Ludwig Maximilian University of Munich (LMU)
Rethinking Economics Munich (RE:MUC)
Summer term 2020

Causal Inference in Econometrics

Graphical Causal Modeling using Directed Acyclical Graphs

Rethinking Economics Munich (RE:MUC) is a student group at LMU Munich engaged in connecting the disciplines of economics and philosophy of science. As a local group of *Netzwerk Plurale Ökonomik*, we strive for pluralism in economics teaching beyond the regular curriculum.

In the summer term 2020, RE:MUC will be discussing the consequences of the "causal revolution" (Judea Pearl), a.k.a. causal inference with directed acyclical graphs (DAGs), for empirical research in economics. We invite economists of all seniority as well as philosophers of science and everyone interested in causal inference with DAGs from all neighboring disciplines to join us. Munich is the perfect place to explore the links between economics and philosophy of science, given the presence of both the Munich Graduate School of Economics (MGSE) as well as the Munich Center for Mathematical Philosophy (MCMP) right across the road from each other.

Directed acyclical graphs (DAGs), developed in computer science since the 1980s (Pearl, 2000; Spirtes et al., 2000), have so far been employed fruitfully in epidemiology (Hernán/Robins 2019), psychology (Steiner 2013), and political science (Imai/Kim 2019). The central claim of this literature is that causality is more fundamental than probability to science – especially the policy sciences. Probability is still a foundational concept – yet causality comes first.

Thus far, the applications to research in applied econometrics remain limited and only one econometrics textbook explicitly discusses DAGs (Cunningham 2020). This is partly due to econometrics having its own modern (treatment focused) approach to causal inference, the potential outcome framework; recently, several leading econometricians like James Heckman (2013) and Guido Imbens (2019) have expressed serious doubts about the usefulness of causal DAGs for empirical research in econometrics. The lack of relevant empirical applications has been claimed to be the greatest obstacle to DAGs setting off in the econometrics literature.

The reading group will discuss several DAG-related topics relevant to applied econometrics. We will start with the philosophical conception of causality underlying this approach to causal inference (Pearl 2018). We then continue to understand the technical details of the do-calculus and d-separation fundamental to the application of DAGs (Pearl 2000). Following Imbens (2019) we then compare DAGs to the potential outcome approach. It turns out that the well-known identification templates can be reproduced in DAG notation (Steiner 2013). Lastly, we discuss several identification strategies facilitated by DAGs (Bellemare 2019).

We expect participants to read the assigned papers before attending the sessions. We will start discussing *The Book of Why* [TBOW, Pearl 2018] in the first three sessions, so it is highly recommended to read it during the semester break. It is largely non-technical and highly readable also for non-specialists trained in basic statistics. Several copies would have been available at LMU's library.

Time: Wednesdays, 6:15 pm – 7:45 pm (22nd April -15th July 2020)
Location: Cyberspace, meet.lrz.de (please request the exact link by email)
Contact: Patrick N. Klösel, patrick.kloesel [at] posteo [dot] de, Twitter: @patrickkloesel

Tentative Schedule (as of 11th March 2020)

#	Date	Title	Literature	Topics
1	22 April 2020	**Introduction: Causal Inference**	TBOW, Introduction and Ch. 1	Econometrics Causal Inference Ladder of Causation
2	29 April 2020	**Causality in Statistics**	TBOW, Ch. 2-6 (focus: 2+5)	Interventionism, History of Causality in Statistics Famous Paradoxes
3	6 May 2020	**The Causal Revolution**	TBOW, Ch. 7-9 (focus: 7)	Back-Door and Front Door Adjustment Counterfactuals Mediation Analysis
4	13 May 2020	**From Bayesian Nets to DAGs**	Cunningham (2020), pp. 67-80 Neapolitan (2013), Ch. 1	Bayesian Nets d-separation Markov Condition
5	20 May 2020	**The Do-Calculus**	Pearl (2000), Ch. 1 *Input by Naftali Weinberger?*	Do-calculus Collider bias Confounding
6	27 May 2020	**Potential Outcomes (PO)**	Imbens (2019), Sections 1-3 (focus: 3)	Potential Outcome Framework
7	3 June 2020	**PO vs. DAGs**	Imbens (2019), Sections 4-5	PO compared to DAGs
8	10 June 2020	**Quasi-experimental designs**	Steiner et al (2013)	RCTs, Regression Discontinuity Design Instrumental Variables
9	17 June 2020	**Causal Inference and Data-Fusion in Econometrics**	Barenboim/Hünermund (2019), *Input by Paul Hünermund?*	Data Fusion Transportability Selection Bias
10	24 June 2020	**The Front-Door Criterion (FDC)**	TBOW, Ch. 7	Identification Mediation analysis, path diagrams,
11	1 July 2020	**Identification Using the FDC**	Bellemare (2019)	Empirical application
12	8 July 2020	**Single-World Intervention Graphs (SWIGs)**	Robins and Richardson (2013)	Single-World Intervention Graphs Unification
13	15 July	**Final Discussion**	-	-

Literature (+ indicates "good place to start")

+Cunningham, Scott (2020): Causal Inference: The Mixtape. *Available from the authors' website.*

Barenboim, Elias und Paul Hünermund (2019): Causal Inference and Data-Fusion in Econometrics. Working Paper. *Available from the authors' website.*

Bellemare, Marc F. and Bloem, Jeffrey R. (2019): The Paper of How: Estimating Treatment Effects Using the Front-Door Criterion. Working Paper. *Available from the authors' website.*

Cartwright, N. (2007): *Hunting Causes and Using Them*. Approaches in Philosophy and Economics. Cambridge University Press.

