# 2023 Northwestern Causal Inference Main Workshop: Detailed Schedule and Readings

All readings, including individual book chapters, but not full books, are posted to the course website.

**Main Workshop: Monday – Friday, August 7-11, 2022**

**Advanced Workshop: Sunday afternoon Monday – Thursday morning, August 13-17, 2022**

**Workshop Location: Northwestern University, Pritzker School of Law, 375 East Chicago Ave., Chicago IL 60611 (if walking East, toward Lake Michigan, this is the last building entry before you reach the lake). There is also an entrance on Superior Street (one block South of Chicago Ave.)**

**The law school is in downtown Chicago. (The “main” Northwestern campus is in Evanston.)** All sessions will be in the “Rubloff” building, most likely in Room 150. (if the room changes, we will let you know.) The Rubloff building is the “new” law building, closest to Lake Michigan. Rubloff 150 is roughly midway between Chicago Ave. on the north side and Superior Ave. on the south side.

**Registration and meals**: Breakfast will be available each morning from 8:30 in Rubloff 155. A registration table will be open on the first day of each workshop beginning at 8:30. Lunch will be provided every day. Snacks and liquids (coffee, tea, sodas, juice, water) will be available throughout the day in Rubloff 155.

**Conference url:** <https://www.law.northwestern.edu/research-faculty/events/conferences/causalinference/>

**Access to Readings:** You can access the workshop materials from the Workshop webpage at <https://www.law.northwestern.edu/research-faculty/events/conferences/causalinference/readings/>.

Login using the email address you used to register for the workshop. We will send you an email when your login is active; please check to make sure you have access it before you arrive! To login using a different email address, please ask [sarah.shoemaker@law.northwestern.edu](mailto:sarah.shoemaker@law.northwestern.edu) to grant access.

**Wireless:** Northwesternuses the “eduroam” network system. If your home institution uses eduroam, please confirm that your login works before you arrive. But we’ll have at IT person available on the first day of each workshop to help with connection issues.

**General schedule:** “Lecture” sessions will run roughly 9:00-12:00, lunch 12:15-1:15, sessions 1:30-4:30. But the schedule will vary a bit when we have a lunch talk. See additional details below. Please plan to arrive the evening before the workshop. All times are approximate, other than the morning starting time; we tend to run “long”.

For departing flights, 7:00 pm or later on the last workshop day from O’Hare is reasonably safe; 6:30 from Midway should be okay.

**Questions during the workshop:** Please email one or more of Bernie Black ([bblack@northwestern.edu](mailto:bblack@northwestern.edu)), Scott Cunningham ([scunning@gmail.com](mailto:scunning@gmail.com)) and Sarah Shoemaker ([sarah.shoemaker@law.northwestern.edu](mailto:sarah.shoemaker@law.northwestern.edu)) The workshop email address -- [causalinference@law.northwestern.edu](mailto:causalinference@law.northwestern.edu) -- will reach Bernie and Sarah.

**Monday August 7 (Don Rubin)**

***Introduction to Workshop* (9:00-9:30) (Bernie Black):**

Overview of some of the main things we hope you will learn during the workshop.

***Introduction to Modern Methods for Causal Inference* (9:30-12:30, 1:30-3:30)**

Overview of causal inference and the Rubin “potential outcomes” causal model. The “gold standard” of a randomized experiment. Treatment and control groups, and the core role of the assignment (to treatment) mechanism. Causal inference as a missing data problem, and imputation of missing potential outcomes. Choosing estimands (the science), and how the estimand affects research design. One-sided and two-sided noncompliance.

***Readings***: Imbens, Guido, and Donald Rubin, *Causal Inference for Statistics, Social, and Biomedical Sciences* (2015), chapters 1-8.

***Monday reception:*** 4:00-5:30: In the law school central outdoor courtyard if weather permits, otherwise inside.

**Tuesday, August 8 (Yiqing Xu)**

***Matching and Balancing Designs for “Pure” Observational Studies* (9:00-12:00; 1:45-4:45)**

We discuss different estimation methods under the unconfoundedness (selection on observables) setup, including regressions, matching, inverse-probability weighting, and doubly robust procedures. We also discuss the importance of common support assumptions, and what we can do when this assumption is challenged.

