ECO 2403
TOPICS IN ECONOMETRICS

Department of Economics. University of Toronto
Winter 2019

Instructors:

Victor Aguirregabiria — Phone: 416-978-4358 Office: 150 St. George Street, Room 309
E-mail: victor.aguirregabiria@utoronto.ca
Web: http://individual.utoronto.ca/vaguirre

Martin Burda — Phone: 416-978-4479 Office: 150 St. George Street, Room 234
E-mail: martin.burda@utoronto.ca
Web: http://www.economics.utoronto.ca/mburda

Yao Luo — Phone: 416-978-5288 Office: 150 St. George Street, Room 322
E-mail: yao.luo@utoronto.ca
Web: http://sites.google.com/site/luo8yao/

Ismael Mourifié — Phone: 416-978-1495 Office: 150 St. George Street, Room 236
E-mail: ismael.mourifie@utoronto.ca
Web: http://sites.google.com/site/ismaelymourifie/

Adonis Yatchew — Phone: 416-978-7128 Office: 150 St. George Street, Room 278
E-mail: yatchew@chass.utoronto.ca
Web: http://www.economics.utoronto.ca/yatchew/

COURSE DESCRIPTION

This course deals with the following topics in advanced econometrics.

1. Nonparametric and Semiparametric Regression Models (1 week)
2. Bayesian Analysis and Markov Chain Monte Carlo (2 weeks)
3. Recent advances in Treatment effects and policy evaluations**.** (3 weeks)
4. Unobserved Heterogeneity in Structural Dynamic Discrete Choice Models (4 weeks)
5. Bargaining (2 weeks)

PREREQUISITES

ECO2400 and ECO2401

MEETINGS

We will have one meeting per week.

1. Regular class time and location: **Fridays, 2-4pm, BL305**
2. A small portion of lectures are re-scheduled to **Thursday 1-3pm at GE106** since in conflict with econometrics seminars.

EVALUATION
The evaluation will be based on an original research paper that each student will submit by the end of the course. The paper should be related to some of the topics covered in the course, and its main contribution can be either empirical or methodological. The due date of the research paper is **April, 27, 2019**.

Topic 1: Nonparametric and Semiparametric Regression Models
Instructor: Adonis Yatchew
Outline
1. Overview of nonparametric and semiparametric regression
2. Estimation of nonparametric, partial linear and index models
3. Treatment of endogenous variables
4. Testing procedures, constrained estimation and shape similarity
5. Models where data on derivatives are available
6. Applications and estimation in R

References:
- Yatchew, A., 2003, Semiparametric Regression for the Applied Econometrician, Themes in Modern Econometrics, Cambridge University Press
- Newey W., 2013, "Nonparametric Instrumental Variable Estimation, American Economic Review", 103:3, 550-556.
- Hall, Peter and A. Yatchew 2007: "Nonparametric Estimation When Data on Derivatives are Available", Annals of Statistics, 35:1, 300-323.
- Hall, Peter, and Joel L. Horowitz. 2005. "Nonparametric Methods for Inference in the Presence of Instrumental Variables." Annals of Statistics 33 (6): 2904–29.

Topic 2: Bayesian Analysis and Markov Chain Monte Carlo
Instructor: Martin Burda
Outline
1. Fundamentals of Probability and Bayesian Analysis
2. Hierarchical Modeling
3. Nonparametric Infinite Mixture Models
4. Posterior Asymptotics and Bernstein von Mises Theorem
5. Model Diagnostics
6. Markov Chain Monte Carlo
7. Hamiltonian Monte Carlo
8. Sequential Monte Carlo and Particle Filtering

References:
- Berger, J. O. (1993): "Statistical Decision Theory and Bayesian Analysis", Springer.
- Brooks, S., Gelman, A., Jones, G. L., and Meng, X.-L. (2011): "Handbook of Markov Chain Monte Carlo", Chapman & Hall/CRC.
- Geweke J. (2005): "Contemporary Bayesian Econometrics and Statistics", Wiley.

