Public Policy 571: Applied Econometrics
Winter 2019 Syllabus

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Office Hours: Mon. 11:00–12:30, Thurs. 12:00–1:30, or by appointment

The objective of this course is to help gain students proficiency in advanced techniques that are employed in the service of causal inference, including instrumental variables, selection models, regression discontinuity, and matching methods. Students will understand how to design, execute, and interpret the results from advanced estimation techniques beyond the standard OLS model. Students will learn to work with data structures in which the observations are not independently and identically distributed: time-series data, panel data, time-series-cross-sectional data, multi-level data, etc.

Prerequisite: it is assumed that students in this course will have previously taken Public Policy 529 and Public Policy 639 (or equivalent coursework).

Class Meeting Schedule

Unless otherwise noted, lectures are Mondays and Wednesdays from 2:30–3:50 pm in 1210 Weill Hall.

Textbooks

There is no single textbook for this course, and readings will be available on the Canvas website. You can log into Canvas at `http://canvas.umich.edu`. The following books, however, will be very good references for course material.

- Joshua D. Angrist and Jörn-Steffen Pischke. 2015. *Mastering 'Metrics: The Path from Cause to Effect*. Princeton: Princeton University Press.
- J. Scott Long. 1997. *Regression Models for Categorical and Limited Dependent Variables*. Sage Publications.
- Jeffrey M. Wooldridge. 2002. *Econometric Analysis of Cross Section and Panel Data*. Cambridge: MIT Press.

There are several resources for learning Stata available on Canvas, including a handbook that I compiled for Public Policy 567. If you wish to purchase a book, consider the following:

- Alan C. Acock. 2016. *A Gentle Introduction to Stata*, 5th edition, Stata Press.

Assignments and Grading

Your grade for this course will be determined by the following:

Problem sets	50%
Midterm exam	25%
Final exam	25%

There will be seven major problem sets in this course, approximately one problem set for every two weeks. Additionally, there will be two exams – one midterm and one final – covering the first-half and second halves of the course respectively. Each exam will have two components: a take-home part and an in-class part.

You are encouraged to help each other figure out the answers to the problem sets, but it is expected that you write up your answers independently. The take-home exams are exams. You are expected to work on these without the assistance of any other person. You may, however, consult any textbook or internet-resources.

Assignment and Exam Calendar

Problem Set 1	January 28
Problem Set 2	February 11
Problem Set 3	February 22
Midterm Exam	February 27
Problem Set 4	March 18
Problem Set 5	April 1
Problem Set 6	April 15
Problem Set 7	April 24
Final Exam	April 30, 10:30-12:30

The final course letter grade reflects the Ford School's guidelines. An A is awarded for work that is Excellent, an A- for work that is Very Good, a B+ for work that is Good, a B for work that is Acceptable, and a B- for work that is below expectations for graduate work. You should know I do not have a predetermined formula to convert numeric point totals into these categories. It would be a mistake, for instance, to assume that a grade of 75% on an exam translates into a C, since exams vary in their difficulty.

Software

Students will use the Stata statistical package for many homework assignments. This application is available on computers in the Ford School computer lab and many of the larger computer labs on campus. Additionally, students can remotely log in to the university's Virtual Sites (see information at http://www.itcs.umich.edu/sites/labs/virtual.php) to access Stata when not on campus. Discussion section will include help with the statistical computing skills required to complete these assignments.

Academic Integrity

It is expected that students are familiar with the Ford School's expectations for academic integrity as described at http://fordschool.umich.edu/academics/expectations, which adhere to the academic integrity policies for Rackham Graduate School. Violations of these policies will be taken seriously.

Students with special needs

If you believe you need an accommodation for a disability, please let me know at your earliest convenience. Some aspects of this course may be modified to facilitate your participation and progress. As soon as you make me aware of your needs, we can work with the Office of Services for Students with Disabilities to help us determine appropriate accommodations. I will treat any information you provide as private and confidential.

