MGMT 737: Applied Empirical Methods

Spring 2026

Instructor:	Paul Goldsmith-Pinkham	**Time:**	TTh, 2:40-4pm
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Course Pages:

1. `https://github.com/paulgp/applied-methods-phd`
2. `https://yale.instructure.com/courses/104052` [Yale students only]

Office Hours: After class, or by appointment.

Course Description: This course is primarily designed for graduate students interested in econometric methods used in empirical research. The goal of this class is to provide an overview of different empirical methods, with an emphasis on practical implementation. I will provide a set of lecture slides. There are additional background papers that are optional, but are important if you want concrete details on the results.

More generally, this is a course where I focus on providing my understanding and intuition of empirical methods, as they are used by practicioners. This means that this is not a course where we will spend a lot of time on the formal details (beyond what is necessary), but instead focus on the intuitive framework that guides these papers. I'll also do my best to communciate how any of these topics fit together.

This is a course very much focused on communication and artisanship. By the end of the term, my hope is for three things:

1. You will have been exposed to a wide range of empirical methods, and have at least a passing familiarity with their pros and cons. Moreover, you will know where to go look if you decide to use these methods.
2. Much of the terminology and jargon that we use in econometric methods will be less intimidating to you. When someone says "I use semiparametric inference," now instead of intimidate you, it will bother you that they are not using clearer language.
3. You will approach research papers with the desire to disentangle the underlying framework and "experiment" that drives their causal inferences.

Assignments: There will be problem sets most weeks. These will involve both theoretical calculations and computer exercises in which you will be asked to analyze data sets.. Solutions will be handed out written in R. Since there will be a fair number of problem sets, and in order to allow me to post the solutions quickly on the webpage for the course, I will not accept late problem sets. If you anticipate difficulty meeting the deadline, you can ask me for the problem set earlier to give you additional time to work on it. Since there are a very large number of students in the class, I will not be providing individual feedback on the problem sets, but I am happy to discuss them in office hours.

In order to access these problem sets, you will need to have a Github account, as I will be using the Github classroom feature to distribute the problem sets. You can work together on the problem sets and discuss them with classmates, but you need to write up the results individually and hand them in separately. Grades will be based on the problem sets, divided evenly over the problem sets.

I expect these assignments to be coded from "scratch." I will specify when canned packages are appropriate. In other words, when the problem is about estimating a regression, and it is not specified otherwise, I am not looking for the results of `lm( y ~ x)`. Rather, I expect you to construct two matrices and calculate the estimates using this. I also expect you to attempt to maintain good coding practices while doing so – this will likely be challenging for those of you who are inexperienced at programming, so please plan according. See the following resources in R for guidance (Many thanks to Max Kasy for organizing these materials):

- Introduction to Base R: https://cran.r-project.org/doc/manuals/r-release/R-intro.pdf
- R for Data Science: https://r4ds.hadley.nz/
- Guidance on Data Visualization: https://socviz.co/

You are also very welcome (and encouraged) to use any and all large language model help when working on the problem sets! However, an important caveat to this is that the purpose of these problem sets is for you to learn – using the tool to finish the task is fine, but not when it replaces any struggle or effort on your part. There will be a particular section on the problem set that is an AI-free-zone, where I will request that you do not use LLMs to give your responses.

Main References: This is a partial list of various interesting and useful books that will be touched during the course.

- Joshua Angrist and Jörn-Steffen Pischke, *Mostly Harmless Econometrics*
- Bruce Hansen, *Econometrics*
- Peter M. Aronow and Benjamin T. Miller, *Foundations of Agnostic Statistics*
- Imbens and Rubin, *Causal Inference for Statistics, Social, and Biomedical Sciences*
- Kieran Healy, *Data Visualization: A Practical Introduction*, https://socviz.co/
- Scott Cunningham, *Causal Inference: The Mixtape*, https://mixtape.scunning.com/

Prerequisites: ECON 550, ECON 551

Course Outline Recommended reading is starred and in bold.