- Robert, C. (2007):" The Bayesian Choice: From Decision-Theoretic Foundations to Computational Implementation", Second Edition, Springer-Verlag.
- Burda, M., Harding, M., and Hausman, J. A. (2012): "A Poisson Mixture Model of Discrete Choice", *Journal of Econometrics*, 166(2), 184–203.
- Chib, S. and Basu, S. (2003): "Marginal Likelihood and Bayes Factors for Dirichlet Process Mixture Models", *Journal of the American Statistical Association*, 98, 224-235.
- Durham, G., and Geweke, J. (2014): "Adaptive Sequential Posterior Simulators for Massively Parallel Computing Environments", in *Advances in Econometrics*, vol. 34, 1-44, Poirier, D. and Jeliazkov, I. (eds), Emerald Group Publishing Limited.
- Geweke, J., and Amisano, G. (2011): "Hierarchical Markov Normal Mixture Models with Applications to Financial Asset Returns", *Journal of Applied Econometrics*, 26(1), 1-29.
- Kleijn, B. and van der Vaart, A.W. (2006): "Misspecification in infinite-dimesional Bayesian statistics", *Annals of Statistics*, 34, 837–877.
- Moon, H. R., and Schorfheide, F. (2012): "Bayesian and Frequentist Inference in Partially Identified Models", *Econometrica*, 80, 2, 755-782.
- Neal, R. M. (2003): "Slice Sampling", *Annals of Statistics,* 31 (3): 705–767.
- Norets, A., and Pelenis, J. (2014): "Posterior Consistency in Conditional Density Estimation by
- Covariate Dependent Mixtures," *Econometric Theory*, 30(3), 606-646.

Topic 3: Recent advances in Treatment effects and policy evaluations.
Instructors: Ismael Mourifié

Abstract: Evaluating the impact of an intervention (treatment) is fundamental for policy and funding allocation choices. It generates knowledge about what works and determines whether a program should be scaled up or discontinued. However, the effects of the treatment may vary widely across economic agents (heterogeneous treatment effect), and expectations about individual treatment effects may trigger strategic participation in the program (endogenous selection). Uncovering aggregate causal effect in such an environment with a high degree of heterogeneity and endogenous selection is very challenging.
We will first visit the main approaches developed to identify those causal effects, i.e. LATE, MTE and RDD. The validity of those methods depends heavily on the so-called "identifying assumptions". Yet, those assumptions have long been claimed to be fundamentally non-testable, their validity is mostly established through economic intuition, creating a great deal of controversy among researchers. Therefore, a part of the of this lecture consist in visiting recent works showing that contrary to the general claim, many of the widely used identifying assumptions impose some restrictions on the data, and then their validity can be tested using the data. Finally, we will see how the partial identification approach can be used to (partially) identify some causal effects when the "identifying assumptions" fail to hold.

OUTLINE

1. Introduction to Potential Outcome Model (POM).
2. Instrumental Variable (IV) estimand and LATE.
3. Local Instrumental Variable (LIV) and marginal treatment effect (MTE).
4. Regression discontinuity designs (RDD).

5. Testing Identifying assumptions in causal inference models (Testing LATE/MTE and RDD identifying assumptions).
6. Gentle Introduction to Partial Identification for policy evaluation.
7. Discussion on the challenges and problems.

READING LIST:

