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Undergraduate Studies

A.B. in Economics (w. minor in Statistics and Machine Learning), Princeton University, *summa cum laude*, 2013-2017

Graduate Studies

Harvard University, 2017 to present
Ph.D. Candidate in Economics
Thesis Title: "*Essays on Identification and Causality*"
Expected Completion Date: May 2022

References:

Professor Isaiah Andrews
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Professor Sendhil Mullainathan
University of Chicago, Booth School of Business
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Teaching and Research Fields

Primary fields: Theoretical and Applied Econometrics

Secondary fields: Machine Learning, Public Economics

Teaching Experience

Fall 2019 — *Time Series Analysis,* Harvard University (Graduate)
Teaching Fellow to Professor James H. Stock

Fall 2018 — *Principles of Econometrics*, Harvard University (Graduate)
Teaching Fellow to Professor Elie Tamer

Research Experience

2019 – 2020 — Research Assistant for Professor Isaiah Andrews

Conferences and Invited Presentations

Scheduled — American Economic Association Annual Meeting (discussant and presenter).

2021 Econometric Society – North American Winter Meeting; Brookings Institution's Artificial Intelligence Conference; ACM FAccT 2021 Tutorial on Algorithmic Fairness and Economics; ETH Online Seminar in Economics + Data Science; ZEW Conference on the Economics of Information and Communication Technologies; NBER Summer Institute (Forecasting and Empirical Methods); Southern Economic Association Annual Meeting.

2020 American Economic Association Annual Meeting; Symposium on the Foundations of Responsible Computing; NBER Economics of Artificial Intelligence Conference; Southern Economic Association Annual Meeting (discussant); Carnegie Mellon Fairness, Ethics, Accountability, and Transparency in Machine Learning Reading Group.

2019 NBER-NSF Time Series Conference, CEMMAP Workshop on Causal Learning with Interactions, European Conference of the Econometrics Community (EC)^2.

Professional Service

Referee *Econometrica, Quarterly Journal of Economics, Journal of Applied Econometrics, Journal of Econometrics, The Econometrics Journal, 35th Conference on Neural Information Processing Systems (NeurIPS 2021).*

Program Committee NeurIPS 2021 Workshop on Machine Learning Meets Econometrics (MLECON).

Honors, Scholarships, and Fellowships

2017 – 2020 National Science Foundation Graduate Research Fellowship

Job Market Paper

"Identifying Prediction Mistakes in Observational Data." 2021.

Decision makers, such as doctors, judges, and managers, make consequential choices based on predictions of unknown outcomes. Do these decision makers make systematic prediction mistakes based on the available information? If so, in what ways are their predictions systematically biased? Uncovering systematic prediction mistakes is difficult as the preferences and information sets of decision makers are unknown to researchers. In this paper, I characterize behavioral and econometric assumptions under which systematic prediction mistakes can be identified in empirical settings such as hiring, pretrial release, and medical testing. I derive a statistical test for whether the decision maker makes systematic prediction mistakes under these assumptions and show how supervised machine learning based models can be used to apply this test. I provide methods for conducting inference on the ways in which the decision maker's predictions are systematically biased. As an illustration, I apply this econometric framework to analyze the pretrial release decisions of judges in New York City, and I estimate that at least 20% of judges make systematic prediction mistakes about failure to appear risk given defendant characteristics.

Publications

"Panel Experiments and Dynamic Causal Effects: A Finite Population Perspective" (with Iavor Bojinov and Neil Shephard). 2021. *Quantitative Economics,* 12 (4), Pp. 1171-1196.

In panel experiments, we randomly expose multiple units to different treatments and measure their subsequent outcomes, sequentially repeating the procedure numerous times. Using the potential outcomes framework, we define finite population dynamic causal effects that capture the relative effectiveness of alternative treatment paths. For the leading example, known as the lag-p dynamic causal effects, we provide a nonparametric estimator that is unbiased over the randomization distribution. We then derive the finite population limiting distribution of our estimators as either the sample size or the duration of the experiment increases. Our approach provides a new technique for deriving finite population central limit theorems that exploits the underlying Martingale property of unbiased estimators. We further describe two methods for conducting inference on dynamic causal effects: a conservative test for weak null hypotheses of zero average causal effects using the limiting distribution and an exact randomization-based test for sharp null hypotheses. We also derive the finite population limiting distribution of commonly-used linear fixed effects estimators, showing that these estimators perform poorly in the presence of dynamic causal effects. We conclude with a simulation study and an empirical application where we reanalyze a lab experiment on cooperation.

"Characterizing Fairness over the Set of Good Models under Selective Labels" (with Amanda Coston and Alexandra Chouldechova). 2021. *Proceedings of the 38th International Conference on Machine Learning in Proceedings of Machine Learning Research*, 139, Pp. 2144-2155.

Algorithmic risk assessments are used to inform decisions in a wide variety of high-stakes settings. Often multiple predictive models deliver similar overall performance but differ markedly in their predictions for individual cases, an empirical phenomenon known as the "Rashomon Effect." These models may have different properties over various groups, and therefore have different predictive fairness properties. We develop a framework for characterizing predictive fairness properties over the set of models that deliver similar overall performance, or "the set of good models." Our framework addresses the empirically relevant challenge of selectively labelled data in the setting where the selection decision and outcome are unconfounded given the observed data features. Our framework can be used to 1) replace an existing model with one that has better fairness properties; or 2) audit for predictive bias. We illustrate these uses cases on a real-world credit-scoring task and a recidivism prediction task.

