EMORY UNIVERSITY

Causal Inference with Longitudinal and Panel Data (PhD level)

(Econ 730)

Instructor:	Pedro Sant'Anna (pedro.santanna@emory.edu)
Teaching Assistant:	Marcelo Ortiz-Villavicencio
Office Hours:	Tuesdays 1:00 PM - 2:00 PM
Classes:	Tu-Th 2:30 PM - 3:45 PM, White Hall 200
Course Website:	`https://psantanna.com/Econ730/`

Course Scope and Mission

Many causal inference problems involve the notion of time: Do states that *expanded Medicaid in a given year* have better mortality rates than states that *have not yet* expanded Medicaid? How does the implementation of a household heat pump affect energy consumption *in the months after* the change? How does a new medical treatment affect the quality of life of patients in the *years to come*? How does unemployment insurance generosity affect *time* out of work? To answer causal questions like these, it is common to explore data from multiple units across different points in time, such as longitudinal and panel data. In recent years, such datasets have become available at incredible levels of detail about the units of interest. With such increased information detail, there is a need to use modern econometric techniques that leverage these additional details in the data. In this course, we will use a combination of lectures, readings, problem sets, and computational exercises to introduce you to Modern Causal Panel and Longitudinal Data techniques and how to apply them. We will cover both methodological and empirical aspects of causal panel data models, and will draw from concrete empirical applications. The focus will concern experimental and quasi-experimental procedures used by economists and social scientists to leverage specific sources of variation in the data that mimic the intervention of interest. These methods are widely used in academia, industry, government, and regulatory agencies.

This course builds on the potential outcomes framework, which allows for rich treatment-effect heterogeneity across units and avoids reliance on strong functional-form assumptions. We will cover various methodological tools, including experimental designs, a variety of difference-in-differences and event study models, Triple Differences, selection based on lagged outcomes, synthetic controls, matrix completion, factor models, panel IV methods, and surrogate models. We will discuss identification, estimation, and inference procedures. We will discuss different falsification and sensitivity analysis procedures to assess the plausibility of the invoked assumptions and the robustness of the empirical findings.

Specific Learning Objectives:

1. Understand how having access to longitudinal and panel data can allow you to answer richer causal questions, using methods that involve less stringent assumptions.

2. Understand the strengths and the limitations of different causal panel data methods.

3. Understand and be comfortable implementing different causal panel data methods, in practice.

4. Identify and summarize the contributions and caveats in specific research papers that use these tools.

Background and Resources

We will build upon your prior learnings in statistics and econometrics. Nothing will be assumed beyond the first-year core coursework in Econometrics, but some experience with data analysis will make your journey easier. In turn, the ability to do causal inference well should be helpful in any area of economics, especially applied microeconomics and econometrics.

In addition, this class will require you to be able to program. We will use `R` as our primary statistical programming language, but you are free to program in your preferred language, e.g., `Python`, `Stata`, or `Julia`. However, my ability to assist you with these alternative languages is more limited, and you should factor that in. I encourage you to explore AI tools to enhance your coding productivity; I use Codex, Claude Code, and GitHub Copilot regularly. I will not be able to assist you with using these tools, though—you should explore that yourself and find what is best for you. You also must verify the codes to avoid embarrassment—these AI tools are meant to improve your coding skills, and not replace them.

The course will build on several articles. We will favor recent research surveys when an overview of the topic is necessary. Below, we list a few surveys we will use in the course.

– Arkhangelsky, Dmitry and Guido Imbens (2024), "Causal models for longitudinal and panel data: a survey," The Econometrics Journal, 27(3), p. C1–C61.

– Baker, Andrew, Brantly Callaway, Scott Cunningham, Andrew Goodman-Bacon, and Pedro H. C. Sant'Anna (2025), "Difference-in-Differences Designs: A Practitioner's Guide," Journal of Economic Literature, Forthcoming.

– 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," Journal of Econometrics, 235 (2), 2218–2244.

– Callaway, Brantly (2023), "Difference-in-Differences for Policy Evaluation," in Klaus F. Zimmermann, ed., Handbook of Labor, Human Resources and Population Economics, Cham: Springer International Publishing, pp. 1–61.

– Abadie, Alberto (2021), "Using synthetic controls: Feasibility, data requirements, and methodological aspects," Journal of Economic Literature, 59(2), 391-425

Students should read the assigned readings and attend all lectures, as much of the course material will not be in the readings. I will provide the Slides after the class. If you have trouble downloading any articles to use in the course, please let me know.

Assignments and Evaluation

Component	Weight	Deadline
Class Participation and Contribution	10%	Ongoing
Problem Set 1	15%	Week 4 (tentative)
Problem Set 2	15%	Week 8 (tentative)
Problem Set 3	15%	Week 12 (tentative)
Short Reports and Presentation	25%	Various
Replication	20%	Last week
Research Proposal	0%	Optional

Class Preparation and Contribution is based on a weekly memo and constructive engagement with topical papers presented in class. Every week, we will have an assignment on Canvas to submit a brief note discussing the content of one main required reading for the following week. The goal of the note is to help you organize your thoughts and to help me understand which issues might be helpful or interesting for further discussion during the class. The note has no specific format and doesn't need to be longer than one or two paragraphs. It can include a thought you had while reading the assigned paper, a question about something you didn't understand, or a related comment on the week's topic. Full credit will be given to a good-faith effort.

