Introduction to Causal Inference

Michael Kühhirt
michael.kuehhirt@uni-koeln.de

Winter 2017
Monday 2:00pm–5:30pm | 335 (Greinstraße 2) | SocioLab

Office hour (*Please write me an email in advance!*):
Wednesday 2:00pm–3:00pm | 335 (Greinstraße 2) | 0.05

CONTENT AND OBJECTIVES

Do negative campaign ads help politicians win elections? Are there learning benefits to regular course attendance at university? Is maternal employment bad for children's development and, if so, why? If you are interested in answering such or similar questions, you are in the business of causal inference; your aim is to use empirical data to learn about causal relations between specific variables.

This course provides an introduction to the state-of-the-art theory and practice for causal inference. It goes beyond the notion that statistical association doesn't necessarily imply causation and specifies precisely under which conditions we can interpret statistical associations as estimates of causal effects. In addition to conventional regression approaches the course introduces inverse probability weighting as a useful alternative technique for causal inference. The main topics of the course are the construction and application of graphical causal models, the precise definition of causal effects in terms of interventions and counterfactual variables, and the conditions and techniques for estimating total effects, direct and indirect effects (i.e., mediation analysis), and the effects of time-varying variables.

The focus is never on the mathematical derivation of statistical methods, but on an intuition for the conditions under which these methods allow valid causal inference, and for the scenarios under which they break down. Providing step-by-step practical guidance for (1) specifying prior knowledge and assumptions about the variables of interest, for (2) defining the effect to be estimated, for (3) assessing whether this effect can be estimated with given data, and for (4) statistical estimation (in *Stata*) and (5) interpretation of the results, this course will strengthen your ability to evaluate existing research, aid you in the formulation of precise and novel research questions, and provide tools for answering them. To facilitate learning, theoretical lectures are complemented with exercises and practical *Stata* labs.

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GOALS AND LEARNING OUTCOMES

The course has three broad goals, which I enumerate below. Each goal is associated with a number of specific learning outcomes, which you should be able to perform as the course concludes. Students who complete the course should be able to

1. formalize a research question about causal relations using causal graphs and counterfactuals. This includes
   - ⋆ translating theoretical arguments about causal relations into a corresponding graphical model,
   - ⋆ specifying the causal relation of interest and defining this relation in terms of counterfactual contrasts,
   - ⋆ being able to conceptually distinguish this causal relation from statistical association.
2. use graphical models to devise strategies for identifying the causal relation of interest. For this, students
   - ⋆ demonstrate that they are capable to derive empirical implications from a graphical causal model,
   - ⋆ understand the theoretical assumptions necessary to test these implications,
   - ⋆ critically evaluate whether these assumptions hold in applied social research.
3. estimate the causal relation of interest and, if feasible, test underlying assumptions. To do so, students
   - ⋆ adapt existing *Stata* code for their purposes,
   - ⋆ correctly interpret the resulting estimates,
   - ⋆ understand and perform tests of the validity of the analyses.

As a bonus, I hope the course leads you to appreciate the opportunities offered by recent advances in the theory and tools for causal inference. The course, by far, doesn't cover everything there is. But it should provide you with enough understanding to learn more on your own.

REQUIREMENTS AND GRADING

In case of successful course completion you're awarded 9 credit points. Please be aware that course completion requires a substantial time investment outside class.[1] This includes required readings, exercises and practical labs. I highly recommend to regularly get together in small groups to discuss course contents and also to prepare comments and questions to be discussed in class.

Methodological prerequisites for the course include basic familiarity with linear regression, statistical inference (e.g., confidence intervals, standard errors) and concepts like variables, levels of measurement, and distributions. Knowing some *Stata* won't hurt, but isn't necessary. For the course, working with *Stata* mostly consists of adapting existing code files with relevant commands to your purposes.

[1] The official amount of time alloted to the module is 270 SWS which comes down to 13.5 hours per week. Only 3 weekly hours are allocated to class time.

The final grade is based on a 60-minute exam written in the last week of the course. The exam assesses your progress in achieving the learning goals outlined above. It includes tasks that directly test your knowledge of the material and others that test its practical application. You can achieve a maximum of 60 points in the exam. A minimum of 30 points is required for a passing grade. I will distribute a mock exam later in the semester. By completing three *Stata* labs you can earn up to 30 bonus points for the final grade. For each lab, you can earn 10 points maximum. Labs are completed through submission on *Ilias* until a specific deadline. It is allowed (even encouraged!) to work on labs in pairs or small groups. Nonetheless, each of you must submit your own work in the end. Identical submissions are awarded 0 points in each case.

