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# **Advanced methods for impact evaluation**

## **Course programme**

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**22-24 May 2019**

**Palazzo Loredan, Venice (Italy)**

Every day there will be four 90-minute lectures,  
9:00-10:30, 11:00-12:30, 14:00-15:30, and 16:00-17:30

**WEDNESDAY, 22 MAY – INSTRUCTOR: ERICH BATTISTIN**

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## **Instrumental Variables**

### Instrumental Variables with Heterogeneous Effects

- A. Abadie, “Bootstrap Tests for Distributional Treatment Effects in Instrumental Variables Models,” *Journal of the American Statistical Association* 97, March 2002, 284-292.
- A. Abadie, “Semiparametric Instrumental Variable Estimation of Treatment Response Models,” *Journal of Econometrics* 113, 2003, 231-263.
- Clement de Chaisemartin, “Tolerating Defiance: LATE Without Monotonicity,” *Quantitative Economics*, 2017.
- T. Kitagawa, “A Test for Instrument Validity,” *Econometrica* 83(5), 2015, 2043-2063.
- M. Huber and G. Mellace, “Testing Instrument Validity for LATE Identification Based on Inequality Moment Constraints”, *The Review of Economics and Statistics* 2015 97:2, 398-411
- I. Mourifié and Y. Wan “Testing Local Average Treatment Effect Assumptions”, *The Review of Economics and Statistics*, 2017, vol. 99, issue 2, 305-313

### Marginal Treatment Effects

- Brinch, C.N., Mogstad, M. and Wiswall, M. (2017). “Beyond LATE with a Discrete Instrument”, *Journal of Political Economy*, Volume 125, Issue 4, pp. 985-1039.
- Heckman, James J. and Edward Vytlacil. "Structural Equations, Treatment Effects, And Econometric Policy Evaluation," *Econometrica*, v73(3,May), 2005, 669-738.
- Kowalski, Amanda. 2016. “Doing More When You’re Running LATE: Applying Marginal Treatment Effect Methods to Examine Treatment Effect Heterogeneity in Experiments.” NBER Paper 22363.
- P. Carneiro, J. Heckman and E. Vytlacil, “Estimating Marginal Returns to Education”, *American Economic Review*, vol. 101, no. 6, October 2011 (pp. 2754-81)

## **Discontinuities**

### Away from the cut-off

- Joshua D. Angrist, and Miikka Rokkanen, 2015, “Wanna Get Away? Regression Discontinuity Estimation of Exam School Effects Away From the Cutoff”, *Journal of the American Statistical Association* 110 (512): 1331-1344.
- Bertanha M., Imbens G., 2014, “External Validity in Fuzzy Regression Discontinuity Designs”, (No. w20773). National Bureau of Economic Research.
- Dong, Yingying, and Arthur Lewbel, 2015, “Identifying the Effect of Changing the Policy Threshold in Regression Discontinuity Models.” *Review of Economics and Statistics* 97 (5): 1081–92

### Inference and selection of the smoothing parameter

- Calonico, Sebastian, Matias D. Cattaneo, and Rocio Titiunik, 2014, “Robust Nonparametric Confidence Intervals for Regression-Discontinuity Designs.” *Econometrica* 82 (6): 2295–2326
- Calonico, Sebastian, Matias D. Cattaneo, and Rocio Titiunik, 2015, “Optimal Data-Driven Regression Discontinuity Plots.” *Journal of the American Statistical Association* 110 (512): 1753–69
- Cattaneo, Matias D., Brigham Frandsen, and Rocío Titiunik, 2015, “Randomization Inference in the Regression Discontinuity Design: An Application to Party Advantages in the U.S. Senate.” *Journal of Causal Inference* 3 (1): 1–24
- Imbens G. and K. Kalyanaraman, 2012, “Optimal Bandwidth Choice for the Regression Discontinuity Estimator.” *Review of Economic Studies* 79(3):933-959

### Multiple cutoffs, multiple running variables

- Cattaneo, Matias D., Luke Keele, Rocío Titiunik, Gonzalo Vazquez-Bare. 2016. “Interpreting Regression Discontinuity Designs with Multiple Cutoffs”, *The Journal of Politics*, 78, 3
- Keele, Luke J., and Rocío Titiunik. 2015. “Geographic Boundaries as Regression Discontinuities.” *Political Analysis* 23 (1):127–55
- Wong, Vivian C., Peter M. Steiner, and Thomas D. Cook. 2013. “Analyzing Regression-Discontinuity Designs with Multiple Assignment Variables: A Comparative Study of Four Estimation Methods.” *Journal of Educational and Behavioral Statistics* 38 (2): 107–41

### Kinks

- Card, David, David S. Lee, Zhuan Pei, and Andrea Weber. 2015. “Inference on Causal Effects in a Generalized Regression Kink Design.” *Econometrica*, 83 (6): 2453–83

## Machine learning and policy evaluation

### Taxation, insurance, and machine learning.

- Review of optimal tax theory and sufficient statistics
- An introduction to Gaussian Processes for machine learning.
- Combining the two.

### Experimental design and machine learning for policy choice.

- Optimal experimental design for estimating treatment effects.
  - An introduction to bandit problems.
  - Adaptive experimental design for policy choice
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- Chetty, R. (2009). Sufficient statistics for welfare analysis: A bridge between structural and reduced-form methods. *Annual Review of Economics*, 1(1):451-488.  
[https://dash.harvard.edu/bitstream/handle/1/9748528/suffstat\\_ar.pdf](https://dash.harvard.edu/bitstream/handle/1/9748528/suffstat_ar.pdf)
  - Williams, C. and Rasmussen, C. (2006). *Gaussian processes for machine learning*. MIT Press, chapters 2 and 7. <http://www.gaussianprocess.org/gpml/chapters/>
  - Kasy, M. (2018). Optimal taxation and insurance using machine learning. *Journal of Public Economics*. <https://maxkasy.github.io/home/files/papers/PolicyDecisions.pdf>
  - Kasy, M. (2016). Why experimenters might not always want to randomize, and what they could do instead. *Political Analysis*, 24(3):324-338.  
<https://maxkasy.github.io/home/files/papers/experimentaldesign.pdf>
  - Russo, D. J., Roy, B. V., Kazerouni, A., Osband, I., and Wen, Z. (2018). A Tutorial on Thompson Sampling. *Foundations and Trends R in Machine Learning*, 11(1):1-96.  
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