Problem Sets: This class requires substantial time on theoretical and empirical problem sets. The problem sets will sometimes involve proofs, simulations, and empirical applications/replication exercises. We will emphasize conducting reproducible research for the empirical component of the problem sets, and you are expected to write well-documented and clear codes. All students must complete all parts of the problem sets. Problem sets will be posted on the course's Canvas site, and the deadlines

Short Reports and Presentation: Starting from week 2 of the course, students will select a topical paper they find interesting to develop a brief report and presentation summarizing the paper for the class. The report should be no more than two pages and should summarize: (i) the research question(s) addressed; (ii) why that is interesting/important; (iii) the key challenges in answering the question; (iv) how the data + research design + model address those challenges; (v) the overall contributions and caveats of the paper in terms of answering the question and pushing forward the knowledge frontier. Each student is expected to complete one of these reports every week throughout the course (starting in week 3). Students only auditing the class are not excused from this, but they are only required to submit one report every other week. Every week, I will randomly assign one or two students to present their reports at the beginning of the class. All students taking the course for credit will be included in the randomization list. Students auditing the class will be listed every other week. Once any student is selected twice (if any), they will be removed from the presentation randomization list. The goal here is to force you to develop presentation skills, create a habit of reading papers, and work hard. My experience has been that hard work is always eventually rewarded.

Replication: I want you to work in pairs and select a paper on a course topic to replicate broadly. Here, you need to first do a narrow replication, making sure that all main results of the paper are reproducible—this is fairly easy these days, with many journals requiring authors to make all code and (publicly shareable) data available. After this step, you should also conduct a broader replication. This involves using data from different periods, different states/regions/countries, and different sets of methods to tackle the same question. You should make everything fully reproducible, and follow the AEA reproducibility guidelines. You should also write a 10-page paper — you can use the Journal of Applied Econometrics' Replication Section papers as a guide. In the last week of the course, I would like you to present your work. Each team should have 10-15 minutes to present, and clarity of the presentation will also be important for the grade.

Research Proposal: I strongly encourage students to begin working on their dissertations early. This is especially true if you want to write a PhD thesis pushing the frontiers of Modern Causal Inference. As such, this course will provide an optional Research Proposal so you can get some feedback. If you decide to follow this path (which is excellent!), I would like you to structure your research proposal so that your research question is very clear. I also want you to describe the data sources and identification strategies used to answer your question of interest, and to provide reproducible code for the analysis.

Grading: The map from numerical to letter grade is the following:

Grade	Lower Limit	Upper Limit
A	95	100
A-	90	94.999
B+	85	89.999
B	80	84.999
B-	60	79.999
C	50	59.999
F	0	49.999

Course Policies

Various policies for this course are described below. Basically, let's all work to be good citizens and take our various roles as students, teachers, friends, colleagues, and humans seriously.

Academic Integrity: The Emory University Honor Code is taken seriously and governs all work in this course. Details about the Honor Code are available in the Laney Graduate School Handbook and available online here. By taking this course, you affirm that it is a violation of the code to plagiarize, to deviate from the instructions about collaboration on work that is submitted for grades, to give false information to a faculty member, and to undertake any other form of academic misconduct. You also affirm that if you witness others violating the code you have a duty to report them to the honor council.

Accessibility Statement: As the instructor of this course, I endeavor to provide an inclusive learning environment. I want every student to succeed. The Department of Accessibility Services (DAS) works with students who have disabilities to provide reasonable accommodations. It is your responsibility to request accommodations. In order to receive consideration for reasonable accommodations, you must register with the DAS at https://accessibility.emory.edu/students/. Accommodations cannot be retroactively applied so you need to contact DAS as early as possible and contact us as early as possible in the semester to discuss the plan for implementation of your accommodations. For additional information about accessibility and accommodations, please contact the DAS at (404) 727-9877 or accessibility@emory.edu.

Brief Soapbox on Writing and Presenting: This course has both written and spoken elements. Time is scarce, so communicating well is a critical skill for all of us, but especially for academics who are teachers and researchers seeking to communicate ideas in a clear and compelling fashion.

Good writing is clear and concise. It is not easy. The writings for this class are short, so you will typically face hard decisions about what NOT to include. If you use a bunch of complex terminology or try to hit every potentially relevant point, you will run out of space. I will look for quality of writing as well as your ideas and analysis.

Like good writing, a good presentation is not an easy thing to do, but it is a valuable skill to develop. Remember that enthusiasm and preparation both go a long way.

Notes on Classroom Climate and Diversity, Inclusion, and Wellness: It is my intent that students from all diverse backgrounds and perspectives be well served by this course, that students' learning needs be addressed both in and out of class, and that the diversity that students bring to this class be viewed as a resource, strength and benefit. It is my intent to present materials and activities that are respectful of diversity: gender, sexuality, disability, age, socioeconomic status, ethnicity, race, and culture. Your suggestions are encouraged and appreciated. Please let me know ways to improve the effectiveness of the course for you personally or for other students or student groups. I (like many people) am still in the process of learning about diverse perspectives and identities. If something was said in class (by anyone) that made you feel uncomfortable, please talk to me about it.

Course Outline

This is a very ambitious outline, so please be ready for adjustments if needed. Mandatory readings are listed first and are marked with ⋆.