***Readings:***

Crump, Richard K, V. Joseph Hotz, Guido W. Imbens, and Oscar A. Mitnik (2009), Dealing with limited overlap in estimation of average treatment effects, 96 *Biometrika 187-199*

Imbens, Guido W., and Jeffrey M. Wooldridge (2009), Recent developments in the econometrics of program evaluation, 47 J*ournal of Economic Literature* 5-86.

Imbens, Guido W. Matching Methods in Practice: Three examples. *Journal of Human Resources* 50.2 (2015): 373-419.

Khan, Shakeeb, and Elie Tamer (2010), Irregular Identification, Support Conditions, and Inverse Weight Estimation, 78 *Econometrica* 2021-2042.

Rosenbaum, Paul R., and Donald B. Rubin (1983), The Central Role of the Propensity Score in Observational Studies for Causal Effects, 70 *Biometrika* 41-55.

Sasaki, Yuya, and Takuya Ura (2022), Inference for moments of ratios with robustness against large trimming bias and unknown convergence rate, 38 *Econometric Theory* 66 – 112.

Seaman, Shaun R., and Stijn Vansteelandt (2018), Introduction to Double Robust Methods for Incomplete Data, 33 *Statistical Science* 184-197.

Stuart, Elizabeth A. (2010), Matching methods for causal inference: A review and a look forward, 35 *Statistical Science* 1-21.

**Tuesday Lunch Talk (Don Rubin (12:30-1:30): Validating Machine Learning Models Using Predictive Accuracy**

**Wednesday, August 9 (Yiqing Xu)**

***Panel Data and Difference-in-Differences* (9:00-12:00; 1:30-4:30)**

Simple two-period DiD. The core “parallel trends” assumption. The no-anticipation assumption. Parallel trends as a functional form assumption. The multiple time periods DiD (without variation in treatment timing). Event-study specifications (dynamic DiD models). Falsifying the parallel-trends assumption in pre-treatment periods. Sensitivity analysis for parallel trends. Very brief introduction to complications for DiD with variation in treatment timing.

***Readings:***

Callaway, Brantly, and Pedro H. C. Sant’Anna (2021), Difference-in-Differences with Multiple Time Periods, 225 *Journal of Econometrics* 200-230.

Roth, Jonathan, Pedro H. C. Sant’Anna, Alyssa Bilinski, and John Poe (2023), What's Trending in Difference-in-Differences? A Synthesis of the Recent Econometrics Literature,235 *Journal of Econometrics* 2218-2244

Roth, Jonathan, and Pedro H. C. Sant’Anna (2023), When Is Parallel Trends Sensitive to Functional Form?, 91 *Econometrica* 737-747.

**Thursday, August 10 (Matias Cattaneo):**

***Regression Discontinuity Designs (*Matias Cattaneo) 9:00-12:00; 1:45-4:45)**

Regression discontinuity (RD) designs: sharp and fuzzy designs; continuity-based methods and bandwidth selection; local randomization methods and window selection; empirical falsification of RD assumptions; extensions and generalizations of canonical RD setup: discrete running variable, multi-cutoff, multi-score, and geographic designs.

***Readings:* See** [https://rdpackages.github.io/](https://urldefense.com/v3/__https:/rdpackages.github.io/__;!!Dq0X2DkFhyF93HkjWTBQKhk!RMJBi2Xm7svLhbg-GdBn_Mz4rmfa_iKn2VG4vCbrDXrFmpRS68zuH7ZJzEb5T0P4f0djdUJ0QUH7cR2WPtarkaJlictLED-KWpU$), but especially:

Cattaneo, Matias, Nicolas Idrobo, and Rocio Titiunik, *A Practical Introduction to Regression Discontinuity Designs: Foundations* (2019)

