the topics covered in this part.

– 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 Interpretation 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.

– RDD as IV

– *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

Instrumental variables – Part II

– *Mogstad, M., & Torgovitsky, A. (2024). Instrumental variables with unobserved heterogeneity in treatment effects. In Handbook of Labor Economics (Vol. 5, pp. 1-114). Elsevier. This handbook chapter covers most of the topics covered in this part.

– 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. (1989). Anatomy of the selection problem. Journal of Human resources, 343-360.

– 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 nonresponse: 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.

– Dutz, D., Huitfeldt, I., Lacouture, S., Mogstad, M., Torgovitsky, A., and van Dijk, W. (2025). Selection in Surveys: Using Randomized Incentives to Detect and Account for Nonresponse Bias (No. w29549). National Bureau of Economic Research.