Week 1: Introduction to Causal Inference with Longitudinal and Panel Data

(a) Potential outcomes that depend on treatment sequences over time

(b) Potential outcomes with staggered treatment adoptions

(c) Potential outcomes with treatment entry and exit

(d) Causal parameters of interest

(e) Mapping questions to causal parameters: the importance of the design

(f) Challenges with very rich treatment sequences

(g) Limited and no-carryover assumptions

Readings:

⋆ Sections 2.1, 2.2, 2.3, and 3.1 of 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," Journal of Econometrics, 235 (2), 2218–2244.

⋆ Robins, James M., "A New Approach To Causal Inference in Mortality Studies With a Sustained Exposure Period - Application To Control of the Healthy Worker Survivor Effect," Mathematical Modelling, 1986, 7, 1393–1512.

– Holland, Paul W., "Statistics and Causal Inference," Journal of the American Statistical Association, 1986, 81 (396), 945–960.

Week 2: Randomizing Treatment Sequences

(a) Randomization at baseline versus sequential randomization

(b) Identification of average, distributional, and quantile Treatment Effects

(c) Estimation and inference for different causal parameters

(d) Efficient estimation with random staggered treatment allocations

Readings:

⋆ Bojinov, Iavor, Ashesh Rambachan, and Neil Shephard (2021), "Panel experiments and dynamic causal effects: A finite population perspective," Quantitative Economics, 12 (4), 1171–1196

⋆ Blackwell, Matthew and Adam N. Glynn (2018), "How to Make Causal Inferences with Time-Series Cross-Sectional Data under Selection on Observables," The American Political Science Review, Vol. 112, No. 4 (November 2018), pp. 1067-1082

⋆ Roth, Jonathan and Pedro H. C. Sant'Anna (2023), ""Efficient Estimation for Staggered Rollout Designs," Journal of Political Economy: Microeconomics, 1 (4), 669–709.

– Athey, Susan and Guido Imbens (2022) "Design-based Analysis in Difference-In-Differences Settings with Staggered Adoption," Journal of Econometrics, 226 (1), 62–79.

– McKenzie, David (2012), "Beyond baseline and follow-up: The case for more T in experiments," Journal of Development Economics, 99 (2), 210–221.

– Rambachan, Ashesh and Jonathan Roth (2024), "Design-Based Uncertainty for Quasi-Experiments," arXiv:2008.00602

– Shaikh, Azeem and Panos Toulis (2021), "Randomization Tests in Observational Studies With Staggered Adoption of Treatment," Journal of the American Statistical Association, 116 (536), 1835–1848.

– Lin, Winston (2013), "Agnostic notes on regression adjustments to experimental data: Reexamining Freedmans critique," Annals of Applied Statistics, 7 (1), 295–318.

– Blackwell, Matthew (2013), "A Framework for Dynamic Causal Inference in Political Science," American Journal of Political Science, 57: 504-520

– Chen, Xinyuan and Fan Li (2025), "Model-assisted inference for dynamic causal effects in staggered rollout cluster randomized experiments," arXiv:2502.10939

– Lindner, Stephan and K John Mcconnell (2021), "Heterogeneous treatment effects and bias in the analysis of the stepped wedge design," Health Services and Outcomes Research Methodology, 21, 419–438.

– Brown, Celia A. and Richard J. Lilford (2006), "The stepped wedge trial design: A systematic review," BMC Medical Research Methodology, 6, 1–9.

– Bojinov, Iavor, David Simchi-Levi, and Jinglong Zhao. (2022), "Design and analysis of switchback experiments," Management Science.

– Card, David, and Alan Krueger (1994), "Minimum wages and employment: A case study of the fast-food industry in New Jersey and Pennsylvania," The American Economic Review, 84(4), 772–793.

Week 3: Introduction to Difference-in-Differences

(a) Allowing for unobserved heterogeneity

(b) Parallel Trends and No-anticipation Assumptions

(c) Identification of the average treatment effect on the treated

(d) Estimation and inference using influence functions

(e) Estimation and inference using regressions

(f) Repeated cross-sections and unbalanced panel data

Readings:

- ⋆ Section 2 of 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," Journal of Econometrics, 235 (2), 2218–2244.
- ⋆ Sections 1, 2, and 3 of Baker, Andrew, Brantly Callaway, Scott Cunningham, Andrew Goodman-Bacon, and Pedro H. C. Sant'Anna (2025), "Difference-in-Differences Designs: A Practioner's Guide," Working Paper.
- ⋆ Sections 1 and 2 of Callaway, Brantly (2023), "Difference-in-Differences for Policy Evaluation," in Klaus F. Zimmermann, ed., Handbook of Labor, Human Resources and Population Economics, Cham: Springer International Publishing, pp. 1–61.
- – Josh Angrist and Steve Pischke (2009), "Mostly Harmless Econometrics", Princeton University Press, Section 5.2
- – Wooldridge, Jeffrey (2021), "Two-way fixed effects, the two-way Mundlak regression, and difference-in-differences estimators," Working Paper.