Student Mental Health and Wellbeing

The University of Michigan is committed to advancing the mental health and wellbeing of its students. We acknowledge that a variety of issues, such as strained relationships, increased anxiety, alcohol/drug problems, and depression, directly impacts students' academic performance. If you or someone you know is feeling overwhelmed, depressed, and/or in need of support, services are available. For help, contact Counseling and Psychological Services (CAPS) and/or University Health Service (UHS). For a listing of other mental health resources available on and off campus, visit: http://umich.edu/~mhealth/.

Inclusivity

Members of the Ford School community represent a rich variety of backgrounds and perspectives. We are committed to providing an atmosphere for learning that respects diversity. While working together to build this community we ask all members to:

- share their unique experiences, values and beliefs
- be open to the views of others
- honor the uniqueness of their colleagues
- appreciate the opportunity that we have to learn from each other in this community
- value one another's opinions and communicate in a respectful manner
- keep confidential discussions that the community has of a personal (or professional) nature
- use this opportunity together to discuss ways in which we can create an inclusive environment in Ford classes and across the UM community

Please refer to http://fordschool.umich.edu/academics/expectations for a full statement on the Ford School's academic expectations.

Advanced Estimation Methods for Cross-Sectional Data

1 Principles of Maximum Likelihood Estimation

In the classical linear regression model and its variants, we find the parameters of interest (i.e. the regression coefficients) though analytic formulas. With Maximum Likelihood Estimation (MLE), these parameters are often found by a search algorithm which tours the parameter space and finds the values of the parameters that are "most likely" given the data. The power of MLE its flexibility. Many different functional forms are possible, facilitating analysis of many kinds of data for which linear regression is not suitable.

- Jae Myung. 2003. "Tutorial on Maximum Likelihood Estimation." *Journal of Mathematical Psychology* 47: 90–100.
- Christian S. Perone. 2019. "A Sane Introduction to Maximum Likelihood Estimation." https://tinyurl.com/ycv99z2g.

2 Limited Dependent Variable Models

When our dependent variables come in the form of discrete categories, OLS can be problematic. For one thing, OLS produces predicted values of the dependent variable that fall into a continuous range rather than discrete values. Other problems arise with non-normality of standard errors and non-linearity of the effects of independent variables. With Maximum Likelihood Estimation, we can use functional forms that are designed for these data: probit analysis, logistic regression, and multinomial logit/probit. The purpose of this section is to become proficient in these techniques.

Dichotomous Dependent Variables

- J. Scott Long. 1997. "Binary Outcomes: The Linear Probability, Probit, and Logit Models" In *Regression Models for Categorical and Limited Dependent Variables*, chapter 3.
- Gary King, Michael Tomz, and Jason Wittenberg. 2000. "Making the Most of Statistical Analyses. Improving Interpretation and Presentation." *American Journal of Political Science* 44(2): 347–361.

Ordinal Categories as Dependent Variables

- J. Scott Long. 1997. "Ordinal Outcomes: Ordered Logit and Ordered Probit Analysis." In *Regression Models for Categorical and Limited Dependent Variables*, chapter 5.
- M. V. Hood, III and Irwin L. Morris. 1998. "Give Us Your Tired, Your Poor, . . . But Make Sure They Have a Green Card: The Effects of Documented and Undocumented Migrant Context on Anglo Opinion toward Immigration." *Political Behavior* 20(1): 1–15.

Nominal Categories as Dependent Variables

- J. Scott Long. 1997. "Nominal Outcomes: Multinomial Logit and Related Models." In *Regression Models for Categorical and Limited Dependent Variables*, chapter 6.

- M. Niaz Asadullah. 2018. "Madrasah for Girls and Private School for Boys? The Determinants of School Type Choice in Rural and Urban Indonesia." *International Journal of Educational Development* 62: 96–111.

3 Selection Models

The purpose of selection models is to address situations in which the cases that make it into the sample are different in important, unmeasured ways from those who do not, and these unmeasured factors are relevant for predicting the dependent variable.

- Christopher Achen. 1986. "Quasi-Experiments with Censored Data: Why Regression and Weighting Fail." In *Statistical Analysis of Quasi-Experiments*, chapters 4 and 5. Berkeley: University of California Press.
- Elisabeth R. Gerber and Justin H. Phillips. 2005. "Evaluating the Effects of Direct Democracy on Public Policy: California's Urban Growth Boundaries." *American Politics Research* 33(2): 310–330.
- Sarah Poggione. 2004. "Exploring Gender Differences in State Legislators' Policy Preferences." *Political Research Quarterly* 57(2): 305–314.

