First Term, Academic Year 2026–2027

Seminar: Intermediate Quantitative Methods

Department of Political and Social Sciences

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Seminar:	Friday, 15–17, [Seminar Room 2]
Lab:	Monday, 17–19, [Seminar Room 2]
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Compulsory seminar

This seminar must be taken during the first or second year of the program. The seminar is suitable for researchers who have previously taken introductory courses in quantitative methods, know the basics of linear regression, and are sufficiently comfortable coding (e.g., in R, Python, Julia, or Stata) to work with data directly. For those with no or little previous experience with quantitative methods, or who want to brush up their basic skills, we recommend they instead take Introduction to Quantitative Methods, which runs in parallel to this seminar.

Course Description and Objectives

This seminar consolidates and extends knowledge of quantitative methods for the political and social sciences, aiming to make students informed consumers of quantitative research while also giving them some footing to produce it themselves.

We begin with **foundations** (Block 1): what quantitative social scientists are actually doing when they do inference, why the replication crisis happened, and how the same regression means different things depending on whether the goal is description, prediction, or causal inference. We then step back to the **two questions that precede any estimation** (Block 2): what exactly is the quantity we want to estimate (estimands), and do our numbers measure the concepts we care about (measurement)? With those foundations in place, we cover a few **model families** (Block 3): maximum likelihood and binary outcomes, nested and panel data, and machine learning. We close at the '**frontier**' (Block 4): the new data types transforming the field, and generative AI across the research pipeline—including what these tools mean for our role as scientists.

By the end of the course, students will be able to: reason about inference and its pathologies (forking paths, publication bias, validity) and adopt reproducible research practices; state whether a given analysis is description, prediction, or causal inference, and why it matters; define an estimand precisely and use DAGs to distinguish good from bad controls; move defensibly from a concept to a measure, argue about validity, generalizability, and transportability, and fit basic latent variable models; derive and interpret maximum likelihood estimators, binary outcome models, and fixed/random effects specifications; understand the logic of machine learning for prediction and measurement, and its limits for causal claims; know the landscape of modern data types and where to start with each; and use (and critically validate) generative AI throughout the research pipeline.

Format and workflow

Each session combines lecture, discussion of the compulsory readings, and hands-on exercises. Students should come to class with a laptop and the week's readings done. Assignments emphasize

simulation and replication rather than textbook problem sets: participants will regularly be asked to (a) simulate a data-generating process, (b) break an assumption, and (c) observe and explain the consequences.

Software

We will work with R, an IDE of your choice (e.g., Positron or RStudio), and Quarto to implement and practice the techniques covered in class. It is assumed that you have some basic prior knowledge of these tools. If not, we strongly encourage you to familiarize yourself with them before the course starts, so that you can focus on the substance during the seminar.

We suggest the following resources for self-guided learning:

R and Positron/RStudio:

- RStudio Education: Beginners
- A Gentle Introduction to Tidy Statistics in R
- R for Data Science
- Positron: Welcome to Positron

Quarto:

- Quarto: Get Started
- Quarto: Using R

Requirements for credit

- Regular attendance (80%, excluding valid documented absences) and active participation.
- Regular short simulation/analysis assignments throughout the term.
- Final exam.

Core books

There is no single textbook; each session points to specific chapters and articles. The following are the useful references:

- Gelman, Andrew, Jennifer Hill, and Aki Vehtari (2020). *Regression and Other Stories*. Cambridge.
- Huntington-Klein, Nick (2025). *The Effect: An Introduction to Research Design and Causal Inference*, 2nd ed. Chapman & Hall/CRC. [Free online: theeffectbook.net]
- Salganik, Matthew (2018). *Bit by Bit: Social Research in the Digital Age*. Princeton. [Free online: bitbybitbook.com]
- Grimmer, Justin, Margaret Roberts, and Brandon Stewart (2022). *Text as Data: A New Framework for Machine Learning and the Social Sciences*. Princeton.
- Agresti, Alan (2018). *Statistical Methods for the Social Sciences*, 5th ed. Pearson. (Refresher reference.)
- Wooldridge, Jeffrey M. (2019). *Introductory Econometrics: A Modern Approach*, 7th ed. Cengage. (Technical reference.)
- DeVellis, Robert, and Carolyn Thorpe (2021). *Scale Development: Theory and Applications*, 5th ed. Sage. (Measurement reference.)
- Carsey, Thomas, and Jeffrey Harden (2013). *Monte Carlo Simulation and Resampling Methods for Social Science*. Sage. (For those who want more on simulation.)