Week 4: Incorporating Covariates into DiD

(a) Limitations of two-way fixed effects linear specifications

(b) Regression adjustment estimators

(c) Inverse probability weighted estimators

(d) Doubly robust estimators

(e) Semiparametric Efficiency

(f) Assessing Overlap

Readings:

- ⋆ Section 4.1 and 4.2 of 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," Journal of Econometrics, 235 (2), 2218–2244.
- ⋆ Section 4 of Baker, Andrew, Brantly Callaway, Scott Cunningham, Andrew Goodman-Bacon, and Pedro H. C. Sant'Anna (2025), "Difference-in-Differences Designs: A Practioner's Guide," Working Paper.
- ⋆ Heckman, James J., Hidehiko Ichimura, and Petra Todd (1997), "Matching as an Econometric Evaluation Estimator: Evidence from Evaluating a Job Training Programme," The Review of Economic Studies, 64 (4), 605–654.
- ⋆ Abadie, Alberto (2005), "Semiparametric Difference-in-Difference Estimators," The Review of Economic Studies, 72, 1–19.
- ⋆ Abadie, Alberto (2005), "Semiparametric Difference-in-Difference Estimators," The Review of Economic Studies, 72, 1–19.
- ⋆ Sant'Anna, Pedro H. C. and Jun Zhao (2020) "Doubly Robust Difference-in-Differences Estimators," Journal of Econometrics, 219 (1), 101–122.

- Sant'Anna, Pedro H. C. and Qi Xu (2024) "Difference-in-Differences with Compositional Changes," arXiv:2304.14256.
- Hong, Seung-Hyun (2013) "Measuring the effect of Napster on recorded music sales: difference-in-differences estimates under compositional changes," Journal of Applied Econometrics, 28 (2), 297–324.
- Khan, Shakeeb and Elie Tamer (2010), "Irregular Identification, Support Conditions, and Inverse Weight Estimation," Econometrica, 78 (6), 2021–2042.
- Ma, Yukun, Pedro H. C. Sant'Anna, Yuya Sasaki, and Takuya Ura (2023), "Doubly Robust Estimators with Weak Overlap," arXiv:2304.08974.
- Caetano, Carolina and Brantly Callaway (2024), "Difference-in-Differences when Parallel Trends Holds Conditional on Covariates," arXiv:2406.15288.
- Chang, Neng-Chieh (2020) "Double/debiased machine learning for difference-in-differences," Econometrics Journal, 23, 177–191.

Week 5: Understanding Uncertainty in DiD Designs + Better Understanding Parallel Trends

(a) Clustering decisions
(b) What part of the model is treated as fixed and what part is treated as random
(c) Sampling Uncertainty vs. Design Uncertainty
(d) Inference with a few clusters
(e) Parallel Trends and Functional Form
(f) Selection and Parallel Trends

Readings:

⋆ Section 5 of 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," Journal of Econometrics, 235 (2), 2218–2244.

⋆ Abadie, Alberto, Susan Athey, Guido W. Imbens, and Jeffrey Wooldridge (2023), "When Should You Adjust Standard Errors for Clustering?," The Quarterly Journal of Economics, 138 (1), 1–35.

⋆ Abadie, Alberto, Susan Athey, Guido W. Imbens, and Jeffrey Wooldridge (2020), "Sampling-based versus design-based uncertainty in regression analysis," Econometrica 88 (1), 265-296

⋆ Wooldridge, Jeffrey M. (2003), "Cluster-Sample Methods in Applied Econometrics," American Economic Review P&P, 93 (2), 133–138

⋆ Bertrand, Marianne, Esther Duflo, and Sendhil Mullainathan (2004), "How Much Should We Trust Differences-in-Differences Estimates?," Quarterly Journal of Economics, 119 (1), 249–275

⋆ Roth, Jonathan and Pedro H. C. Sant'Anna (2023) "When Is Parallel Trends Sensitive to Functional Form?," Econometrica, 2023, 91 (2), 737–747.

⋆ Ghanem, Dalia, Pedro H. C. Sant'Anna, and Kaspar Wüthrich, (2025) "Selection and parallel trends," arXiv:2203.09001.

- Rambachan, Ashesh and Jonathan Roth (2024), “Design-Based Uncertainty for Quasi-Experiments,” arXiv:2008.00602
- Hagemann, Andreas (2019), “Placebo inference on treatment effects when the number of clusters is small,” Journal of Econometrics 213 (1), 190-209.
- MacKinnon, James, G. and Matthew D. Webb (2018), “The wild bootstrap for few (treated) clusters,” The Econometrics Journal, 21 (2), 114–135.
- MacKinnon, James, G., Morten Ørregaard Nielsen, and Matthew D. Webb (2023), “Cluster-robust inference: A guide to empirical practice,” Journal of Econometrics, 232 (2), 272-299
- Canay, Ivan A., Andres Santos, and Azeem M. Shaikh (2021), “The wild bootstrap with a small number of large clusters,” Review of Economics and Statistics, 103 (2), 346–363.
- Canay, Ivan A., Joseph P. Romano, and Azeem M. Shaikh (2017) “Randomization Tests Under an Approximate Symmetry Assumption,” Econometrica, 85 (3), 1013–1030.
- Hagemann, Andreas (2025) “Inference with a single treated cluster,” The Review of Economic Studies, Forthcoming
- Hagemann, Andreas (2023), “Permutation inference with a finite number of heterogeneous clusters,” The Review of Economics and Statistics, Forthcoming
- Conley, Timothy G. and Christopher R. Taber (2011) “Inference with “Difference in Differences” with a Small Number of Policy Changes,” Review of Economics and Statistics, 93 (1), 113–125.
- Ferman, Bruno and Cristine Pinto (2019), “Inference in Differences-in-Differences with Few Treated Groups and Heteroskedasticity,” The Review of Economics and Statistics, 101 (3), 452–467.
- Donald, Stephen G. and Kevin Lang (2007), “Inference with Difference-in-Differences and Other Panel Data,” The Review of Economics and Statistics, 89 (2), 221–233.
- Marx, Philip, Elie Tamer, and Xun Tang (2024), “Parallel Trends and Dynamic Choices,” Journal of Political Economy Microeconomics, 2 (1), 129–171.
- Blundell, Richard and Monica Costa Dias (2009), “Alternative approaches to evaluation in empirical microeconomics,” Journal of Human Resources 44(3), 565-640.
- Meyer, Bruce D., W. Kip Viscusi, and David L. Durbin (1995) “Workers’ Compensation and Injury Duration: Evidence from a Natural Experiment,” The American Economic Review, 85 (3), 322–340.
- Kahn-Lang, Ariella and Kevin Lang (2020) “The Promise and Pitfalls of Differences-in-Differences: Reflections on 16 and Pregnant and Other Applications,” Journal of Business& Economic Statistics, 38 (3), 613–620.
- Chabé-Ferret, S. (2015)“Analysis of the bias of matching and difference-in-difference under alternative earnings and selection processes,” Journal of Econometrics, 185(1), 110–123