Cattaneo, Matias, Nicolas Idrobo, and Rocio Titiunik, *A Practical Introduction to Regression Discontinuity Designs: Extensions* (2022)

***RD software website***: [https://rdpackages.github.io/](https://urldefense.com/v3/__https:/rdpackages.github.io/__;!!Dq0X2DkFhyF93HkjWTBQKhk!RMJBi2Xm7svLhbg-GdBn_Mz4rmfa_iKn2VG4vCbrDXrFmpRS68zuH7ZJzEb5T0P4f0djdUJ0QUH7cR2WPtarkaJlictLED-KWpU$)

***Thursday Lunch Talk:* *Bloopers in Research Design: How Smart People Get Causal Inference Wrong* (Bernie Black (12:15-1:15)**

Examples, drawn from different areas, of how to get causal inference wrong. Time permitting, I plan to use the following papers as examples, in case you want to look at them before the talk and see if you can figure out what I think is wrong:

1. Sanjai Bhagat & Bernard Black, The Non-Correlation Between Board Independence and Long-Term Firm Performance, 27 *Journal of Corporation Law* 231-274 (2002) (<http://ssrn.com/abstract=133808>)
2. John Donohue and Daniel Ho, *The Impact of Damage Caps on Malpractice Claims: Randomization Inference with Difference-in-Differences*, 4 J Empirical Legal Studies 69-102 (2007)
3. Daniel Kessler & Mark McClellan (1996), *Do Doctors Practice Defensive Medicine?*, 111 Quarterly Journal of Economics 353-390 (1996). and Kessler, Daniel, and Mark B. McClellan, (2002), Malpractice Law and Health Care Reform: Optimal Liability Policy in an Era of Managed Care, 84 *Journal of Public Economics* 175-197.
4. Gompers, Paul, Joy Ishii & Andrew Metrick, Corporate Governance and EquityPrices, 118 *Quarterly Journal of Economics* 107-155 (2003).
5. Daron Acemoglu & Simon Johnson, Unbundling Institutions, 113 *Journal of Political Economy* 949-995 (2005).
6. Kathryn Dewenter, Xi Han and Paul Malatesta, *Firm Values and Sovereign Wealth Fund Investments*, 98 Journal of Financial Economics 256-278 (2010).
7. Ran Duchin, Paul Matsusaka and Oguzhan Ozbas, When are Outside Directors Effective?, 96 *Journal of Financial Economics* 195-214 (2010) and their reply (2015) to Atanasov and Black, *The Trouble with Instruments: Re-examining Shock-Based IV Design* (working paper 2017), at <http://ssrn.com/abstract=2697098>.

**Friday, August 11 (Matias Cattaneo)**

***Instrumental variable methods* (9:00-12:00)**

Causal inference with instrumental variables (IV): the role of the exclusion restriction and first stage assumption; the monotonicity assumption and local average treatment effect (LATE) interpretation; applications to randomized experiments with imperfect compliance, including intent-to-treat designs and two-stage estimation. Connections between IV and fuzzy RD designs.

***Readings:*** Imbens and Rubin, chapters 23-24.

Angrist, Joshua D., and Jorn-Steffen Pischke, *Mostly Harmless Econometrics* (2009), chap. 4.

Angrist, Joshua, Guido Imbens, and Donald Rubin (1996), Identification of Causal Effects Using Instrumental Variables, 91 *Journal of the American Statistical Association* 444-455.

Imbens and Rubin, chapter 25 (Bayesian approach to IV)

**Friday Lunch Talk (Scott Cunningham, 12:15-1:00):** An introduction to Scott’s Causal Inference “Mixtape” and how to find and use his and Pedro Sant’Anna’s Stata and R-Based examples

**Friday afternoon (1:15-4:45):  Feedback on your own research (parallel sessions)**

Attendees will have an opportunity to present their own research design questions from current work in breakout sessions. Goal: obtain feedback on research design; *not* present results from a complete paper. [We ask presenters to stay for the full session, and can’t promise an early slot for those who must leave early.] (15 min to present, 15 min discussion). Session leaders:  Bernie Black, Scott Cunningham, Matias Cattaneo; Joshua Lerner; we’ll add additional sections as needed.