1. Causality, Statistics, and Economics
   (a) Class 1: Potential Outcomes and Directed Acyclic Graphs
   - **"Potential Outcome and Directed Acyclic Graph Approaches to Causality: Relevance for Empirical Practice in Economics", Imbens (2020)****
   - Chapter 7, Aronow and Miller
   - Chapter 1, Imbens and Rubin
   - Chapter 3, Cunningham
   - "Structural vs. Reduced Form" Language, Confusion and Models in Empirical Economics, Haile http://www.econ.yale.edu/~pah29/intro.pdf (or on course website)
   - "Models, Measurement, and the Language of Empirical Economics", Haile https://sites.google.com/view/philhaile/home/teaching
   - "Statistics and Causal Inference", Holland 1986
   - "The Identification Zoo: Meanings of Identification in Econometrics", Lewbel, 2019

   (b) Class 2: Research Design, Randomization, and Model- vs. Design-Based Inference
   - **"The Credibility Revolution in Empirical Economics: How Better Research Design is Taking the Con out of Econometrics", Angrist and Pischke (2010)****
   - Chapter 3+4, Imbens and Rubin
   - "Causality and design-based inference", Bowers, J. & Leavitt, T. (2020)
   - "Instruments, Randomization, and Learning about Development" Deaton (2010)
   - "Better LATE Than Nothing: Some Comments on Deaton (2009) and Heckman and Urzua (2009)" Imbens (2010)

- "Building Bridges between Structural and Program Evaluation Approaches to Evaluating Policy"
- "Let's take the Con out of Econometrics", Leamer (1983)

(c) Class 3: Propensity Scores

- **LaLonde (1986) after Nearly Four Decades: Lessons Learned, Imbens and Xu (2024)****
- "The central role of the propensity score in observational studies for causal effects" Rosenbaum and Rubin (1983)
- "Matching As An Econometric Evaluation Estimator", Heckman, Ichimura, and Todd (1998)
- "Efficient Estimation of Average Treatment Effects Using the Estimated Propensity Score", Hirano, Imbens and Ridder (2003)
- "Propensity Score-Matching Methods for Nonexperimental Causal Studies", Dehijia and Wahba (2002)
- "Does matching overcome LaLonde's critique of nonexperimental estimators?", Smith and Todd (2005)
- "Practical propensity score matching: a reply to Smith and Todd", Dehijia (2005)
- "Nonparametric Estimation of Average Treatment Effects Under Exogeneity: A Review", Imbens (2004)
- "Contamination Bias in Linear Regression," Goldsmith-Pinkham, Hull and Kolesár (2022)

(d) Class 4: Interference, Spillovers and Dynamics

- **"Toward Causal Inference With Interference", Hudgens and Halloran (2008)****
- "Identification of Endogenous Social Effects: The Reflection Problem" Manski (1993)
- "Social Networks and the Identification of Peer Effects" Goldsmith-Pinkham and Imbens (2013)
- "Identification of treatment response with social interactions" Manski (2013)
- "Estimating average causal effects under general interference." Aronow, P. M. & Samii, C. (2017)
- "Exact p-Values for Network Interference", Athey, Eckles and Imbens (2018)
- "Estimating peer effects in networks with peer encouragement designs" Eckles, Kizilcec and Bakshy (2016)
- "Causal Inference under Temporal and Spatial Interference." Wang (2020) https://www.yewang-polisci.com/publications
- "How to Use Natural Experiments to Measure Misallocation" Sraer and Thesmar (2022)

2. Linear Regression

(a) Class 5: Inference

- **"When Should You Adjust Standard Errors for Clustering?" Abadie et al. (2022)****
- "Robust Standard Errors in Small Samples: Some Practical Advice." Imbens and Kolesár (2016)
- "GMM estimation with cross sectional dependence" Conley (1999)
- "The Standard Errors of Persistence" Kelly (2019)
- "Clustering, spatial correlations, and randomization inference." Barrios et al. (2012)
- "Robust Inference with multiway clustering" Cameron et al. (2011)
- "Estimating standard errors in finance panel data sets: Comparing approaches" Petersen (2009)
- "Sampling-based vs. Design-based Uncertainty in Regression Analysis." Abadie et al. (2019)

- "Using Wasserstein Generative Adversarial Networks for the Design of Monte Carlo Simulations" Athey et al.