Week 6: Event-studies and DiD designs with multiple periods

(a) Learning about treatment effect dynamics

(b) Different types of parallel trends

(c) Constructing DiD and ES estimators that respect the identification assumptions

(d) Assessing the plausibility of parallel trends

(e) Sensitivity Analsysis

Readings:

⋆ Section 5.1 of Baker, Andrew, Brantly Callaway, Scott Cunningham, Andrew Goodman-Bacon, and Pedro H. C. Sant'Anna (2025), "Difference-in-Differences Designs: A Practioner's Guide," Working Paper.

⋆ Sections 4.3, 4.4, and 4.5 of 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," Journal of Econometrics, 235 (2), 2218–2244.

⋆ Roth, Jonathan (2022), "Pretest with caution: Event-study estimates after testing for parallel trends," American Economic Review: Insights, 4 (3), 305–322.

⋆ Callaway, Brantly and Pedro H. C. Sant'Anna (2021), "Difference-in-differences with multiple time periods," Journal of econometrics, 225 (2), 200–230.

⋆ Rambachan, Ashesh and Jonathan Roth (2023), "A More Credible Approach to Parallel Trends," Review of Economic Studies, 2023, 90 (5), 2555–2591.

⋆ Chen, Xiaohong, Pedro H. C. Sant'Anna, and Haitian Xie (2025), "Efficient Difference-in-Differences and Event Study Estimators," Working Paper

⋆ Fadlon, Itzik and Torben Heien Nielsen (2021) "Family Labor Supply Responses to Severe Health Shocks: Evidence from Danish Administrative Records," American Economic Journal: Applied Economics, 13 (3), 1–30

⋆ Malani, Anup and Julian Reif (2015), "Interpreting pre-trends as anticipation: Impact on estimated treatment effects from tort reform," Journal of Public Economics, 124, 1–17.

– Wooldridge, Jeffrey (2021), "Two-way fixed effects, the two-way Mundlak regression, and difference-in-differences estimators," Working Paper.

– Autor, David H. (2003), "Outsourcing at Will: The Contribution of Unjust Dismissal Doctrine to the Growth of Employment Outsourcing," Journal of Labor Economics, 21 (1), 1-42

– Borusyak, Kirill, Xavier Jaravel, and Jann Spiess (2024) "Revisiting Event Study Designs: Robust and Efficient Estimation," Review of Economic Studies, 91 (6), 3253–3285.

Week 7: DiD with variation in treatment timing

(a) Causal Parameters

(b) Problems with standard two-way fixed effects specifications

(c) Heterogeneous-robust DiD estimators

(d) Semiparametric Efficiency

Readings:

- ⋆ Sections 5.2 and 5.3 of Baker, Andrew, Brantly Callaway, Scott Cunningham, Andrew Goodman-Bacon, and Pedro H. C. Sant'Anna (2025), "Difference-in-Differences Designs: A Practioner's Guide," Working Paper.
- ⋆ Section 3 of 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," Journal of Econometrics, 235 (2), 2218–2244.
- ⋆ Callaway, Brantly and Pedro H. C. Sant'Anna (2021), "Difference-in-differences with multiple time periods," Journal of econometrics, 225 (2), 200–230.
- ⋆ Wooldridge, Jeffrey (2021), "Two-way fixed effects, the two-way Mundlak regression, and difference-in-differences estimators," Working Paper.
- ⋆ Chen, Xiaohong, Pedro H. C. Sant'Anna, and Haitian Xie (2025), "Efficient Difference-in-Differences and Event Study Estimators," Working Paper
- ⋆ Goodman-Bacon, Andrew (2021) "Difference-in-differences with variation in treatment timing," Journal of Econometrics, 225 (2), 254–277.
- ⋆ Sun, Liyang and Sarah Abraham (2021) "Estimating dynamic treatment effects in event studies with heterogeneous treatment effects," Journal of Econometrics, 225 (2), 175–199.
- ⋆ de Chaisemartin, Clément and Xavier D'Haultfœuille (2020), "Two-Way Fixed Effects Estimators with Heterogeneous Treatment Effects," American Economic Review, 110 (9), 2964–2996
- – Braghieri, Luca, Ro'ee Levy, and Alexey Makarin (2022), "Social Media and Mental Health," American Economic Review, 112 (11), 3660–93.
- – Baker, Andrew C, David F Larcker, and Charles CY Wang (2022), "How much should we trust staggered difference-in-differences estimates?," Journal of Financial Economics, 144 (2), 370–395.
- – Chiu, Albert, Xingchen Lan, Ziyi Liu, and Yiqing Xu (2025) "Causal Panel Analysis Under Parallel Trends: Lessons from a Large Reanalysis Study," American Political Science Review.
- – Marcus, Michelle, and Pedro H. C. Sant'Anna (2021), "The role of parallel trends in event study settings: An application to environmental economics," Journal of the Association of Environmental and Resource Economists 8 (2), 235-275.
- – Garthwaite, Craig, Tal Gross, and Matthew J. Notowidigdo (2014) "Public Health Insurance, Labor Supply, and Employment Lock," Quarterly Journal of Economics, 129(2): 653-696.
- – Strezhnev, Anton (2018) "Semiparametric weighting estimators for multi-period difference-indifferences designs," Working Paper
- – Imai, Kosuke and In Song Kim (2021), "On the Use of Two-way Fixed Effects Regression Models for Causal Inference with Panel Data," Political Analysis, 29 (3), 405–415.
- – Gardner, John (2021), "Two-stage differences in differences," Working Paper.
- – Liu, Licheng, Ye Wang, and Yiqing Xu (2024), "A Practical Guide to Counterfactual Estimators for Causal Inference with Time-Series Cross-Sectional Data," American Journal of Political Science, 68 (1), 160-176