4 Count Models

Count models are for cases in which the dependent variable is a count of the number of times something occurs.

- Stefany Coxe, Stephen G. West, and Leona S. Aiken. 2009. "The Analysis of Count Data: A Gentle Introduction to Poisson Regression and Its Alternatives." *Journal of Personality Assessment* 91(2): 121–136.
- Gary King. 1989 "Event Count Models for International Relations: Generalizations and Applications." *International Studies Quarterly* 33(2): 123–147.
- Frederick J. Boehmke and Richard Witmer. 2004. "Disentangling Diffusion: The Effects of Social Learning and Economic Competition on State Policy Innovation and Expansion." *Political Research Quarterly* 57(1): 39–51.

Causal Inference for Cross-Sectional Data

5 Instrumental Variables Analysis

Oftentimes, there is strong reason to believe that the relationship between our dependent variable, and one or more of our independent variables, is endogenous. In such cases, our estimate of the coefficient on the independent variable will be biased. If we can find a third variable, however, which only has an effect on the dependent variable through the endogenous independent variable, we can identify the correct relationship.

- Joshua D. Angrist and Jörn-Steffen Pischke. "Instrumental Variables." In *Mastering 'Metrics: The Path from Cause to Effect*, chapter 3. Princeton: Princeton University Press. (this may be a refresher for you)
- Allison J. Sovey and Donald P. Green. "Instrumental Variables Estimation in Political Science: A Readers' Guide." *American Journal of Political Science* 55(1): 188–200.
- "Friends Don't Let Friends do IV," September 28, 2015.

6 Multivariate Matching Methods

With observational data, we face inherent challenges in estimating the average treatment effect (ATE) of some policy intervention because the treatment is not randomly-assigned. The treatment group and control group may differ from each other, in the aggregate, on both observable and unobservable characteristics in ways other than the treatment, and we cannot adequately control for these other factors. Matching methods are intended to bring balance to the treatment groups on these other characteristics to reduce bias in estimating the ATE. In this section of the course we will learn various matching methods and develop awareness of their limitations.

- Peter C. Austin. 2011. "An Introduction to Propensity Score Methods for Reducing the Effects of Confounding in Observational Studies." *Multivariate Behavioral Research* 46: 399–424.
- Paul R. Rosenbaum. 2010. *Design of Observational Studies*, chapters 7-8. New York: Springer.
- Per G. Fredriksson and Jim R. Wollscheid. 2007. "Democratic Institutions Versus Autocratic Regimes: The Case of Environmental Policy." *Public Choice* 130: 381–393.

7 Regression Discontinuity Models

Regression discontinuity models are useful for scenarios in which assignment into the treatment group is based upon a cutoff score on some observable characteristic or a particular date of implementation. In short, the difference between the predicted outcomes on either side of the cutoff point becomes a way to estimate the size of the treatment effect. This section of the course explores various uses of these models.

- Joshua D. Angrist and Jörn-Steffen Pischke. "Regression Discontinuity Designs." In *Mastering 'Metrics: The Path from Cause to Effect*, chapter 4. Princeton: Princeton University Press. (this may be a refresher for you)
- Robin Jacob and Pei Zhu. 2012. "A Practical Guide to Regression Discontinuity." MDRC, July 2012)
- David S. Lee. 2008. "Randomized Experiments from Non-Random Selection in U.S. House Elections." *Journal of Econometrics* 142: 675–697.

Estimation Methods for Time-Series and Panel Data

8 Regression with Time-Series Data

The standard assumption is that our data are independent and identically distributed. When we have time-series data, such as the results of monthly polls on presidential approval or some other case of repeated observations of the same object, this assumption is violated. The stochastic component of one observation may be correlated with the one preceding it and the one that follows. We spend about two sessions on this topic.