(b) Class 6: Semiparametrics and Visualization
- **"On Binscatter" Cattaneo et al. (2019)****
- "Validation of Visual Statistical Inference, Applied to Linear Models", Majumder, Hoffman and Cook (2014)
- "Visual Inference and Graphical Representation in Regression Discontinuity Designs," Kortin, Lieberman, Matsudaira, and Shen (2020)
- "Better Data Visualizations: A Guide for Scholars, Researchers, and Wonks" Schwabish (2021)
- "Data Visualization: A Practical Introduction", https://socviz.co/, Healy
- "Contamination Bias in Linear Regression", Goldsmith-Pinkham, Hull and Kolesár (2022)

(c) Class 7: Quantile Regression
- Koenker and Hallock. "Quantile Regression". 2001
- Koenker. "Quantile Regression: 40 Years On". 2017

(d) Class 8: Penalized linear regression
- "Regression shrinkage and selection via the lasso" Tibshiriani (1996)
- "The adaptive lasso and its oracle properties", Zou (2006)
- "Sparse estimators and the oracle property, or the return of Hodges' estimator" Leeb and Potscher (2008)
- "Preconditioning the lasso for sign consistency" Jia and Rohe (2015)
- "Machine learning: an applied econometric approach" Mullainathan and Spiess (2017)
- "Double/debiased/neyman machine learning of treatment effects" Chernozhukov et al. (2017)
- "Double/debiased machine learning for treatment and structural parameters" Chernozhukov et al. (2018)
- "Generic machine learning inference on heterogenous treatment effects in randomized experiments" Chernozhukov et al. (2020)
- "High-Dimensional Methods and Inference on Structural and Treatment Effects", Belloni, Chernozhukov and Hansen (2014)
- "Inference on treatment effects after selection among high-dimensional controls" Belloni, Chernozhukov and Hansen (2014)
- "On model selection consistency of Lasso" Zhao and Yu (2006)
- "Omitted variable bias of Lasso-based inference methods: A finite sample analysis" Wuthrich and Zhu (2020)
- "Taming the factor zoo: A test of new factors" Feng, Giglio, and Xiu (2020)

3. <u>Likelihood Methods</u>

(a) Class 9: Binary Discrete Choice, GLM and Computational Methods
- "Discrete Choice Methods with Simulation" Train (2009) https://eml.berkeley.edu/books/choice2.html
- "Analysis of covariance with qualitative data" Chamberlain (1980)
- "Binary Response Models for Panel Data: Identification and Information" Chamberlain (2010)
- "Count (and count-like) data in finance" Cohn, Liu and Wardlaw (2022)

(b) Class 10: Multiple Discrete Choices

- "Best practices for differentiated products demand estimation with pyblp" Conlon and Gortmaker (2020)
- "Bayesian analysis of random coefficient models using aggregate data" Jiang, Manchanda, and Rossi (2009)
- "Improving the Numerical Performance of Static and Dynamic Aggregate Discrete Choice Random Coefficients Demand Estimation" Dubé, Fox, and Su (2012)
- "A demand system approach to asset pricing" Koijen and Yogo (2019)

(c) Class 11: Duration models

- "Econometric Methods for the Duration of Unemployment", Lancaster (1979)
- "Generalised residuals and heterogeneous duration models: With applications to the Weibull model", Lancaster (1985)
- "Duration Dependence and Labor Market Conditions: Evidence from a Field Experiment", Kroft, Lange and Notowidigdo (2013)
- "Economic duration data and hazard functions", Kiefer (1988)
- "Duration Models: Specification, Identification and Multiple Durations", Van Den Berg (2001)
- "Autoregressive Conditional Duration: A New Model for Irregularly Spaced Transaction Data", Engle and Russell (1998)
- "A nonlinear autoregressive conditional duration model with applications to financial transaction data", Zhang, Russell and Tsay (2001)
- "The Econometrics of Financial Duration Modeling", Cavaliere et al. (2022)