– Callaway, Brantly (2023), “Difference-in-Differences for Policy Evaluation,” in Klaus F. Zimmermann, ed., Handbook of Labor, Human Resources and Population Economics, Cham: Springer International Publishing, pp. 1–61.

– Bailey, Martha J. and Andrew Goodman-Bacon (2015), “The War on Poverty’s Experiment in Public Medicine: Community Health Centers and the Mortality of Older Americans,” American Economic Review, 105 (3), 1067–1104.

Week 8: Triple Differences + DiD with Continuous Treatments

(a) DiD with continuous and multi-valued Treatments

(b) Triple Differences

Readings:

⋆ Callaway, Brantly, Andrew Goodman-Bacon, and Pedro H. C. Sant’Anna (2024) “Difference-in-Differences with a Continuous Treatment,” arXiv:2107.02637.

⋆ Ortiz-Villavicencio, Marcelo and Pedro H. C. Sant’Anna (2025), “Better Understanding Triple Differences Estimators,” Working Paper.

– Olden, Andreas and Jarle Møen (2022) “The triple difference estimator,” The Econometrics Journal, 2022, 25 (3), 531–553.

– Strezhnev, Anton (2023), “Decomposing Triple-Differences Regression under Staggered Adoption,” Working Paper.

– Walker, W. Reed (2013), “The Transitional Costs of Sectoral Reallocation: Evidence From the Clean Air Act and the Workforce,” The Quarterly Journal of Economics, 2013, 128 (4), 1787–1835

– Gruber, Jonathan (1994), “The Incidence of Mandated Maternity Benefits,” The American Economic Review, 1994, 84 (3), 622-641

– Acemoglu, Daron and Amy Finkelstein (2008), “Input and Technology Choices in Regulated Industries: Evidence from the Health Care Sector,” Journal of Political Economy, 2008, 116 (5), 837-880.

Week 9: More Complex DiD Designs

(a) DiD when treatment can turn on and off

(b) Instrumented and Fuzzy DiD

Readings:

⋆ de Chaisemartin, Clément and Xavier D’Haultfœuille (2020), “Two-Way Fixed Effects Estimators with Heterogeneous Treatment Effects,” American Economic Review, 110 (9), 2964–2996

⋆ de Chaisemartin, Clément and Xavier D’Haultfoeuille (2018), “Fuzzy Differences-in-Differences,” The Review of Economic Studies, 85 (2), 999–1028.

⋆ de Chaisemartin, Clément and Xavier D’Haultfœuille (2024), “Difference-in-Differences Estimators of Intertemporal Treatment Effects,” The Review of Economics and Statistics, Forthcoming

⋆ Miyaji, Sho (2024), "Instrumented Difference-in-Differences with Heterogeneous Treatment Effects," arXiv:2405.12083.

Week 10: Introduction to Synthetic Controls

(a) Causal Inference with few units

(b) The classical synthetic control estimator

(c) Variations of the synthetic control estimator

(d) Inference with synthetic controls

Readings:

⋆ Abadie, Alberto (2021), "Using synthetic controls: Feasibility, data requirements, and methodological aspects," Journal of Economic Literature, 59(2), 391-425

– Abadie, Alberto and Javier Gardeazabal (2003), "The Economic Costs of Conflict: A Case Study of the Basque Country." American Economic Review, 93 (1), 113–132.

– Abadie, Alberto, Alexis Diamond, and Jens Hainmueller (2010), "Synthetic Control Methods for Comparative Case Studies: Estimating the Effect of California's Tobacco Control Program," Journal of the American Statistical Association, 105, 493–505.

– Chernozhukov, Victor, Kaspar Wüthrich, and Yinchu Zhu, "An Exact and Robust Conformal Inference Method for Counterfactual and Synthetic Controls," Journal of the American Statistical Association, 2021, 116 (536), 1849–1864.

– Arkhangelsky, Dmitry and Guido Imbens (2024), "Causal models for longitudinal and panel data: a survey," The Econometrics Journal, 27(3), p. C1–C61.

– Ben-Michael, Eli, Avi Feller, and Jesse Rothstein (2021), "The Augmented Synthetic Control Method", Journal of the American Statistical Association, 114, 1789-1803

– Xu, Yiqing (2017) "Generalized Synthetic Control Method: Causal Inference with Interactive Fixed Effects Models," Political Analysis 25.