**Advanced Workshop Outline**

**Sunday afternoon August 13 (Christian Hansen) (1:00-5:00)**

**Primer on Machine Learning for Novices**

**Introduction to “machine-learning” approaches to prediction algorithms,** aimed at attendees with limited knowledge of machine learning methods. **Predicting without overfitting and high-dimensional model selection: bias/variance tradeoff, regularization and tuning, training and test sets, cross-validation. Popular machine learning prediction methods: regularized regression (e.g. Lasso, ridge), regression trees, random forests, and deep neural nets. Combining models – “ensembles” (ensemble models, bagging, boosting, stacking). Implementation.**

***Readings:***

Susan Athey and Guido Imbens (2019), Machine Learning Methods that Economists Should Know About, *Annual Review of Economics*, 11, 685-725.

Gareth James, Daniela Witten, Trevor Hastie, Robert Tibshirani (2021), An Introduction to Statistical Learning with Applications in R, Second Edition. (Free download at [https://www.statlearning.com/](https://urldefense.com/v3/__https:/www.statlearning.com/__;!!Dq0X2DkFhyF93HkjWTBQKhk!TVnMtQqweKxJvU0OQSQFbl_uoMOf2fH2d3TZTI3VHjjwirkFCCw6DGaFxLa1-x0R9wDicXpuJAaEFH0LQswQ8h49aKC_tUJwPpnM2vFcQqNoDKw$)), Chapters 2.1, 2.2, 5.1, 6.1, 6.2, 8.1, 8.2, 10.1, 10.2 (and the rest of the book is great)

Mullainathan, Sendhil, and Jann Spiess (2017), Machine Learning: An Applied Econometric Approach, 31(Spring) *Journal of Economic Perspectives* 87-106.

**Monday August 14 (Christian Hansen) (9:00-12:00; 1:30-4:30)**

**Applications of machine learning to causal inference and policy evaluation**

**When and how machine learning methods can be applied to policy evaluation and causal inference. Limitations: black box prediction models vs inference. Prediction as quantity of interest. Hypothesis generation. Using high-dimensional instruments and confounders: orthogonal moments, cross-fitting, applications (linear model coefficients, ATE/LATE estimation, panel data). Heterogeneous treatment effects. Implementation.**

***Readings:***

[also for the introduction on Sunday]: Susan Athey and Guido Imbens (2019), Machine Learning Methods that Economists Should Know About, *Annual Review of Economics*, 11, 685-725.

Alexandre Belloni, Victor Chernozhukov, Iván Fernández-Val, and Christian Hansen (2017), Program evaluation and causal inference with high-dimensional data, *Econometrica*, 85(1), 233–298.

Victor Chernozhukov, Denis Chetverikov, Mert Demirer, Esther Duflo, Christian Hansen, Whitney Newey, and James Robins (2018), Double/debiased machine learning for treatment and structural parameters, *The Econometrics Journal*, 21(1), C1–C68, [https://doi.org/10.1111/ectj.12097](https://urldefense.com/v3/__https:/doi.org/10.1111/ectj.12097__;!!Dq0X2DkFhyF93HkjWTBQKhk!TVnMtQqweKxJvU0OQSQFbl_uoMOf2fH2d3TZTI3VHjjwirkFCCw6DGaFxLa1-x0R9wDicXpuJAaEFH0LQswQ8h49aKC_tUJwPpnM2vFcjx3oKPw$)

Jens Ludwig and Sendhil Mullainathan (2022), Algorithmic behavioral science: Machine learning as a tool for scientific discovery, URL <http://dx.doi.org/10.2139/ssrn.4164272>, Chicago Booth Research Paper No. 22-15.

Jon Kleinberg, Himabindu Lakkaraju, Jure Leskovec, Jens Ludwig, and Sendhil Mullainathan (2018), Human decisions and machine predictions, *The Quarterly Journal of Economics*, 133(1), 237–293.

