POL-GA 1251

Quantitative Political Analysis II

Spring 2019

Instructor:	Professor Cyrus Samii NYU Politics Department 19 West 4th Street, Office 424 cdsamii@gmail.com
Class time/location:	Mondays & Wednesdays, 10:00am-12:00pm 19 West 4th Street, Room 217
Office hours:	Wed 3:00pm-4:30pm (use online sign up sheet)
Course website:	`http://cyrussamii.com/?page_id=2761`
Teaching Assistants:	Antonella Bandiera aab639@nyu.edu Ye Wang yw1576@nyu.edu

Overview

This course provides a current perspective on identifying and estimating causal effects in social science research. We focus on non-parametric identification methods and then non-parametric and semi-parametric estimation and frequentist inference methods. We will emphasize research design and robust estimation and inference.

Prerequisites and Restrictions

The course has two prerequisites. First, students should have working knowledge of probability theory, matrix algebra, and calculus at the level of POL-GA 1250, "Quant I." Second, students should have some background in writing scripts to implement statistical analyses in either R or Stata.

There is also a restriction with respect to taking the course for credit. The course provides foundational methodological training to Politics PhD students in their first or second year as part of their required sequence of courses. Only Politics PhD students will be allowed to take the course for a grade. (We do not have adequate teaching assistant and other resources to service students from other departments taking this for a grade, unfortunately.) People from other programs may audit or attend informally if space permits.

Texts

The course will draw a lot from the following textbooks:

1. Angrist, Joshua, and Steffan Jorg Pischke. 2009. *Mostly Harmless Econometrics*. Princeton: Princeton University Press. (Referred to as MHE.)

2. Imbens, Guido W., and Donald B. Rubin. 2015. *Causal Inference for Statistics, Social, and Biomedical Sciences: An Introduction*. Cambridge: Cambridge University Press. (Referred to as CIS.)

3. Morgan, Stephen L., and Christopher Winship. 2014. *Counterfactuals and Causal Inference: Methods and Principles for Social Research, Second Edition*. Cambridge, UK: Cambridge University Press. (Referred to as CCI.)

The course will mostly follow MHE and CIS, using CCI to provide more intuitive background and illustrations. I will also supplement the textbooks with notes, sections from other textbooks, and journal articles. I have listed "further reading" for each topic, and my lectures will sometimes draw on these. Readings will be available in a public Dropbox (see course website).

The books are each detailed, up to date, and they complement each other well. You can get PDFs of CIS and CCI from the Cambridge website, and MHE is quite inexpensive. MHE and CIS can be mathematically difficult at times, but you are strongly encouraged to dive in, replicate proofs, and work hard to understand. CCI provides intuition to keep you sane and grounded.

Some excellent textbooks that provide the proper statistical background for this course are the following:

- Aronow, Peter M., and Benjamin Miller. 2015. *Foundations of Agnostic Statistics*. Cambridge: Cambridge University Press. (Most direct foundation for this class.)
- Freedman, David A. 2009. *Statistical Models: Theory and Practice*. Cambridge: Cambridge University Press. (Lots of great exercises.)
- Goldberger, Arthur S. 1991. *A Course in Econometrics*. Cambridge, MA: Harvard University Press. (Out of print but you can get used copies on Amazon.)
- Hansen, Bruce E. 2017. *Econometrics*. Typescript, University of Wisconsin. (Free PDF on Hansen's website.)

The following provide additional insights and perspectives on causal identification and I will sometimes reference them:

- Pearl, Judea. 2009. *Causality: Models, Reasoning, and Inference, Second Edition*. Cambridge: Cambridge University Press.
- Pearl, Judea, Madelyn Glymour, and Nicholas P. Jewell. 2016. *Causal Inference in Statistics: A Primer*. West Sussex: Wiley.