(d) Class 12: Hierarchical modeling + Bayesian Shrinkage

- "The Impacts of Neighborhoods on Intergenerational Mobility II: County-Level Estimates" Chetty and Hendren (2018)
- "Understanding the average impact of microcredit expansions: A bayesian hierarchical analysis of seven randomized experiments" Meager (2019)
- "Investing for the Long Run when Returns Are Predictable." Barberis (2000)
- "Is there a replication crisis in finance?" Jensen, Kelly and Pedersen (2021)
- "SI 2022 Methods Lectures - Empirical Bayes Methods, Theory and Application", Gu and Walters (2022) https://www.nber.org/conferences/si-2022-methods-lectures-empirical-bay

4. Canonical Research Designs

(a) Class 13: Difference-in-differences (Part I): single timing and staggered timing

- "Difference-in-differences with variation in treatment timing", Goodman-Bacon (2018)
- "Two-way fixed effects estimators with heterogeneous treatment effects" de Chaisemartin and d'Haultfoeuille (2020)
- "Design-based analysis in difference-in-differences settings with staggered adoption" Athey and Imbens (2018)
- "Difference-in-differences with multiple time periods", Callaway and Santa'Anna (2020)
- "Pre-event trends in the panel event-study design", Freyaldenhoven et al. (2019)
- "On the Use of Two-Way Fixed Effects Regression Models for Causal Inference with Panel Data", Imai and Kim (2020)
- "Fuzzy differences-in-differences" de Chaisemartin and d'Haultfoeuille (2018)
- "Semiparametric difference-in-differences estimators" Abadie (2005)
- "How Much Should We Trust Staggered Difference-In-Differences Estimates?" Baker, Larcker and Wang (2021)

(b) Class 14: Difference-in-differences (Part II): Event Studies, Synthetic Control + Synthetic DinD

- “Using synthetic controls: Feasibility, data requirements, and methodological aspects” Abadie (2019)
- “Synthetic control methods for comparative case studies: Estimating the effect of California’s tobacco control program” Abadie, Diamond and Hainmueller (2010)
- “Synthetic Difference In Differences”, Arkhangelsky et al. (2019)
- “Abnormal Return Event Studies and Difference-in-Differences”, Goldsmith-Pinkham and Lyu (2023)
- “The econometrics of financial markets” Campbell Lo and Mackinley (2012), Chapter 4

(c) Class 15: Difference-in-differences (Part III): The Checklist and Extensions

- “What’s Trending in Difference-in-Differences? A Synthesis of the Recent Econometrics Literature” Roth, Sant’Anna, Bilinski, and Poe (2022)
- “Efficient Estimation for Staggered Rollout Designs” Roth and Sant’Anna (2022)
- “A More Credible Approach to Parallel Trends” Roth and Rambachan (2022)
- “When Is Parallel Trends Sensitive to Functional Form?” Roth and Sant’Anna (2022)
- “Difference-in-Differences with a Continuous Treatment” Callaway, Goodman-Bacon and Sant’Anna (2021)

(d) Class 16: Instrumental Variables (Part I)

- “Identification and estimation of local average treatment effects” Imbens and Angrist (1994)
- “Identification of causal effects using instrumental variables” Angrist, Imbens and Rubin (1996)
- “Identification of Causal Effects Using Instrumental Variables: Comment”, Heckman (1996)
- “Instrumental Variables: A Study of Implicit Behavioral Assumptions Used in Making Program Evaluations” Heckman (1997)
- “Comment on James J. Heckman,‘Instrumental Variables: A Study of Implicit Behavioral Assumptions Used in Making Program Evaluations”’ Angrist and Imbens (1999)
- “Instrumental variables: response to Angrist and Imbens” Heckman (1999)
- “What Explains the 2007–2009 Drop in Employment?” Mian and Sufi (2014)
- “Broken Instruemnts” Gallen (2022)