Mullainathan, Sendhil, and Jann Spiess (2017), Machine Learning: An Applied Econometric Approach, 31(Spring) *Journal of Economic Perspectives* 87-106.

**Tuesday, August 15 (Jeffrey Wooldridge)**

***Advanced matching and balancing methods* (9:00-12:00; 1:30-4:30)**

**Choosing among covariate balancing estimators. Doubly robust estimators assuming unconfoundedness with binary and multiple treatments, including inverse probability regression adjustment. Doubly robust estimation of LATE and the local average treatment effect on the treated (LATT) with covariates. Regression-based methods, matching, and doubly robust strategies with staggered interventions and panel data. Nonlinear DiD with staggered interventions.**

***Readings:***

Borusyak, K., X. Jaravel, and J. Spiess (2023), “Revisiting Event Study Designs: Robust and Efficient Estimation,” working paper. <https://arxiv.org/pdf/2108.12419.pdf>

Callaway, B., and P.H.C. Sant'Anna (2021), “Difference-in-Differences with Multiple Time Periods,” *Journal of Econometrics* 225, 200-230.

Frölich, M. (2007), “Nonparametric IV Estimation of Local Average Treatment Effects with Covariates,” *Journal of Econometrics* 139, 35-75.

Heiler, P. (2022), “Efficient Covariate Balancing for the Local Average Treatment Effect,” *Journal of Business & Economic Statistics* 40, 1569-1582.

Imai, K. and M. Ratkovic (2014), “Covariate Balancing Propensity Score,” *Journal of the Royal Statistical Society: Series B* 76, 243-263.

Lee, S.-J., and J.M. Wooldridge (2023), “A Simple Transformation Approach to Difference-in-Differences Estimation for Panel Data,” working paper. <https://www.dropbox.com/s/8khja5sop4dci5g/Lee_Wooldridge_20230720.pdf?dl=0>

Słoczyński, T., S.D. Uysal, and J.M. Wooldridge (2022), “Doubly Robust Estimation of Local Average Treatment Effects Using Inverse Probability Weighted Regression Adjustment,” working paper. <https://arxiv.org/pdf/2208.01300.pdf>

Sun, L. and S. Abraham (2021), “Estimating Dynamic Treatment Effects in Event Studies with Heterogeneous Treatment Effects,” *Journal of Econometrics* 225, 175-199.

Tan, Z. (2006), “Regression and Weighting Methods for Causal Inference Using Instrumental Variables,” *Journal of the American Statistical Association* 101, 1607-1618.

Wooldridge, J.M. (2021), “Two-Way Fixed Effects, the Two-Way Mundlak Regression, and Difference-in-Differences Estimators,” working paper. <https://www.dropbox.com/s/vxopj3p5so5iyp8/two_way_mundlak_20210928.pdf?dl=0>

Wooldridge, J.M. (2023), “Simple Approaches to Nonlinear Difference-in-Differences with Panel Data,” forthcoming, *Econometrics Journal*. <https://www.dropbox.com/s/8k6rc84dnddt7d0/nonlinear_did_tej_20230719.pdf?dl=0>

Zhan, M., F. Ying, and M. Lin (2022), “Comparision of Covariate Balancing Weighting Methods in Estimating Treatment Effects,” *Journal of Systems Science and Complexity* 35, 2263-2277.

***Monday reception:*** 4:45-6:00: In the law school central outdoor courtyard if weather permits, otherwise inside.

**Wednesday August 16 (Brantly Callaway)**

***Advanced panel data methods* (9:00-12:00; 1:45-4:45)**

New developments in causal inference with panel data with an emphasis on methods that can be implemented with “short” panels (in general) and difference-in-differences (in particular).  Limitations of two-way fixed effects regressions in this context.  Comparison of alternative estimation strategies that have been proposed to address these weaknesses.  Ways to weaken the parallel trends assumption and to diagnose and/or deal with violations of parallel trends.  Introduction to recent work on dealing with more complicated treatment regimes.