Software

You will have the choice to work in R or Stata. It is useful to obtain fluency in both. R is great for programming estimators and algorithms "from scratch," programming simulations, and making graphics. Stata's pre-programmed estimation routines are often more reliable, and some assignments could be done using them; however Stata is very clumsy (for me) for programming, simulations, or graphics.

I encourage using RMarkdown or Stata Markdown for your assignments. This is a great investment that will pay off in the long run in terms of productivity as well as reproducibility.

- RMarkdown runs most easily through RStudio. Details here: https://rmarkdown.rstudio.com/
- Stata Markdown is a package that run within Stata. Details here: https://data.princeton.edu/stata/markdown/

Requirements and policies

Homework

You will receive homework every week or two. You will have to submit your completed assignment within a week; exact deadlines will be made clear on the assignment. You can work with others, but to receive credit, your homework must comply with the following guidelines:

- You must turn in a *hard copy of your own homework* by the stated deadline.
- The assignment that you turn in must *clearly reflect your own thinking*. Sets of verbatim copies of homework will have credit reduced by half.
- Homework assignments may be hand written or typed, but they must be clearly *legible*.
- Estimates obtained from data analysis programs (e.g., Stata or R) must be *formatted properly* into tables or graphs resembling journal presentation styles. You should use a table formatting function (e.g., `outreg2` or `esttab` in Stata, or `apsrtable` or `stargazer` in R). Use a reasonable (2 or at most 3) number of digits after decimal points, report standard errors or confidence intervals along with coefficients, clarify what are the dependent variables in each table or figure, and explain in footnotes to your tables or figures what kinds of estimators or adjustments have been used. *Print outs of "raw" screen output or commented logs will not receive any credit*. However, you may include such output as an appendix so that the grader can troubleshoot.
- Mathematical derivations should include *all key steps with explanations* for important techniques.

Homework will be graded for points as indicated on each assignment and count toward 50% of your grade.

Mid-term exam

An in-class mid-term exam will take place mid-way through the semester (exact date to be confirmed). The mid-term serves the purpose of evaluating individual progress, which in turn helps me to understand where to place emphasis for the remainder of the semester. If you are unable to make it to the exam, you must provide notice *at least a week prior* so that we can arrange an alternative time. The mid-term will count toward 15% of your grade.

Final exam

A take-home final exam will be scheduled during the final examination period. The final also serves the purpose of evaluating individual progress, which in turn allows me to provide individualized recommendations on where students should apply effort to strengthen their methodological foundations. If you are unable to work during the exam period, you must provide notice *at least a week prior* so that we can arrange an alternative time. The final will count toward 25% of your grade.

Attendance and participation

Attendance and participation in class discussions is *required* and counts toward 10% of your grade.

Special needs

Students with special needs should come to office hours or schedule an appointment with the instructor to discuss possible accommodation.

Topics

Topics listed below will be covered in around 1-2 class sessions each. Required reading sometimes corresponds directly to material covered in the sessions and sometimes builds up background needed for future sessions. Most of the required reading comes from MHE and CCI, although the topics covered toward the end of the semester will draw on other texts that will be made available.

1 Causal Identification

Potential outcomes, causal graphs, and definitions of causal effects.

Required reading: MHE Ch. 1; CIS Ch. 1-2; CCI Ch. 1-3.

Further reading: Angrist and Pischke (2010); Heckman and Vytlacil (2007); Holland (1986); Freedman (1991); Pearl (2009, Ch. 3); Rosenbaum (1999); Rubin (1974); Rubin (1978); Rubin (1986).

2 Identification, Estimation, and Inference in Randomized Experiments

Estimands and estimators, bias, consistency, and efficiency. Finite and infinite populations, implications of randomization and sampling, exact distributions, and asymptotic distributions.

Required reading: CIS Ch. 6.

Further reading: CIS, rest of Part II; Athey and Imbens (2016); Blair et al. (2019); Freedman (2008); Lin (2013); Samii and Aronow (2012).