Please note: Always check your submissions carefully with regard to spelling, grammar, and formatting (particularly ensuring that Stata output is readable). Bonus points are only counted until you reach the maximum number of 60 points in combination with the exam.

The final grade is awarded according to the following rules:

1,0: $60 \geq \text{points} \leq 58$
1,3: $58 > \text{points} \leq 55$
1,7: $55 > \text{points} \leq 51$
2,0: $51 > \text{points} \leq 48$
2,3: $48 > \text{points} \leq 45$
2,7: $45 > \text{points} \leq 42$
3,0: $42 > \text{points} \leq 39$
3,3: $39 > \text{points} \leq 36$
3,7: $36 > \text{points} \leq 33$
4,0: $33 > \text{points} \leq 30$
n.p.: $30 > \text{points} \leq 0$

READINGS AND OTHER MATERIALS

The course schedule below specifies required readings and references for further reading for each class. All required readings (and selected further readings) as well as lecture slides, data, code files, etc. are available on the *Ilias* page of this course. You will also use the *Ilias* page to take part in online exercises and upload your completed labs. Moreover, *Ilias* hosts a discussion forum which you should use to post questions of general interest regarding course organization and content and to engage in conversation about the material with me and your classmates. Use email only in case of personal matters, such as illness, appointments for office hours, etc.

The course, for the most part, builds on the following three textbooks, which—in the course schedule—will be abbreviated as PGJ, HR, and VDW, respectively, when excerpts are designated as required readings for class:

Pearl, J., Glymour, M., and Jewell, N. P. (2016). *Causal Inference in Statistics: A Primer*. West Sussex, UK: Wiley = PGJ.

Hernán, M. A. and Robins, J. M. (2018). *Causal Inference (v. 04-10-17)*. Boca Raton, FL: Chapman & Hall/CRC. URL: `http://www.hsph.harvard.edu/miguel-hernan/causal-inference-book/` = HR.

VanderWeele, T. J. (2015). *Explanation in Causal Inference: Methods for Mediation and Interaction*. New York: Oxford University Press = VDW.

Required readings not taken from these books are cited in full in the course schedule.

Apart from the required readings, I also highly recommend you work through the following two articles independently during the semester:

Petersen, M. L. and Laan, M. J. van der (2014). "Causal models and learning from data: Integrating causal modeling and statistical estimation". In: *Epidemiology* 25 (3), pp. 418–426. DOI: 10.1097/EDE.0000000000000078.

Pearl, J. (2009). "Causal inference in statistics: An overview". In: *Statistics Surveys* 3, pp. 96–146. DOI: 10.1214/09-SS057.

There is a number of additional textbooks about causal inference from different branches of social science, which you may use to gain an alternative take on the topic or, perhaps, to later refresh and expand your knowledge on causal inference.

Angrist, J. D. and Pischke, J.-S. (2009). *Mostly Harmless Econometrics: An Empiricist's Companion*. Princeton, NJ: Princeton University Press.

Angrist, J. D. and Pischke, J.-S. (2015). *Mastering 'Metrics. The Path from Cause to Effect*. Princeton, NJ: Princeton University Press.

Hong, G. (2015). *Causality in a Social World: Moderation, Mediation, and Spill-Over*. West Sussex, UK: Wiley-Blackwell.

Imbens, G. W. and Rubin, D. B. (2015). *Causal Inference in Statistics, Social, and Biomedical Sciences: An Introduction*. New York: Cambridge University Press.

Morgan, S. L. (2013). *Handbook of Causal Analysis for Social Research*. Handbooks of Sociology and Social Research. Dordrecht: Springer.

Morgan, S. L. and Winship, C. (2015). *Counterfactuals and Causal Inference: Methods and Principles for Social Research. Second Edition*. New York: Cambridge University Press.

The following list includes some foundational references for the graphical causal models used throughout the course, which are much more technical and complete than the course readings. Of course, this makes them also more demanding.

Glymour, C. (2001). *The Mind's Arrows: Bayes Nets and Graphical Causal Models in Psychology*. Cambridge, MA: MIT Press.

Pearl, J. (2009[2000]). *Causality: Models, Reasoning, and Inference. Second Edition*. New York: Cambridge University Press.