- Arai, Y., Y-C. Hsu, T. Kitagawa, I. Mourifié, & Y. Wan (2016): Testing Identifying assumptions in Fuzzy Regression Discontinuity Design, Working Paper.
- Chenozhukov, V., S. Lee, and A. M. Rosen (2013): "Intersection Bounds: Estimation and Inference," Econometrica, 81(2), 667–737.
- Chernozhukov, V., W. Kim, S. Lee, and A. M. Rosen, "Implementing Intersection Bands in Stata," Stata Journal 15 (2015), 21–44.
- Deaton, A. S., J. J. Heckman, and G. W. Imbens (2010): Forum on the Estimation of Treatment Effects," The Journal of Economic Literature, 48, 356--455.
- Carneiro, P., Heckman, J. J., and E. Vytlacil (2011): Estimating Marginal Return to Education: American Economic Review 101, October 2011: 2754--2781.
- Imbens, G. W., and J. D. Angrist (1994): Identification and Estimation of Local Average Treatment Effects," Econometrica, 62(2), 467--475.
- Heckman, J. J., and E. Vytlacil (2005): Structural Equations, Treatment Effects, and Econometric Policy Evaluation," Econometrica, 73(3), 669--738.
- Heckman, J. J. (2010): Building Bridges between Structural and Program Evaluation Approaches to Evaluating Policy, Vol 48(2) 356--398.
- HAHN, J., P. TODD, AND W. VAN DER KLAAUW (2001): "Identification and estimation of treatment effects with a regression-discontinuity design," Econometrica, 69(1), 201–209.
- Manski, C. F. (1990): Nonparametric Bounds on Treatment Effects, American Economic Reviews, Papers and Proceedings of the Hundred and Second Annual Meeting of the American Economic Association, 80(2), 319--323.
- Kitagawa, T: A test for instrumental Validity, Econometrica Vol. 83 (5), 2043--2063.
- Kedagni and Mourifié (2018): Generalized Instrumental inequalities: Testing IV independence assumption. Working Paper.
- Mourifié and Wan (2017): "Testing local average treatment effect assumptions," Review of Economics and Statistics, 99(2), 305–313.

Topic 4: Unobserved Heterogeneity in Structural Dynamic Discrete Choice Models
Instructor: Victor Aguirregabiria
<u>Outline</u>

1. Introduction and examples. [1], [5], [6], [13]
2. Random effects (RE) models and methods
    a. Finite mixture – Full solution – Maximum likelihood method (Keane & Wolpin). [18]
    b. EM algorithm (Arcidiacono & Miller). [4]
    c. Nonparametric methods (Kasahara & Shimotsu). [17]
3. Fixed effects (FE) methods

a. Sufficient statistics – Conditional MLE method in non-structural models (Chamberlain). [3], [8], [9], [10], [14], [15]
b. Bias reduction methods in non-structural models. [7]
c. Sufficient statistics – Conditional MLE in structural models (Aguirregabiria-Gu-Luo). [2], [12]
d. Bias reduction methods structural models.
e. Identification of marginal effects and counterfactuals (Chernozhukov et al). [11], [16]

References:

[1] Aguirregabiria, V. and P. Mira (2010): "Dynamic Discrete Choice Structural Models: A Survey," *Journal of Econometrics,* 156(1), 38-67.

[2] Aguirregabiria, V., J. Gu, and Y. Luo (2017): "Sufficient Statistics for Unobserved Heterogeneity in Dynamic Structural Logit Models," manuscript.

[3] Andersen, E (1970): "Asymptotic Properties of Conditional Maximum Likelihood Estimators," Journal of the Royal Statistical Society, Series B, 32, 283-301.

[4] Arcidiacono, P., and R. Miller (2011): "Conditional choice probability estimation of dynamic discrete choice models with unobserved heterogeneity," Econometrica, 79(6), 1823-1867.

[5] Arellano, M., and S. Bonhomme (2011): "Nonlinear Panel Data Analysis", Annual Review of Economics, 3, 395-424.

[6] Arellano, M., and B. Honoré (2001): "Panel Data Models: Some Recent Developments," in J. J. Heckman and E. Leamer (eds.) Handbook of Econometrics, Volume 5, Chapter 53, North-Holland, 3229-3296.

[7] Bonhomme, S., Lamadon, T. and E. Manresa (2017), Discretizing Unobserved Heterogeneity, manuscript.

[8] Chamberlain, G. (1980): "Analysis of Covariance with Qualitative Data," Review of Economic Studies, 47(1), 225-238.