3 Agnostic Regression and Causal Effects

Frisch-Waugh-Lovell; omitted variable bias formula; effect heterogeneity and nonlinearity; leverage; multiple regression weights; testing restrictions.

Required reading: MHE Ch. 3; CCI Ch. 6; Aronow and Samii (2016).

Further reading: Angrist and Krueger (1999); Aronow and Miller (2019, Ch. 4); DiNardo and Lee (2011); Imbens and Wooldridge (2009).

4 Notions of bias

Biased data and biased methods.

Required reading: CCI Ch. 8; Samii (2016).

Further reading: Bound et al. (2000, pp. 1-39); Frangakis and Rubin (2002); Heckman (1979); Heckman et al. (1998); Hyslop and Imbens (2001); Imai et al. (2008); King and Zeng (2006); Lalonde (1986); Pearl (2009, Ch. 3, 6); Pearl et al. (2016, Ch 2-3); Pei et al. (2017); Rosenbaum (1984).

5 Control and balance via matching and weighting

Identification under conditional exogeneity; alternative matching and weighting algorithms; estimation and inference after matching.

Required reading: CCI Ch. 4, 5,7; CIS Ch. 12, 17-18.

Further reading: CIS (rest of Parts III and IV); Abadie and Imbens (2006); Abadie and Imbens (2008); Abadie and Imbens (2011); Arbour and Dimmery (2019); Busso et al. (2014); D'Amour et al. (2018); Dehejia and Wahba (2002); De Luna et al. (2011); Hainmueller (2011); Hirano and Imbens (2004); Ho et al. (2007); Iacus et al. (2011); Imai and van Dyk (2004); Imbens (2000); King and Nielsen (2016); Lu et al. (2001); Rosenbaum and Rubin (1983); Sekhon (2009); Todd (2008).

6 Robust statistical inference

Clustering, autocorrelation, and spatial dependence; Moulton's problem; heteroskedasticity and cluster robust standard errors; bootstrapping; estimating the exact randomization variance; permutation tests.

Required reading: MHE Ch. 8.

Further reading: Aronow et al. (2015); Barrios et al. (2012); Bertrand et al. (2004); Cameron et al. (2008); Cameron et al. (2009); Chung and Romano (2013); Conley (1999); Efron and Tibshirani (1993); Freedman (2009, Ch. 8); Horowitz (2001); Imbens and Kolesar (2016); Janssen (1997); Moulton (1986); Pustejovsky and Tipton (2018); Romano (1990); Young (2015a); Young (2015b).

7 Instrumental variables

Exclusion restriction; valid first stage; principal strata; local average treatment effect (LATE); weak instrument; sensitivity analysis.

Required reading: MHE Ch. 4; CCI Ch. 9; CIS Ch 23-24.

Further reading: Abadie (2003); Angrist et al. (2000); Angrist et al. (1996); Baum et al. (2003); Bazzi and Clemens (2013); Bound et al. (1995); Conley et al. (2010); Deaton (2010); Heckman and Urzua (2009); Imbens (2010); Imbens and Rosenbaum (2005); Kolesar et al. (2011); Sovey and Green (2011); Staiger and Stock (1997); Stock et al. (2002); Young (2018).

8 Repeated observations

Adjusting for unobserved heterogeneity via fixed effects and difference-in-differences; synthetic control; event studies.

Required reading: MHE Ch. 5; CCI Ch. 11.

Further reading: Abadie and Gardeazabal (2003); Abadie (2005); Abadie et al. (2010); Athey et al. (2018); Athey and Imbens (2006); Borusyak and Jaravel (2017); Bound and Solon (1999); Doudchenko and Imbens (2017); Ferman and Pinto (2019); Mora and Reggio (2017); Xu (2017).

9 Regression discontinuity (RD)

Forcing variables; sharp and fuzzy RD; conditional average treatment effect (CATE); local linearity, bandwidth, and non-parametric regression; kernel weighting; multiway discontinuities; checks for sorting around cut-points; endogenous forcing variables; measurement error in forcing variables.