(e) Class 17: Instrumental Variables (Part II)

- “On the structure of IV estimands” Andrews (2019)
- “Weak instruments in instrumental variables regression: Theory and practice” Andrews, Stock and Sun (2019)
- “Jackknife instrumental variables estimation” Angrist, Imbens and Krueger (1999)
- “Random effects estimators with many instrumental variables” Chamberlain and Imbens (2004)
- “Tolerating defiance? Local average treatment effects without monotonicity” de Chaisemartin
- “Weak Instruments in Instrumental Variables Regression: Theory and Practice”, Andrews, Stock and Sun (2018)
- “Local instrumental variables and latent variable models for identifying and bounding treatment effects” Heckman and Vytlacil (1999)

(f) Class 18: Instrumental Variables (Part III)

- “On the structure of IV estimands” Andrews (2019)
- “Weak instruments in instrumental variables regression: Theory and practice” Andrews, Stock and Sun (2019)
- “Jackknife instrumental variables estimation” Angrist, Imbens and Krueger (1999)

- "Random effects estimators with many instrumental variables" Chamberlain and Imbens (2004)
- "Tolerating defiance? Local average treatment effects without monotonicity" de Chaisemartin
- "Weak Instruments in Instrumental Variables Regression: Theory and Practice", Andrews, Stock and Sun (2018)
- "Local instrumental variables and latent variable models for identifying and bounding treatment effects" Heckman and Vytlacil (1999)

(g) Class 19: Bartik, Simulated, Recentered, and Granular Instruments

- "Bartik Instruments: What, When, Why and How" Goldsmith-Pinkham, Sorkin and Swift (2020)
- "Quasi-experimental shift-share research designs" Borusyak, Hull and Jaravel (2020)
- "Shift-share designs: Theory and inference" Adao, Kolesar and Morales (2019)
- "Non-random exposure to exogenous shocks: Theory and applications" Borusyak and Hull (2021)
- "Efficient Estimation with Non-Random Exposure to Exogeneous Shocks" Borusyak and Hull (2022)
- "The Estimation of Treatment Effects in Simulated Instrument Designs", Aronow, Goldsmith-Pinkham and Sorkin (mimeo)
- "Granular Instrumental Variables", Gabaix and Koijen (2022)
- "Included and Excluded Instruments in Structural Estimation," Andrews, Barahona, Gentzkow, Rambachan, and Shapiro (2022)

(h) Class 20: Examiners, Leniency, and Hausman Instruments

- "Consumer bankruptcy and financial health" Dobbie, Goldsmith-Pinkham and Yang (2016)
- "How Do Consumers Fare When Dealing with Debt Collectors? Evidence from Out-of-Court Settlements" Cheng, Severino and Townsend (2020)
- "The criminal and labor market impacts of incarceration." Mueller-Smith (2015)
- "Judging Judge Fixed Effects" Frandsen, Lefgren and Leslie (2020)
- "Racial bias in bail decisions" Arnold, Dobbie, and Yang (2018)
- "Family Welfare Cultures", Dahl, Kostol and Mogstad (2014)

(i) Class 21: Regression Discontinuity I: Identification and Groundwork

- "Identification and estimation of treatment effects with a regression-discontinuity design" Hahn, Todd and Van Der Klaauw (2001)
- "A Practical Introduction to Regression Discontinuity Designs: Foundations", Cattaneo, Idrobo and Titiunik, (2020)
- "A Practical Introduction to Regression Discontinuity Designs: Extensions," Cattaneo, Idrobo and Titiunik, (2021)
- "Inference in Regression Discontinuity Designs with a Discrete Running Variable", Kolear and Rothe (2018)
- "Why High-Order Polynomials Should Not Be Used in Regression Discontinuity Designs", Gelman and Imbens (2018)
- "Inference on causal effects in a generalized regression kink design" Card et al. (2015)
- "Robust nonparametric confidence intervals for regression-discontinuity designs" Calanico et al. (2014)
- "Regression discontinuity designs using covariates" Calanico et al (2019)
- "Investment and financing constraints: Evidence from the funding of corporate pension plans" Rauh (2006)