Block 1 (Weeks 1–2) — Inference, hypothesis testing, and the practice of quantitative research (KM)

Before any model, method, or dataset: what are we doing when we do quantitative social science? This block sets the epistemic foundations of the course—the logic of inference and its well-documented

pathologies, the practices that make research credible and reproducible, and the crucial habit of asking what a given analysis is for.

Week 1 — The logic of statistical inference… and what we are doing when we do it

Compulsory readings:

- McElreath, R. (2023). The Golem of Prague. *Statistical Rethinking 2023*, Lecture 1. [Video: YouTube] (Or Ch. 1 of *Statistical Rethinking*, 2nd ed., 2020.)
- Gigerenzer, G. (2004). Mindless statistics. *Journal of Socio-Economics* 33(5): 587–606.
- Freedman, D. (1991). Statistical models and shoe leather. *Sociological Methodology* 21: 291–313.

Optional readings:

- Gelman, A., & Loken, E. (2014). The statistical crisis in science. *American Scientist* 102(6): 460–465.
- Simmons, J., Nelson, L., & Simonsohn, U. (2011). False-positive psychology. *Psychological Science* 22(11): 1359–1366.
- Breznau, N., et al. (2022). Observing many researchers using the same data and hypothesis reveals a hidden universe of uncertainty. *PNAS* 119(44).
- Colquhoun, D. (2014). An investigation of the false discovery rate and the misinterpretation of p-values. *Royal Society Open Science* 1(3): 140216.
- Carsey & Harden, Ch. 1–4.

Week 2 — Regression anatomy: Description, prediction, or inference?

Compulsory readings:

- Gelman, Hill & Vehtari, *Regression and Other Stories*, Ch. 6–8, 10.
- Munger, K., Guess, A., & Hargittai, E. (2021). Quantitative description of digital media: A modest proposal to disrupt academic publishing. *Journal of Quantitative Description: Digital Media* 1.

Optional readings:

- Brambor, T., Clark, W. R., & Golder, M. (2006). Understanding interaction models: Improving empirical analyses. *Political Analysis* 14(1): 63–82.
- Hainmueller, J., Mummolo, J., & Xu, Y. (2019). How much should we trust estimates from multiplicative interaction models? *Political Analysis* 27(2): 163–192.
- King, G., & Roberts, M. (2015). How robust standard errors expose methodological problems they do not fix. *Political Analysis* 23(2): 159–179.
- Agresti, Ch. 9; Wooldridge, Ch. 2–5, 8; Carsey & Harden, Ch. 5–6.

Block 2 (Weeks 3–5) — Causal thinking and measurement (SRR)

Two questions come before any estimation: what exactly is the quantity we are trying to estimate, and do our numbers actually measure the concepts we care about?

Week 3 — Thinking causally: Estimands, DAGs, and model specification

Compulsory readings:

- Lundberg, I., Johnson, R., & Stewart, B. (2021). What is your estimand? Defining the target quantity connects statistical evidence to theory. *American Sociological Review* 86(3): 532–565.
- Knox, D., Lowe, W., & Mummolo, J. (2020). Administrative records mask racially biased policing. *American Political Science Review* 114(3): 619–637.
- Bronner, L. (2020). Why statistics don't capture the full extent of the systemic bias in policing. *FiveThirtyEight*. [Permalink: perma.cc/U78B-NS9W]

Optional readings:

- Cunningham, S. (2021). *Causal Inference: The Mixtape*, Ch. 3–4.
- Cinelli, C., Forney, A., & Pearl, J. (2024). A crash course in good and bad controls. *Sociological Methods & Research* 53(3): 1071–1104.
- Elwert, F., & Winship, C. (2014). Endogenous selection bias: The problem of conditioning on a collider variable. *Annual Review of Sociology* 40: 31–53.
- Imbens, G. (2020). Potential outcome and directed acyclic graph approaches to causality. *Journal of Economic Literature* 58(4): 1129–1179.

Week 4 — Measurement I: From concepts to numbers

Compulsory readings:

- Adcock, R., & Collier, D. (2001). Measurement validity: A shared standard for qualitative and quantitative research. *American Political Science Review* 95(3): 529–546.
- Flake, J. K., & Fried, E. I. (2020). Measurement schmeasurement: Questionable measurement practices and how to avoid them. *Advances in Methods and Practices in Psychological Science* 3(4): 456–465.
- Loken, E., & Gelman, A. (2017). Measurement error and the replication crisis. *Science* 355(6325): 584–585.