– Doudchenko, Nikolay and Guido W. Imbens (2017), "Balancing, Regression, Difference-In-Differences and Synthetic Control Methods: A Synthesis," arXiv:1610.07748

– Cattaneo, Matias D., Yingjie Feng, and Rocio Titiunik (2021), "Prediction Intervals for Synthetic Control Methods," Journal of the American Statistical Association, 116, 1865-1880

– Chernozhukov, Victor, Kaspar Wuthrich and Yinchu Zhu (2024), "A t-test for synthetic controls," arXiv:1812.10820

– Gobillon, Laurent and Thierry Magnac (2016), "Regional policy evaluation: Interactive fixed effects and synthetic controls," The Review of Economics and Statistics 98 (3), 535 551.

– Ferman, Bruno and Christine Pinto (2021), "Synthetic Controls with Imperfect pre-Treatment Fit," Quantitative Economics, 12(4):1197-1221.

– Firpo, Sergio and Vitor Possebom (2018), "Synthetic control method: Inference, sensitivity analysis and confidence sets," Journal of Causal Inference, 6(2).

Week 11: Some advances in Synthetic Controls and related methods

(a) Synthetic controls with staggered designs

(b) Matrix Completion

(c) Synthetic Difference-in-Differences

(d) Interactive Fixed effects models

(e) Synthetic Controls and Selection on Unobservables

Readings:

⋆ Ben-Michael, Eli, Avi Feller, and Jesse Rothstein (2023), "Synthetic controls with staggered adoption," Journal of the Royal Statistical Society: Series B, 84 (2), 351–381.

⋆ Athey, Susan, Mohsen Bayati, Nikolay Doudchenko, Guido Imbens, and Khashayar Khosravi (2021), "Matrix Completion Methods for Causal Panel Data Models," Journal of the American Statistical Association, 116(536), 1716–1730.

⋆ Arkhangelsky, Dmitry, Susan Athey, David A. Hirshberg, Guido W. Imbens, and Stefan Wager (2021), "Synthetic Difference-in-Differences," American Economic Review, 111 (12), 4088–4118.

– Gobillon, Laurent and Thierry Magnac (2016), "Regional policy evaluation: Interactive fixed effects and synthetic controls," The Review of Economics and Statistics 98 (3), 535 551.

– Bai, Jushan and Serena Ng (2021), "Matrix completion, counterfactuals, and factor analysis of missing data," Journal of the American Statistical Association, 116, 1746-1763

– Callaway, Brantly and Sonia Karami (2023), "Treatment effects in interactive fixed effects models with a small number of time periods," Journal of Econometrics, 233 (1), 184-208

– Arkhangelsky, Dmitry and David Hirshberg (2023), "Large-sample properties of the synthetic control method under selection on unobservables," arXiv:2311.13575.

– Imbens, Guido and Davide Viviano (2023), "Identification and inference for synthetic controls with confounding," Working Paper

– Abadie, Alberto and Jérémy L'hour (2021), "A penalized synthetic control estimator for disaggregated data," Journal of the American Statistical Association, 116(536):1817–1834.

– Arkhangelsky, Dmitry and Aleksei Samkov (2024), "Sequential synthetic difference in differences," arXiv:2404.00164.

– Wooldridge, Jeffrey M. (2005), "Fixed-effects and related estimators for correlated random-coefficient and treatment-effect panel data models." The Review of Economics and Statistics, 87 (2), 385–390.

– Bai, Jushan (2009), "Panel data models with interactive fixed effects," Econometrica, 77(4), 1229–1279.

– Gunsilius, Florian (2023), "Distributional Synthetic Controls," Econometrica, 91 (3), 1105-1117

– Masini, Ricardo and Marcelo C Medeiros (2021), "Counterfactual analysis with artificial controls: Inference, high dimensions, and nonstationarity," Journal of the American Statistical Association, 116(536):1773–1788.

– Masini, Ricardo and Marcelo C Medeiros (2022), “Counterfactual analysis and inference with nonstationary data,” Journal of Business & Economic Statistics, 40(1):227–239.

Week 12: Other Causal Panel Data Methods

(a) Identification based on Lagged Dependent Variables

(b) Other Fixed Effects estimators

(c) Bridge Functions

(d) Marginal Structural Models

Readings:

⋆ Athey, Susan, and Guido W. Imbens (2006), “Identification and Inference in Nonlinear Difference-inDifferences Models,” Econometrica, 74 (2), 431–497.

⋆ Arkhangelsky, Dmitry and Guido W. Imbens (2022), “Doubly robust identification for causal panel data models,” The Econometrics Journal, 25 (3), 649–674

⋆ Ding, Peng and Fan Li (2019), “A bracketing relationship between difference-in-differences and lagged-dependent-variable adjustment,” Political Analysis, 27(4), 605–615.

⋆ Viviano, Davide. and Jelena Bradic (2024), “Dynamic covariate balancing: estimating treatment effects over time,” arXiv:2103.01280.

– d’Haultfoeuille, Xavier, Stefan Hoderlein, and Yuya Sasaki (2023), “Nonlinear Difference-in-Differences in Repeated Cross Sections with Continuous Treatments,” Journal of Econometrics, 234 (2), 664-690

– d’Haultfoeuille, Xavier, Stefan Hoderlein, and Yuya Sasaki (2024), “Testing and relaxing the exclusion restriction in the control function approach,” Journal of Econometrics, 240 (2).