Spirtes, P., Glymour, C., and Scheines, R. (2001[1993]). *Causation, Prediction, and Search. Second Edition*. Cambridge, MA: MIT Press.

There's a score of other books that deal, albeit in some cases only tangentially, with causal inference and that I generally find very useful for empirical social researchers.

Firebaugh, G. (2008). *Seven Rules for Social Research*. Princeton, NJ: Princeton University Press..

King, G., Keone, R., and Verba, S. (1994). *Designing Social Inquiry: Scientific Inference in Qualitative Research*. Princeton, NJ: Princeton University Press.

Manski, C. F. (1995). *Identification Problems in the Social Sciences*. Cambridge, MA: Harvard University Press.

Manski, C. F. (2007). *Identification for Prediction and Decision*. Cambridge, MA: Harvard University Press.

Rosenbaum, P. R. (2010). *Design of Observational Studies*. New York: Springer.

Shadish, W., Cook, T., and Campbell, D. (2002). *Experimental and Quasi-Experimental Designs for Generalized Causal Inference*. Belmont, CA: Wadsworth Cengage Learning.

Shalizi, C. R. (2016). *Advanced Data Analysis from an Elementary Point of View*. New York: Cambridge University Press. URL: http://www.stat.cmu.edu/~cshalizi/ADAfaEPoV/ADAfaEPoV.pdf.

Sloman, S. (2005). *Causal Models: How People Think About the World and its Alternatives*. Oxford, UK: Oxford University Press.

Wooldridge, J. (2010). *Econometric Analysis of Cross Section and Panel Data. Second Edition*. Cambridge, MA: MIT Press.

References for further reading are provided in the course schedule below.

SCHEDULE[2]

9 OCT • INTRODUCTION AND COURSE ORGANIZATION

Further reading

PGJ, Preface, Ch. 1.1.

16 OCT • STATISTICAL PARAMETERS AND THEIR INTERPRETATION

Required reading

PGJ, Ch. 1.1–1.3.10.

23 OCT • GRAPHICAL CAUSAL MODELS

Required reading

PGJ, Ch. 1.4–2.5.

Further reading

Other introductions to causal graphs:

Elwert, F. (2013). "Graphical causal models". In: *Handbook of Causal Analysis for Social Research*. Ed. by Morgan, S. L. New York: Springer, pp. 245–272. DOI: 10.1007/978-94-007-6094-3_13.

Glymour, M. M. and Greenland, S. (2008). "Causal diagrams". In: *Modern Epidemiology. Third Edition*. Ed. by Rothman, K. J., Greenland, S., and Lash, T. L. Philadelphia, PA: Lippincott Williams & Wilkins, pp. 183–209.

On collider variables and endogenous selection bias:

Elwert, F. and Winship, C. (2014). "Endogeneous selection bias: The problem of conditioning on a collider variable". In: *Annual Review of Sociology* 40, pp. 31–53. DOI: 10.1146/annurev-soc-071913-043455.

Hernán, M. A., Hernández-Diaz, S., and Robins, J. M. (2004). "A structural approach to selection bias". In: *Epidemiology* 15 (5), pp. 615–625. DOI: 10.1097/01.ede.0000135174.63482.43.

30 OCT • DEFINITION OF (AVERAGE TOTAL) CAUSAL EFFECTS

Required reading

PGJ, Ch. 3.1, 4.1–4.2.2, 4.3.2.

HR, Ch. 1.1–1.3, 1.5, 4.1, 4.3.

Further reading

Interventions and counterfactuals in causal graphs:

Pearl, J. (1995). "Causal diagrams for empirical research (with discussion)". In: *Biometrika* 82 (4), pp. 669–710.

Shpitser, I. and Pearl, J. (2008). "Complete identification methods for the causal hierarchy". In: *Journal of Machine Learning Research* 9 (9), pp. 1941–1979.

Counterfactuals in the potential outcome framework:

[2] Subject to change.

Holland, P. W. (1986). "Statistics and causal inference". In: *Journal of the American Statistical Association* 81 (396), pp. 945–960.

Neyman, J. (1923). "On the application of probability theory to agricultural experiments. Essay on principles. Section 9". In: *Statistical Science* 5 (4), pp. 465–480.

Rubin, D. B. (1974). "Estimating Causal Effects of Treatments in Randomized and Nonrandomized Studies". In: *Journal of Educational Psychology* 66 (5), pp. 688–701.