[9] Chamberlain, G. (1985): "Heterogeneity, Omitted Variable Bias, and Duration Dependence," in Longitudinal Analysis of Labor Market Data, edited by J. J. Heckman and B. Singer. Cambridge: Cambridge University Press.

[10] Chamberlain, G. (2010): "Binary response models for panel data: Identification and information," Econometrica, 78(1), 159-168.

[11] Chernozhukov, V., I. Fernandez-Val, J. Hahn, and W. Newey (2013): "Average and Quantile Effects in Nonseparable Panel Models," *Econometrica*, Vol. 81, No. 2 (March, 2013), 535–580.

[12] Chintagunta, P., E. Kyriazidou, and P. Perktold (2001): "Panel Data Analysis of Household Brand Choices," Journal of Econometrics, 103(1), 111-153.

[13] Heckman, J. (1981): "The incidental parameters problem and the problem of initial conditions in estimating a discrete time - discrete data stochastic process," in C. Manski and D. McFadden (eds.), Structural Analysis of Discrete Data with Econometric Applications. MIT Press.

[14] Honoré, B. , and E. Kyriazidou (2000): "Panel data discrete choice models with lagged dependent variables," Econometrica, 68(4), 839-874.

[15] Honoré, B. , and E. Kyriazidou (2017): "Panel Vector Autoregressions with Binary Data," manuscript. Princeton University.

[16] Honoré, B. E. and Tamer, E. (2006), Bounds on Parameters in Panel Dynamic Discrete Choice Models. Econometrica, 74: 611–629.

[17] Kasahara, H., and K. Shimotsu (2009): “Nonparametric Identification of Finite Mixture Models of Dynamic Discrete Choices," Econometrica, 77(1), 135-175.
[18] Keane, M. and K. Wolpin (1997): "The career decisions of young men," Journal of Political Economy, 105, 473-522.

Topic 5: Bargaining

Instructor: Yao Luo

Abstract. Bargaining models have found broad applications in different fields. We discuss the identification and estimation of such models under different data scenarios.

References:

- Muthoo, A., 1999. Bargaining theory with applications. Cambridge University Press.
- Merlo, A. and Tang, X., 2012. Identification and estimation of stochastic bargaining models. Econometrica, 80(4), pp.1563-1604.
- Larsen, B., 2014. The efficiency of real-world bargaining: Evidence from wholesale used-auto auctions (No. w20431). National Bureau of Economic Research.
- Silveira, B.S., 2017. Bargaining with asymmetric information: An empirical study of plea negotiations. Econometrica, 85(2), pp.419-452.
- Backus, M., Blake, T., Larsen, B. and Tadelis, S., 2018. Sequential Bargaining in the Field: Evidence from Millions of Online Bargaining Interactions (No. w24306). National Bureau of Economic Research.

SCHEDULE OF LECTURES

WEEK	**DATE**	**TOPIC**
Week 1:	Fri. Jan. 11	Topic 1: Nonparametric & Semiparametric Regression
Week 2:	Fri. Jan. 18	Topic 2: Bayesian Analysis and MCMC
Week 3:	Fri. Jan. 25	Topic 2: Bayesian Analysis and MCMC
Week 4:	Fri. Feb. 1	Topic 3: Recent advances in Treatment effects.
Week 5:	Fri. Feb. 8	Topic 3: Recent advances in Treatment effects.
Week 6:	Fri. Feb. 15	Topic 3: Recent advances in Treatment effects.
	Fri. Feb. 22	Reading Week
Week 7:	Thur. Feb. 28	Topic 4: Unobserved Heterogeneity in Structural DDC Models.
Week 8:	Thur. Mar. 7	Topic 4: Unobserved Heterogeneity in Structural DDC Models.
Week 9:	Thur. Mar. 14	Topic 4: Unobserved Heterogeneity in Structural DDC Models.
Week 10:	Fri. Mar. 22	Topic 4: Unobserved Heterogeneity in Structural DDC Models.
Week 11:	Thur. Mar. 28	Topic 5: Bargaining
Week 12:	Fri. April. 5	Topic 5: Bargaining