- Jon C. Pevehouse and Jason D. Brozek. 2008. "Time-Series Analysis." In *The Oxford Handbook of Political Methodology*, chapter 19.
- Virginia A. Chanley, Thomas J. Rudolph, and Wendy M. Rahn. 2000. "The Origins and Consequences of Public Trust in Government." *Public Opinion Quarterly* 64: 239–256.

9 Multi-Level Models

When our data consist of individual cases that are embedded within higher-level units – such as school children inside classrooms, which are inside schools – we need methods that can estimate both individual and unit-level effects. In this section of the course, we explore the use of multi-level models for this purpose.

- Andrew Gelman and Jennifer Hill. 2007. "Why?" In *Data Analysis Using Regression and Multilevel/Hierarchical Models*, chapter 1. Cambridge: Cambridge University Press.
- Ana V. Diez-Roux. 2000. "Multilevel Analysis in Public Health Research." *Annual Review of Public Health* 21: 171–192.

10 Regression with Panel Data

We have a panel when our data contain repeated observations of a sample of objects, such as a set of individuals who are surveyed periodically or a time series of cross-national data. In this scenario, we need to think about the non-independence of our observations both across time and space.

- Nathaniel Beck and Jonathan N. Katz. 2011. "Modeling Dynamics in Time-Series-Cross-Section Political Economy Data." *Annual Review of Political Science* 14: 331–52.
- Christopher W. Gibson. 2018. "Determinants of State Spending Patterns in Arab League Member States: a Post-Arab Spring Analysis, 1996-2014." *International Journal of Politics*, published online.

11 Duration Models

Duration models, also known as survival models, deal with situations in which we model the amount of time that some phenomenon lasts as a function of independent variables.

- Bradford S. Jones and Regina P. Branton. 2005. "Beyond Logit and Probit: Cox Duration Models of Single, Repeating, and Competing Events for State Policy Adoption." *State Politics and Policy Quarterly* 5(4): 420–443.

- Adam J. Berinsky, Nancy Burns, and Michael W. Traugott. 2001. "Who Votes By Mail? A Dynamic Model of the Individual-Level Consequences of Voting-By-Mail Systems." *Public Opinion Quarterly* 65: 178–197.

Causal Inference for Time-Series and Panel Data

12 Difference-in-Difference Models

Difference-in-difference models are useful when: 1) we have observations of each of the members of the sample for at least two periods in time; and, 2) one group within the sample experienced the treatment between these two periods, while the other did not. We can thus observe whether group-level differences in the outcome of interest changed from one period to the next, facilitating an estimate of the treatment effect.

- Joshua D. Angrist and Jörn-Steffen Pischke. "Differences in Differences." In *Mastering 'Metrics: The Path from Cause to Effect*, chapter 5. Princeton: Princeton University Press. (this may be a refresher for you)

- Janet Currie and Reed Walker. 2011. "Traffic Congestion and Infant Health: Evidence from E-ZPass." *American Journal of Applied Economics*, 3: 65–90.

13 Interrupted Time Series

With cross-sectional data, we used regression discontinuity models to make a causal inference around a cutoff point on an observable characteristic. With time-series data, that cutoff point can be a point in time.

- Catherine Hausman and David S. Rapson. 2018. "Regression Discontinuity in Time: Considerations for Empirical Applications." *Annual Review of Resource Economics* 10(21): 1–20.

- Hinda Ruton et al. 2018. "The Impact of an mHealth Monitoring System on Health Care Utilization by Mothers and Children: An Evaluation Using Routine Health Information in Rwanda." *Health Policy and Planning* 33: 920–927.

14 Synthetic Control Method

This method builds upon matching methods by creating a . Ideally, we would be able to compare a case that has undergone some treatment to the counterfactual scenario in which it had not undergone the treatment. Since this counterfactual scenario does not exist, we construct one using a weighted average of similar cases that did not undergo the treatment. We then can compare the observed outcomes against those predicted by under the counterfactual.

- Alberto Abadie, Alexis Diamond, and Jens Hainmueller. "Comparative Politics and the Synthetic Control Method." *American Journal of Political Science* 59(2): 495–510.
- John Springford. 2018. "The Cost of Brexit to June 2018." Center for European Reform Insight, September 30, 2018.