Causal effect heterogeneity and effect moderation:

Morgan, S. L. and Winship, C. (2012). "Bringing context and variability back into causal analysis". In: *Oxford Handbook of the Philosophy of the Social Sciences*. Ed. by Kincaid, H. New York: Oxford University Press, pp. 319–354.

Pearl, J. (2015). "Detecting latent heterogeneity". In: *Sociological Methods & Research* Advance Access, August 27, 2015. DOI: 10.1177/0049124115600597.

Shpitser, I. and Pearl, J. (2009). "Effects of treatment on the treated: Identification and generalization". In: *Proceedings of the 25th conference on Uncertainty and Artificial Intelligence*, pp. 514–521. URL: http://dl.acm.org/citation.cfm?id=1795174.

VanderWeele, T. J. and Robins, J. M. (2007). "Four types of effect modification: A classification based on directed acyclic graphs". In: *Epidemiology* 18 (5), pp. 561–568. DOI: 10.1097/EDE.0b013e318127181b.

Xie, Y. (2013). "Population heterogeneity and causal inference". In: *Proceedings of the National Academy of Sciences of the United States of America* 110 (16), pp. 6262–6268. DOI: 10.1073/pnas.1303102110.

6 NOV • IDENTIFICATION OF TOTAL EFFECTS I

Required reading

PGJ, Ch. 3.2 (until p.58).

HR, Ch. 2.1, 7.1, 7.2, 8.1, 8.2, 8.3, 8.4.

13 NOV • IDENTIFICATION OF TOTAL EFFECTS II

Required reading

PGJ, Ch. 3.3.

HR, Ch. 2.2, 2.3, 3.1–3.3, 3.6, 4.2, 4.4–4.6.

Further reading

Entner, D., Hoyer, P. O., and Spirtes, P. (2013). "Data-driven covariate selection for nonparametric estimation of causal effects". In: *Proceedings of the 16th International Conference on Artificial Intelligence and Statistics*, pp. 256–264.

Shpitser, I., VanderWeele, T. J., and Robins, J. M. (2010). "On the validity of covariate adjustment for estimating causal effects". In: *Proceedings of the 26th conference on Uncertainty and Artificial Intelligence*, pp. 527–536.

VanderWeele, T. J. and Shpitser, I. (2011). "A new criterion for confounder selection". In: *Biometrics* 67 (4), pp. 1406–1413. DOI: 10.1111/j.1541-0420.2011.01619.x.

20 NOV • ESTIMATION OF TOTAL EFFECTS I

Required reading

HR, Ch. 10.1, 10.2, 10.5, 11, 15.1.

Further reading

Interpretation and pitfalls of statistical significance:

Freedman, D. A. (1983). "A note on screening regression equations". In: *American Statistician* 37 (2), pp. 152–155.

Krämer, W. (2011). "The cult of statistical significance – What economists should and should not do to make their data talk." In: *Schmollers Jahrbuch* 131, pp. 455–468.

Implicit assumptions of regression methods:

Elwert, F and Winship, C (2010). "Effect heterogeneity and bias in main-effects-only regression models". In: *Heuristics, Probability and Causality: A Tribute to Judea Pearl*. Ed. by Dechter, R., Geffner, H., and Halpern, J. Y. Milton Keynes, UK: College Publications, pp. 327–336.

Morgan, S. L. and Todd, J. J. (2008). "A diagnostic routine for the detection of consequential heterogeneity of causal effects". In: *Sociological Methodology* 38, pp. 231–281.

27 NOV • ESTIMATION OF TOTAL EFFECTS II

Required reading

HR, Ch. 2.4, 12.

4 DEC • DIRECT AND INDIRECT EFFECTS I

Required reading

VDW, Ch. 1.2.1, 1.3.1, 2.16, 2.2–2.3, 2.13–2.15.

Further reading

Imai, K. et al. (2011). "Unpacking the black box of causality: Learning about causal mechanisms from experimental and observational studies". In: *American Political Science Review* 105 (4), pp. 765–789. DOI: 10.1017/S0003055411000414.

Imai, K., Tingley, D., and Yamamoto, T. (2013). "Experimental designs for identifying causal mechanisms (with comments)". In: *Journal of the Royal Statistical Society, Series A (Statistics in Society)* 176 (1), pp. 5–51.