Required reading: MHE Ch. 6; CCI Ch. 11.

Further reading: Card et al. (2015); Cattaneo et al. (2017); Froelich (2007); Green et al. (2009); Imbens and Kalyanaraman (2009); Imbens and Lemieux (2008); Lee and Lemieux (2010); McCrary (2008); Papay et al. (2011); Urquiola and Verhoogen (2009).

10 Moderators, mediators, and causal explanation

Moderators and effect heterogeneity; mediators and mechanisms; sequential ignorability.

Required reading: CCI Ch. 10; Angrist et al. (2013); Imai et al. (2011).

Further reading: Acharya et al. (2016); Bullock et al. (2010); Glynn (2011); Heckman et al. (1997); Jo et al. (2011); Ludwig et al. (2011); VanderWeele (2008); VanderWeele (2015).

11 Distributional effects and quantile regression

Quantile treatment effect; minimum absolute deviations; rank invariance.

Required reading: MHE Ch. 7.

Further reading: Bitler et al. (2006); Chernozhukov and Hansen (2005); Heckman et al. (1997); Koenker and Hallock (2000).

12 Multiple endpoints

Index and mean effects; multiple comparisons adjustments.

Required reading: Anderson (2008).

Further reading: Casey et al. (2011); Caughy et al. (2015); Clingingsmith et al. (2009); Farcomeni (2008); Gibson et al. (2011); Kling and Liebman (2004);O'Brien (1984); Romano and Wolf (2007); Shaffer (1995).

13 Missing data and attrition

Bounds; inverse probability weighting; imputation.

Required reading: CCI Ch. 12; Gerber and Green (2012, Ch. 7).

Further reading: Aronow et al. (2015); Horton and Kleinman (2007); King et al. (2001); Lee (2009); Manski (1995, Ch. 2); Jones (1996); Puma et al. (2009); Vansteelandt et al. (2010).

14 Limited dependent variable effects

Structural versus causal estimands.

Required reading: Angrist (2001); Beck (2015).

Further reading: Davidson and MacKinnon (2004, Ch. 10-11) Fox (2002); Freedman (2006); Greene (2004); Hubbard et al. (2010); Imbens and Rubin (2011, Ch. 8); Liang and Zeger (1986); Van der Laan and Rose (2011, Ch. 7, 11, 16-17); Wooldridge (2002, Ch. 15, 19-20).

15 Machine learning and causal inference

Data-driven estimation; ensemble methods; machine learning for implementing CIA, characterizing effect heterogeneity, and discovering instruments.

Required reading: Athey and Imbens (2017).

Further reading: Athey and Imbens (2015); Belloni et al. (2014); Green and Kern (2012); Imai and Ratkovic (2012); Imai and Strauss (2011); Kleinberg et al. (2015); Pearl (2009, Ch. 2); Samii et al. (2015). Van der Laan and Rose (2011); Wager and Athey (2015).

16 Generalization and external validity

Unconfounded location; external validity; generalizability; target validity.

Required reading: Imbens (2010).

Further reading: Aronow and Carnegie (2013); Angrist and Fernandez-Val (2010); Angrist and Rokkanen (2014); Bisbee et al. (2015); Dehejia et al. (2019); Gechter (2015); Greenland (1994); Hernan and VanderWeele (2011); Hotz et al. (2005); Rubin (1992); Westreich et al. (2019).

17 Structure and identification

Policy effects versus structural parameters; spill-over and equilibrium effects.

Required reading: Acemoglu (2010); Angrist and Pischke (2010); Heckman (2010).

Further reading: Acemoglu et al. (2015); Aronow and Samii (2015); Banerjee et al. (2017); Brollo and Nannicini (2012); Chassang et al. (2012); Chetty (2009); Rosenzweig and Wolpin (2000); Todd and Wolpin (2006); Wolpin (2013).

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