***Readings*** *Main readings*Callaway, Brantly, 2023. “Difference-in-differences for policy evaluation,” Handbook of Lobar, *Human Resources and Population Economics*. E. by Zimmermann, Klaus F. Springer International Publishing, 2023, pages 1-61.

Liu, Licheng, Ye Wang, and Yiqing Xu. 2022. “A Practical Guide to Counterfactual Estimators for Causal Inference with Time-Series Cross-Sectional Data.” *American Journal of Political Science*, forthcoming

*Additional useful readings:*

Callaway, Brantly, Andrew Goodman-Bacon, and Pedro Sant’Anna, 2021, “Difference-in-differences with a continuous treatment.” arXiv preprint arXiv:2107.02637.

Gardner, John, 2022 “Two-stage difference in differences.” arXiv preprint arXiv:2207.05943.

Rambachan, Ashesh ,and Jonathan Roth (2023), “A more credible approach to parallel trends.” *Review of Economic Studies*.

**Wednesday lunch talk (Bernie Black): Bloopers II: How Other Smart People Get Causal Inference Wrong (12:15-1:15)**

Examples, drawn from different areas, of how to get causal inference wrong. I currently plan to use the following papers as examples, in case you want to look at them before the talk and see if you can figure out what I think is wrong:

1. Desai, Mihir, and Dhammika Dharmapala (2009), Corporate Tax Avoidance and Firm Value, 91 *Review of Economics and Statistics* 537-546.
2. Duchin, Ram, John Matsusaka, and Oguzhan Ozbas (2010), When Are Outside Directors Effective?, 95 *Journal of Financial Economics* 195-214.
3. Frey, Bruno, and Stephan Meier (2004), Social Comparisons and Pro-Social Behavior:  Testing “Conditional Cooperation” in a Field Experiment, 94 *American Economic Review* 1717-1722.
4. Iliev, Peter (2010), The Effect of SOX Section 404:  Costs, Earnings Quality, and Stock Prices, 65 *Journal of Finance* 1163-1196.
5. Rauh, Joshua (2006), Own Company Stock in Defined Contribution Pension Plans:  A Takeover Defense?, 81 *Journal of Financial Economics*  379-410
6. Sommers, Benjamin D., Sharon K. Long, and Katherine Baicker (2014), Changes in Mortality after Massachusetts Health Care Reform”  A Quasi-experimental Study, 160 *Annals of Internal Medicine* 585-594.

**Thursday morning, August 17 (Christopher Walters): 9:00-1:00**

***Empirical Bayes Methods***

**Empirical Bayes methods for studying heterogeneity and estimating individual effects in settings with many unit-specific parameters (e.g., school, teacher, or physician quality; neighborhood effects on economic mobility; firm effects on wages; employer-specific labor market discrimination). Topics will include methods for quantifying variation in effects, empirical Bayes shrinkage for estimating individual effects, and connections to multiple testing and decision theory.**

**Readings**

Angrist, Joshua, Peter Hull, Parag Pathak, and Christopher Walters, “Leveraging lotteries for school value-added: testing and estimation." *Quarterly Journal of Economics* 132(2): 871-919 (2017).

Bradley Efron, *Large-scale inference: Empirical Bayes methods for estimation, testing, and prediction*. Cambridge University Press (2012).

Kline, Patrick, Evan Rose, and Christopher Walters, “Systemic discrimination among large US employers.” *Quarterly Journal of Economics*137(4): 1-74 (2022).

Kline, Patrick, Raffaele Saggio, and Mikkel Sølvsten, "Leave-out estimation of variance components." *Econometrica*88(5): 1859-1898 (2020).

Kline, Patrick, and Christopher Walters, "Experimental detection of job-level employment discrimination." *Econometrica*89(2): 765–792 (2021).

Koenker, Roger, and Jaiying Gu, “REBayes: an R package for empirical Bayes mixture methods.” *Journal of Statistical Software*82(8): 1-26 (2017).