Knight, C. and Winship, C. (2013). "The causal implications of mechanistic thinking: Identification using directed acyclic graphs (DAGs)". In: *Handbook of Causal Analysis for Social Research*. Ed. by Morgan, S. L. Dordrecht u.a.: Springer, pp. 275–299. DOI: 10.1007/978-94-007-6094-3_14.

Pearl, J. (2005). "Direct and indirect effects". In: *Proceedings of the American Statistical Association Joint Statistical Meetings*, pp. 1572–1581.

Robins, J. M. and Greenland, S. (1992). "Identifiability and exchangeability for direct and indirect effects". In: *Epidemiology* 3 (2), pp. 143–155.

Shpitser, I. and VanderWeele, T. J. (2011). "A complete graphical criterion for the adjustment formula in mediation analysis". In: *International Journal of Biostatistics* 7 (1), pp. 1–24. DOI: 10.2202/1557-4679.1297.

11 DEC • DIRECT AND INDIRECT EFFECTS II

Required reading

VDW, Ch. 2.1, 2.6, 2.12.

Further reading

Baron, R. M. and Kenny, D. A. (1986). "The moderator-mediator variable distiction in social psychological research: Conceptual, strategic, and statistical considerations". In: *Journal of Personality and Social Psychology* 51 (6), pp. 1173–1182.

Hicks, R. and Tingley, D. (2011). "Causal mediation analysis". In: *Stata Journal* 11 (4), pp. 605–619.

Imai, K., Keele, L., and Tingley, D. (2010). "A general approach to causal mediation analysis". In: *Psychological Methods* 15 (4), pp. 309–334. DOI: 10.1037/a0020761.

Judd, C. M. and Kenny, D. A. (1981). "Process analysis: Estimating mediation in treatment evaluations". In: *Evaluation Review* 5 (5), pp. 602–619.

Liu, H. and Emsley, R. A. (forthcoming). "PARAMED: Stata module to perform causal mediation analysis using parametric regression models". In: *Stata Journal*. URL: http://econpapers.repec.org/software/bocbocode/s457581.htm.

Valeri, L. and VanderWeele, T. J. (2013). "Mediation analysis allowing for exposure-mediator interactions and causal interpretation: Theoretical assumptions and implementation with SAS and SPSS Macros". In: *Psychological Methods* 18 (2), pp. 137–150. DOI: 10.1037/a0031034.

18 DEC • DIRECT AND INDIRECT EFFECTS III

Required reading

VDW, Ch. 5.3.

Further reading

Acharya, A., Blackwell, M., and Sen, M. (2016). "Explaining causal findings without bias: Detecting and assessing direct effects". In: *American Political Science Review* 110 (3), pp. 512–529. DOI: 10.1017/S0003055416000216.

VanderWeele, T. J. (2009). "Marginal structural models for the estimation of direct and indirect effects". In: *Epidemiology* 20 (1), pp. 18–26. DOI: 10.1097/EDE.0b013e31818f69ce.

8 JAN • CUMULATIVE EFFECTS I

Required reading

HR, Ch. 19.

Further reading

Pearl, J. and Robins, J. M. (1995). "Probabilistic evaluation of sequential plans from causal models with hidden variables". In: *Proceedings of the 11th conference on Uncertainty and Artificial Intelligence*, pp. 444–453.

Robins, J. M. (1999). "Association, causation, and marginal structural models". In: *Synthese* 121 (1-2), pp. 151–179.

Robins, J. M., Hernán, M. A., and Brumback, B. (2000). "Marginal structural models and causal inference in epidemiology". In: *Epidemiology* 11 (5), pp. 550–560.

15 JAN • CUMULATIVE EFFECTS II

Required reading

HR, Ch. 20.

Cole, S. R. and Hernán, M. A. (2008). "Constructing inverse probability weights for marginal structural models". In: *American Journal of Epidemiology* 168 (6), pp. 656–

664. DOI: 10.1093/aje/kwn164.

Further reading

Blackwell, M. (2013). "A framework for dynamic causal inference in political science". In: *American Journal of Political Science* 57 (2), pp. 504–520. DOI: 10.1111/j.1540-5907.2012.00626.x.

22 JAN • CUMULATIVE EFFECTS III

Required reading

Fewell, Z. et al. (2004). "Controlling for time-dependent confounding using marginal structural models". In: *Stata Journal* 4 (4), pp. 402–420.

29 JAN • EXAM