Optional readings:

- Egami, N., & Hartman, E. (2023). Elements of external validity: Framework, design, and analysis. *American Political Science Review* 117(3): 1070–1088.
- Findley, M., Kikuta, K., & Denly, M. (2021). External validity. *Annual Review of Political Science* 24: 365–393.
- Ansolabehere, S., Rodden, J., & Snyder, J. (2008). The strength of issues: Using multiple measures to gauge preference stability, ideological constraint, and issue voting. *American Political Science Review* 102(2): 215–232.
- McNeish, D. (2018). Thanks coefficient alpha, we'll take it from here. *Psychological Methods* 23(3): 412–433.
- Wooldridge, Ch. 9 (errors-in-variables).

Week 5 — Measurement II: Latent variables

Compulsory readings:

- Campos, N., & Federico, C. (2026). A new measure of affective polarization. *American Political Science Review* 120(1): 160–178.
- Claassen, C., et al. (2025). Measuring rural and urban consciousness in Europe. *Electoral Studies* 95: 102912.

Optional readings:

- Claassen, C., et al. (2025). Conceptualizing and measuring support for democracy: A new approach. *Comparative Political Studies* 58(6): 1171–1198.
- Treier, S., & Jackman, S. (2008). Democracy as a latent variable. *American Journal of Political Science* 52(1): 201–217.
- Davidov, E., Meuleman, B., Cieciuch, J., Schmidt, P., & Billiet, J. (2014). Measurement equivalence in cross-national research. *Annual Review of Sociology* 40: 55–75.
- Jackman, S. (2008). Measurement. In *The Oxford Handbook of Political Methodology*. Oxford.
- DeVellis & Thorpe, *Scale Development*, Ch. 1–8.

Block 3 (Weeks 6–8) — Modeling (KM & SRR)

With estimands and measures in hand, we turn to the model families that do most of the work in applied political science and sociology. Each week pairs the mechanics of estimation with the question of interpretation: what does this model let us say, and what does it not?

Week 6 — Maximum likelihood and binary outcomes (SRR)

Compulsory readings:

- Stock, J. H., & Watson, M. W. *Introduction to Econometrics*, Ch. 11 (Regression with a binary dependent variable).
- Mood, C. (2010). Logistic regression: Why we cannot do what we think we can do, and what to do about it. *European Sociological Review* 26(1): 67–82.
- Buis, M. L. (2017). Logistic regression: When can we do what we think we can do? Working paper. [Available online: maartenbuis.nl/wp/odds_ratio_3.1.pdf]

Optional readings:

- Kuha, J., & Mills, C. (2020). On group comparisons with logistic regression models. *Sociological Methods & Research* 49(2): 498–525.
- Breen, R., Karlson, K. B., & Holm, A. (2018). Interpreting and understanding logits, probits, and other nonlinear probability models. *Annual Review of Sociology* 44: 39–54.
- Ward, M., & Ahlquist, J. (2018). *Maximum Likelihood for Social Science*. Cambridge.

Week 7 — Nested data: Fixed effects, random effects, and multilevel basics (KM)

Compulsory readings:

- Bell, A., Fairbrother, M., & Jones, K. (2019). Fixed and random effects models: Making an informed choice. *Quality & Quantity* 53(2): 1051–1074.

Optional readings:

- Snijders, T. A. B., & Bosker, R. J. (2012). *Multilevel Analysis*, 2nd ed. Sage. Ch. 1–5.
- Stegmueller, D. (2013). How many countries for multilevel modeling? *American Journal of Political Science* 57(3): 748–761.
- Schmidt-Catran, A., & Fairbrother, M. (2016). The random effects in multilevel models. *European Sociological Review* 32(1): 23–38.
- Roth, J., Sant'Anna, P., Bilinski, A., & Poe, J. (2023). What's trending in difference-in-differences? *Journal of Econometrics* 235(2): 2218–2244. (Signpost reading.)

Week 8 — Machine learning: Prediction and measurement (SRR)

Compulsory readings:

- Mullainathan, S., & Spiess, J. (2017). Machine learning: An applied econometric approach. *Journal of Economic Perspectives* 31(2): 87–106.
- Grimmer, J., Roberts, M., & Stewart, B. (2021). Machine learning for social science: An agnostic approach. *Annual Review of Political Science* 24: 395–419.