– Bonhomme, Stéphane and Ulrich Sauder (2011), “Recovering distributions in difference-indifferences models: A comparison of selective and comprehensive schooling,” Review of Economics and Statistics, 93 (2), 479–494.

– Callaway, Brantly, and Tong Li (2019) “Quantile treatment effects in difference in differences models with panel 50data,” Quantitative Economics, 10 (4), 1579–1618.

– Abadie, Alberto, Anish Agarwal, Raaz Dwivedi, and Abhin Shah (2024), “Doubly robust inference in causal latent factor models,” arXiv:2402.11652.

– Arkhangelsky, Dmitry and Guido W Imbens (2024), “Fixed Effects and the Generalized Mundlak Estimator,” The Review of Economic Studies, 91 (5), 2545–2571

– Arkhangelsky, Dmitry, Guido W. Imbens, Lihua Lei, and Xiaoman Luo (2024), “Design-robust two-way-fixed-effects regression for panel data,” Quantitative Economics, 15(4), 999-1034

– Imbens, Guido, Nathan Kallus, and Xiaojie Mao (2021), “Controlling for Unmeasured Confounding in Panel Data Using Minimal Bridge Functions: From Two-Way Fixed Effects to Factor Models,” arXiv:2108.03849

– Blackwell, Matthew and Adam N. Glynn (2018), "How to Make Causal Inferences with Time-Series Cross-Sectional Data under Selection on Observables," The American Political Science Review, Vol. 112, No. 4 (November 2018), pp. 1067-1082

– Blackwell, Matthew (2013), "A Framework for Dynamic Causal Inference in Political Science," American Journal of Political Science, 57: 504-520

– Hahn, Sukjin (2021), "Identification in nonparametric models for dynamic treatment effects," Journal of Econometrics, 225 (2), 132-147.

– Heckman, James J. and Salvador Navarro (2007), " Dynamic discrete choice and dynamic treatment effects," Journal of Econometrics, 136(2):341–396.

– Murphy, Susan A. (2003), "Optimal dynamic treatment regimes," Journal of the Royal Statistical Society Series B: Statistical Methodology, 65(2):331–355.

– Robins, James M., Miguel A. Hernan, and Babette Brumback (2000), "Marginal structural models and causal inference in epidemiology," Epidemiology, 11:550–560.

– Viviano, Davide and Jelena Bradic (2023), "Synthetic learner: model-free inference on treatments over time, Journal of Econometrics, 234(2):691–713.

Week 13: Surrogate Analysis and Related Topics

(a) Surrogate Analysis for estimating long-term effects

(b) Combining experimental and observational data

Readings:

⋆ Athey, Susan, Raj Chetty, Guido W. Imbens and Hyunseung Kang (2024), "The Surrogate Index: Combining Short-Term Proxies to Estimate Long-Term Treatment Effects More Rapidly and Precisely,", The Review of Economic Studies, Forthcoming

⋆ Chen, Jiafeng, and David M Ritzwoller (2023), "Semiparametric estimation of long-term treatment effects," Journal of Econometrics, 237(2).

⋆ Athey, Susan, Raj Chetty, and Guido Imbens (2020), "Combining experimental and observational data to estimate treatment effects on long term outcomes"

– Ghassami, AmirEmad, Alan Yang, David Richardson, Ilya Shpitser, and Eric Tchetgen Tchetgen (2022), "Combining experimental and observational data for identification and estimation of long-term causal effects," arXiv:2201.10743.

– Kallus, Nathan and Xiaojie Mao (2024), "On the role of surrogates in the efficient estimation of treatment effects with limited outcome data," Journal of the Royal Statistical Society Series B: Statistical Methodology, Forthcoming.

– Alonso, Ariel, Geert Molenberghs, Helena Geys, Marc Buyse, and Tony Vangeneugden (2006), "A unifying approach for surrogate marker validation based on Prentice's criteria," Statistics in medicine, 25(2): 205–221

- Chetty, Raj, John N Friedman, Nathaniel Hilger, Emmanuel Saez, Diane Whitmore Schanzenbach, and Danny Yagan (2011), "How does your kindergarten classroom affect your earnings? Evidence from Project STAR," The Quarterly Journal of Economics, 126(4): 1593–1660.
- Hotz, V Joseph, Guido W Imbens, and Julie H Mortimer (2005), "Predicting the efficacy of future training programs using past experiences at other locations," Journal of Econometrics, 125(1): 241–270.
- Gray-Lobe, Guthrie, Parag A Pathak, and Christopher R Walters (2023) "The Long-Term Effects of Universal Preschool in Boston," The Quarterly Journal of Economics, 138 (1), 363–411
- Park, Yechan and Yuya Sasaki (2024)"A Bracketing Relationship for Long-Term Policy Evaluation with Combined Experimental and Observational Data," Working Paper
- Obradović, Filip (2024), "Identification of Long-Term Treatment Effects via Temporal Links, Observational, and Experimental Data," Working Paper
- Park, Yechan and Yuya Sasaki (2024)"The Informativeness of Combined Experimental and Observational Data under Dynamic Selection," Working Paper
- Bugni, Federico, Ivan A. Canat, and Steve McBride (2024), "Decomposition and Interpretation of Treatment Effects in Settings with Delayed Outcomes," Working Paper.

Week 14: Replication Presentations

(a) Student Presentations as part of their learnings