MICHAEL POLLMANN

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EDUCATION

Ph.D. in Economics, Stanford University,
Expected Completion: June 2022.
M.A. in Economics, Stanford University, 2020.

M.Sc. in Econometrics and Operations Research, Maastricht University, 2015, (*highest honors)*.
Thesis: "Stationarity in Random Coefficient Autoregressive Models: Theory, Estimation, and Testing" *(Best Thesis Award)*.
B.Sc. in Econometrics and Operations Research, Maastricht University, 2014, (*highest honors)*.
Thesis: "Are you sure you are using the correct model? Model Selection and Averaging of Impulse Responses" *(Best Thesis Award)*.

DISSERTATION COMMITTEE

Prof. Guido W. Imbens
Economics Department, Stanford University
imbens@stanford.edu

B. Douglas Bernheim
Economics Department, Stanford University
bernheim@stanford.edu

Prof. Jann Spiess
Graduate School of Business, Stanford University
jspiess@stanford.edu

RESEARCH AND TEACHING FIELDS

Primary fields: Econometrics, Causal Inference, Machine Learning.
Secondary field: Public Economics.

RESEARCH PAPERS

Causal Inference for Spatial Treatments (**Job Market Paper**) [Code]

ABSTRACT: Many events and policies (treatments), such as opening of businesses, building of hospitals, and sources of pollution, occur at specific spatial locations, with researchers interested in their effects on nearby individuals or businesses (outcome units). However, the existing treatment effects literature primarily considers treatments that could experimentally be assigned directly at the level of the outcome units, potentially with spillover effects. I approach the *spatial treatment* setting from a similar

experimental perspective: What ideal experiment would we design to estimate the causal effects of spatial treatments? This perspective motivates a comparison between individuals near realized treatment locations and individuals near counterfactual (unrealized) candidate locations, which is distinct from current empirical practice. I derive standard errors based on this design-based perspective that are straightforward to compute irrespective of spatial correlations in outcomes. Furthermore, I propose machine learning methods to find counterfactual candidate locations and show how to apply the proposed methods on observational data. I study the causal effects of grocery stores on foot traffic to nearby businesses during COVID-19 shelter-in-place policies. I find a substantial positive effect at a very short distance. Correctly accounting for possible effect "interference" between grocery stores located close to one another is of first order importance when calculating standard errors in this application.

Causal Inference from Hypothetical Evaluations,
with B. Douglas Bernheim, Daniel Björkegren, and Jeffrey Naecker
ABSTRACT: This paper develops a method that learns the relationship between hypothetical responses and real choices in observational data, and then uses that estimated relationship to predict the effect of counterfactuals. After developing the econometric theory for the estimator, we demonstrate that it can be applied in settings where standard methods are not applicable. In both a lab and field setting we show it can recover accurate estimates of treatment effects that are close to ground truth experimental estimates.

Semiparametric Estimation of Treatment Effects in Randomized Experiments,
with Susan Athey, Peter J. Bickel, Aiyou Chen, and Guido W. Imbens
ABSTRACT: We develop new semiparametric methods for estimating treatment effects. We focus on a setting where the outcome distributions may be thick-tailed, where treatment effects are small, where sample sizes are large and where assignment is completely random. We propose using parametric models for the treatment effects, as opposed to parametric models for the full outcome distributions. This leads to semiparametric models for the outcome distributions. We derive the semiparametric efficiency bound for this setting, and propose efficient estimators. In the case with a constant treatment effect one of the proposed estimators has an interesting interpretation as a weighted average of quantile treatment effects, with the weights proportional to the second derivative of the log of the density of the potential outcomes.

Price and Income Effects of Hospital Reimbursements,
with Matthias Bäuml and Tilman Dette *(Revision Requested, Journal of Health Economics)*
ABSTRACT: Health insurance systems in many countries reimburse hospitals through fixed prices based on the diagnosis-related groups (DRGs) of patients. We quantify the effects of price and income changes for the full spectrum of hospital services as average and heterogeneous elasticities of quantities (number of admissions) and quality-related outcomes. For our empirical analysis, we use data on over 160 million hospital admissions, constituting the universe of hospital admissions in Germany between 2005 and 2016. Our identification strategy is based on instruments exploiting a two-year lag in regulatory price setting. The strategy lends itself to a placebo test demonstrating that our instruments do not have substantive anticipatory direct effects. We find that the compensated own-price elasticity of quantity is positive, while the income elasticity is negative. On net, increasing all prices leads to a further increase in cost due to a behavioral response of larger quantities.

RESEARCH IN PROGRESS

Estimation of Treatment Effects with Measurement Error in Confounders
Synthetic Controls for Spatial Treatments
Geographic Instruments for Spatial Treatments

PUBLICATIONS

Susan Athey, Guido W. Imbens & Michael Pollmann (2019) Comment on: "The Blessings of Multiple Causes" by Yixin Wang and David M. Blei, Journal of the American Statistical Association, 114:528, 1602-1604, DOI:10.1080/01621459.2019.1691008 *(invited comment)*.

TEACHING EXPERIENCE

2019-21	Teaching Assistant for Prof. Guido W. Imbens, Stanford University, Econ 271 (Intermediate Econometrics II, graduate). *Outstanding Teaching Assistant Award 2019.*
2018-21	Primary Instructor for Econ PhD Math Camp, Stanford University.
2018	Teaching Assistant for Prof. Guido W. Imbens, Stanford University, Econ 272 (Intermediate Econometrics III, graduate). *Outstanding Teaching Assistant Award 2018.*
2018	Teaching Assistant for Prof. Caroline M. Hoxby, Stanford University, Econ 242 (Public Economics II, graduate).

RELEVANT POSITIONS

2016-21	Research Assistant for Prof. Guido W. Imbens, Stanford University.
2017	Research Assistant for Prof. Bradley J. Larsen, Stanford University.
2013	Research Assistant for Prof. Bertrand Candelon, Maastricht University.

SCHOLARSHIPS, HONORS AND AWARDS

2022	7th Lindau Nobel Laureate Meeting on Economic Sciences (postponed from 2020).
2021-22	B.F. Haley and E.S. Shaw Fellowship for Economics, Stanford Institute for Economic Policy Research.
2018, 2019	Outstanding Teaching Assistant Award.
2017	Research grant by The Europe Center at Stanford University, \$3,500.
2015	Student Prize 2015 (Best Thesis Award), Maastricht University.
2014	Student Prize 2014 (Best Thesis Award), Maastricht University.

PROFESSIONAL ACTIVITIES

2020-	Co-Organizer of the Gary Chamberlain Online Seminar in Econometrics.
2022	Presentation, Lightning Round for PhD Students on the 2021-22 Academic Job Market, North American Winter Meeting of the Econometric Society (scheduled).
2021	Presentation, Stanford Causal Science Center, Data Science Institute (scheduled).
2021	Machine Learning in Economics Summer Institute.
2021	Presentation, Econometric Society European Meeting.
2021	Presentation, North American Summer Meeting of the Econometric Society.
2018, 2019	Presentation, Berkeley-Stanford Econometrics Jamboree.