Optional readings:

- Molina, M., & Garip, F. (2019). Machine learning for sociology. *Annual Review of Sociology* 45: 27–45.
- Knox, D., Lucas, C., & Cho, W. K. T. (2022). Testing causal theories with learned proxies. *Annual Review of Political Science* 25: 419–441.

- Fong, C., & Tyler, M. (2021). Machine learning predictions as regression covariates. *Political Analysis* 29(4): 467–484.

Block 4 (Weeks 9–10) — Advanced tools for quantitative and computational analysis (KM & SRR)

Week 9 — Modern data in quantitative social science: Where the frontier is (KM)

Compulsory readings:

- Salganik, *Bit by Bit*, Ch. 2 (Observing behavior).
- Lazer, D., Hargittai, E., Freelon, D., et al. (2021). Meaningful measures of human society in the twenty-first century. *Nature* 595: 189–196.
- Munger, K. (2019). The limited value of non-replicable field experiments in contexts with low temporal validity. *Social Media + Society* 5(3).

Optional readings (a non-exhaustive "start here" shelf, by data type):

- Lazer, D., Kennedy, R., King, G., & Vespignani, A. (2014). The parable of Google Flu: Traps in big data analysis. *Science* 343(6176): 1203–1205. [found data]
- Sen, I., et al. (2021). A total error framework for digital traces of human behavior on online platforms. *Public Opinion Quarterly* 85(S1): 399–422. [found data]
- Grimmer, Roberts & Stewart, *Text as Data*, Ch. 2–4. [text]
- Rodriguez, P., & Spirling, A. (2022). Word embeddings: What works, what doesn't, and how to tell the difference for applied research. *Journal of Politics* 84(1): 101–115. [text]
- Webb Williams, N., Casas, A., & Wilkerson, J. (2020). *Images as Data for Social Science Research.* Cambridge Elements. [images]
- Torres, M., & Cantú, F. (2021). Learning to see: Convolutional neural networks for the analysis of social science data. *Political Analysis* 30(1): 113–131. [images]
- Mestre, R., & Ryan, M. (2026). Potential and pitfalls of audio as data for political research: Alignment, features, and classification models. *Political Analysis* 34(3): 312–328. [audio]
- Knox, D., & Lucas, C. (2021). A dynamic model of speech for the social sciences. *American Political Science Review* 115(2): 649–666. [audio]
- Druckman, J. N., & Green, D. P. (Eds.) (2021). *Advances in Experimental Political Science*, Part I (Experimental designs). Cambridge University Press. [field experiments]
- Schachter, A., & Weisshaar, K. (2025). Survey experiments in sociology. *Annual Review of Sociology* 51: 149–169. [survey experiments]
- Hainmueller, J., Hopkins, D., & Yamamoto, T. (2014). Causal inference in conjoint analysis. *Political Analysis* 22(1): 1–30. [survey experiments]
- Salganik, *Bit by Bit*, Ch. 4 (Running experiments). [digital experiments]

Week 10 — Generative AI in the quantitative research pipeline: Opportunities and risks (KM & SRR)

Compulsory readings:

- Bail, C. (2024). Can Generative AI improve social science? *PNAS* 121(21): e2314021121.
- Messeri, L., & Crockett, M. J. (2024). Artificial intelligence and illusions of understanding in scientific research. *Nature* 627: 49–58.
- Munger, K. (2025). AI as normal science. Substack
- Munger, K. (2026). AI allows more diversity in the forms of social science. Substack

Optional readings:

- Ollion, É., Shen, R., Macanovic, A., & Chatelain, A. (2024). The dangers of using proprietary LLMs for research. *Nature Machine Intelligence* 6: 4–5.
- Ornstein, J., Blasingame, E., & Truscott, J. (2025). How to train your stochastic parrot: Large language models for political texts. *Political Science Research and Methods* 13(2).
- Argyle, L., et al. (2023). Out of one, many: Using language models to simulate human samples. *Political Analysis* 31(3): 337–351.
- Bisbee, James, et al. (2024). Synthetic replacements for human survey data? The perils of large language models. *Political Analysis* 32.4: 401-416
- Törnberg, P. (2024). Best practices for text annotation with large language models. *Sociologica* 18(2).