- "Threshold Events and Identification: A Study of Cash Shortfalls" Bakke and WHited (2012)

(j) Class 22: Regression Discontinuity II: The Checklist

(k) Class 23: Regression Discontinuity III: Extensions

- "Approximate Permutation Tests and Induced Order Statistics in the Regression Discontinuity Design", Canay and Kamat (2017)
- "Manipulation of the running variable in the regression discontinuity design: A density test", McCrary (2008)
- "External Validity in Fuzzy Regression Discontinuity Designs", Bertanha and Imbens (2019)
- "Bounds on treatment effects in regression discontinuity designs with a manipulated running variable", Gerard, Rokkanen and Rothe (2020)
- "A Simple Adjustment for Bandwidth Snooping", Armstrong and Kolesar (2018)

5. Machine Learning

(a) Class 24: Supervised Machine Learning I: Prediction

- "Machine Learning Methods Economists Should Know About."Athey S, Imbens G. (2019)
- "Predictably Unequal? The Impact of Machine Learning on Credit Markets" Fuster et al. (2020)
- "Deep Neural Networks for Estimation and Inference" Ferrell, Liang and Misra (2020)

(b) Class 24: (IF TIME PERMITS) Unstructured Data and Unsupervised Machine Learning

- "Text as Data", Kelly, Gentzkow and Taddy (2020)
- "Measuring Technological Innovation Over the Long Run", Kelly et al. (2020)
- "Parsing the content of bank supervsision", Goldsmith-Pinkham, Hirtle and Lucca (2017)
- "Grouped Patterns of Heterogeneity in Panel Data", Bonhomme and Manresa (2015)
- "Computer Vision and Real Estate: Do Looks Matter and Do Incentives Determine Looks", Glaeser, Kincaid, and Naik (2018)
- "Word Power: A New Approach for Content Analysis", Jegadeesh and Wu (2013)
- "Text Selection", Kelly, Manela and Moreira (2020)
- "The Structure of Economic News", Bybee et al. (2020)

(c) Class 25: Supervised Machine Learning II: Heterogeneous Treatment Effects

- "Estimation and Inference of Heterogeneous Treatment Effects using Random Forests" Wager and Athey (2019)
- "Recursive partitioning for heterogeneous causal effects" Athey and Imebns (2016)
- "Using Causal Forests to Predict Treatment Heterogeneity: An Application to Summer Jobs" Davis and Heller (2017)
- "Generic Machine Learning Inference On Heterogenous Treatment Effects In Randomized Experiments, With An Application To Immunization In India" Chernozhukov et al. (2020)

6. Miscellaneous

(a) Class 26: Partial Identification

- "Nonparametric bounds on treatment effects" Manski. (1990)
- "Confidence intervals for partially identified parameters" Imbens and Manski (2004)
- "Inference on regressions with interval data on a regressor or outcome" Manski and Tamer (2002)
- "Estimation and Confidence Regions for Parameter Sets in Econometric Models" Chernozhukov, Hong and Tamer (2007)

- “Training, Wages, and Sample Selection: Estimating Sharp Bounds on Treatment Effects” Lee (2009)
- “Better Lee Bounds” Semenova (2020)
- “Monotone Treatment Response” Manski (1997)
- “Partial Identification in Econometrics”, Tamer (2010)
- “Microeconometrics with Partial Identification”, Molinari (2020)

Grading Policy: Grades will be based on the problem sets, divided evenly over the problem sets. There will be no mid-term or final exam

Class Policy:

- Regular attendance is not required, but is preferred. If you plan to miss more than 3 classes, please consult with me.