Eberhardt, Frederick (2017): Introduction to the foundations of causal discovery. *International Journal of Data Science,* 3/81.

Glynn, A.N. and Kashin, K. (2017): Front-Door Difference-in-Differences Estimators, *American Journal of Political Science*, 61/4, pp. 989-1002.

Glynn, A.N. and Kashin, K. (2018): Front-Door Versus Back-Door Adjustment With Unmeasured Confounding: Bias Formulas for Front-Door and Hybrid Adjustments With Application to a Job Training Program, *Journal of the American Statistical Association*, 113/523, pp. 1040-1049.

Heckman, James J. und Rodrigo Pinto (2013): *Causal Inference after Havelmoo*. NBER Working Paper Series.

+Hernán, Miguel A. und James M. Robins (2019): Causal Inference: What If. *Available from the authors' website.*

Imai, Kosuke und In Song Kim (2019): When Should We Use Unit Fixed Effects Regression Models for Causal Inference with Longitudinal Data? *American Journal of Political Science*, 63/2, pp. 467–490.

Imai, K., Keele, L., Tingley, D., and Yamamoto, T. (2011): Unpacking the black box of causality: Learning about causal mechanisms from experimental and observational studies. *American Political Science Review*, 105/4, pp. 265–289.

Imai, K., Keele, L., and Yamamoto, T. (2010): Identification, Inference and Sensitivity Analysis for Causal Mediation Effects, *Statistical Science*, 25/1, pp. 51-71.

+Imbens, Guido (2019): Potential Outcome and Directed Acyclic Graph Approaches to Causality: Relevance for Empirical Practice in Economics. *Available from the authors' website.*

Morgan, Stephen L. (2013): *Handbook of Causal Analysis for Social Research*. Springer Netherlands.

Neapolitan, Richard E. (2003): *Learning Bayesian Networks*. Pearson, Upper Saddle River.

Koller, Daphne, and Friedman, Nir (2009): *Probabilistic Graphical Models*. Principles and Techniques. The MIT Press.

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

Morgan, S. L., and Winship, C. (2007). *Counterfactuals and causal inference: Methods and principles for social research*. New York: Cambridge University Press.

Pearl, J. (2000). *Causality*: Models, reasoning and inference. Cambridge University Press.

+Pearl, J./Glymour, Madelyn/Jewell, Nicholas P. (2016): *Causal Inference in Statistics*. A Primer. Wiley.

+Pearl, Judea und Dana Mackenzie (2018): *The Book of Why*. The New Science of Cause and Effect. Penguin Books. [TBOW]

Robins, James, and Greenland, Sander (1992). Identifiability and exchangeability for direct and indirect effects. *Epidemiology*, 3/2, pp. 143–155.

Thomas Richardson and James Robins (2013): Single World Intervention Graphs (SWIGs): A Unification of the Counterfactual and Graphical Approaches to Causality, *Working Paper 128, Center for Statistics and the Social Sciences,* University of Washington, 2013.

Thomas Richardson and James Robins (2013): Single World Intervention Graphs (SWIGs). A Primer. *Available from the authors' website*

+Steiner, Peter M./Kim, Yongnam/Hall, Courtney E./Su, Dan (2017): Graphical Models for Quasi-experimental Designs, *Sociological Methods & Research*, 46/2, pp. 155-188.

Spirtes, Peter/Glymour, Clark/Scheines, Richard (2000): *Causation, Prediction, and Search.* MIT Press.

Van der Weele, T. J., and Robins, J.M. (2007). Directed acyclic graphs, sufficient causes, and the properties of conditioning on a common effect. *American Journal of Epidemiology*, 166/9, 1096-1104.

Woodward, James (2003): *Making Things Happen.* A Theory of Causal Explanation. Oxford University Press.

Additional Resources (+ again indicates "good place to start")

There are several online courses and tools available which provide a first introduction to directed acyclical graphs, as well as many people who regularly tweet about DAGs. Also check out Judea Pearl's website: http://bayes.cs.ucla.edu/jp_home.html

Online courses (MOOCs):

+Causal Data Analysis with Directed Acyclical Graphs (Udemy, Hünermund):
Causal Graphs (U Maryland, Steiner): https://education.umd.edu/CAUSAL-2020
Causal Mediation Analysis (VanderWeele): https://www.youtube.com/watch?v=EI5y6pV87-Q
Causal Diagrams: Draw Your Assumptions Before Your Conclusions (EdX HarvardX - PH559x)
A Crash Course in Causality: Inferring Causal Effects from Observational Data (Coursera)
Probability – The Science of Uncertainty and Data (EdX MITx - 6.431x)

Online tools:

DAGitty (software for representing DAGs) http://dagitty.net/
+Fusion (similar to DAGitty, yet more comprehensive) https://causalfusion.net/ (beta version!)

Whom to follow (on Twitter):

+@yudapearl	+@juli_schuess	+@causalinf	@AndersHuitfeldt
@eliasbareinboim	@marcfbellemare	@NoahHaber	+@EpiEllie
+@PHuenermund	@DAGophile	@JohannesTextor	@casualinfer