"An Economic Perspective on Algorithmic Fairness" (with Jon Kleinberg, Jens Ludwig and Sendhil Mullainathan). 2020. *AEA Papers and Proceedings,* 110, Pp. 91-95.

There are widespread concerns that the growing use of machine learning algorithms in important decisions may reproduce and reinforce existing discrimination against legally protected groups. Most of the attention to date on issues of "algorithmic bias" or "algorithmic fairness" has come from computer scientists and machine learning researchers. We argue that concerns about algorithmic fairness are at least as much about questions of how discrimination manifests itself in data, decision-making under uncertainty, and optimal regulation. To fully answer these questions, an economic framework is necessary—and as a result, economists have much to contribute.

"Bias In, Bias Out? Evaluating the Folk Wisdom" (with Jonathan Roth). 2020. *1st Symposium on the Foundations of Responsible Computing (FORC 2020),* LIPIcs, 156, 6:1-6:15.

We evaluate the folk wisdom that algorithmic decision rules trained on data produced by biased human decision-makers necessarily reflect this bias. We consider a setting where training labels are only generated if a biased decision-maker takes a particular action, and so "biased" training data arise due to discriminatory selection into the training data. In our baseline model, the more biased the decision-maker is against a group, the more the algorithmic decision rule favors that group. We refer to this phenomenon as bias reversal. We then clarify the conditions that give rise to bias reversal. Whether a prediction algorithm reverses or inherits bias depends critically on how the decision-maker affects the training data as well as the label used in training. We illustrate our main theoretical results in a simulation study applied to the New York City Stop, Question and Frisk dataset.

"Algorithmic Fairness" (with Jon Kleinberg, Jens Ludwig and Sendhil Mullainathan). 2018. *AEA Papers and Proceedings,* 108, Pp. 22-27.

Concerns that algorithms may discriminate against certain groups have led to numerous efforts to 'blind' the algorithm to race. We argue that this intuitive perspective is misleading and may do harm. Our primary result is exceedingly simple, yet often overlooked. A preference for fairness should not change the choice of estimator. Equity preferences can change how the estimated prediction function is used (e.g., different threshold for different groups) but the function itself should not change. We show in an empirical example for college admissions that the inclusion of variables such as race can increase both equity and efficiency.

Working Papers

"An Economic Approach to Regulating Algorithms" (with Jon Kleinberg, Jens Ludwig and Sendhil

Mullainathan). 2021.

There is growing concern about "algorithmic bias" - that predictive algorithms used in decision-making might bake in or exacerbate discrimination in society. We argue that such concerns are naturally addressed using the tools of welfare economics. This approach overturns prevailing wisdom about the remedies for algorithmic bias. First, when a social planner builds the algorithm herself, her equity preference has no effect on the training procedure. So long as the data, however biased, contain signal, they will be used and the learning algorithm will be the same. Equity preferences alone provide no reason to alter how information is extracted from data - only how that information enters decision-making. Second, when private (possibly discriminatory) actors are the ones building algorithms, optimal regulation involves algorithmic disclosure but otherwise no restriction on training procedures. Under such disclosure, the use of algorithms strictly reduces the extent of discrimination relative to a world in which humans make all the decisions.

"An Honest Approach to Parallel Trends" (with Jonathan Roth). 2021.

This paper proposes tools for robust inference for difference-in-differences and event-study designs. Instead of requiring that the parallel trends assumption holds exactly, we impose that pre-treatment violations of parallel trends (pre-trends") are informative about the possible post-treatment violations of parallel trends. Such restrictions allow us to formalize the intuition behind the common practice of testing for pre-existing trends while avoiding issues related to pre-testing. The causal effect of interest is partially identified under such restrictions. We introduce two approaches that guarantee uniformly valid (honest") inference under the imposed restrictions, and we derive novel results showing that they have good power properties in our context. We recommend that researchers conduct sensitivity analyses to show what conclusions can be drawn under various restrictions on the possible differences in trends.

"When Do Common Time Series Estimands have Nonparametric Causal Meaning?" (with Neil Shephard). 2021.

In this paper, we introduce the nonparametric, direct potential outcome system as a foundational framework for analyzing dynamic causal effects of assignments on outcomes in observational time series settings. Using this framework, we provide conditions under which common predictive time series estimands, such as the impulse response function, generalized impulse response function, local projection, and local projection instrument variables, have a nonparametric causal interpretation in terms of such dynamic causal effects.

"Design-Based Uncertainty in Quasi-Experiments" (with Jonathan Roth). 2020.

Social scientists are often interested in estimating causal effects in settings where all units in the population are observed (e.g. all 50 US states). Design-based approaches, which view the realization of treatment assignments as the source of randomness, may be more appealing than standard sampling-based approaches in such contexts. This paper develops a design-based theory of uncertainty suitable for quasi-experimental settings, in which the researcher estimates the treatment effect as if treatment were randomly assigned, but in reality treatment probabilities may depend in unknown ways on the potential outcomes. We first study the properties of the simple difference-in-means (SDIM) estimator. The SDIM is unbiased for a finite-population design-based analog to the average treatment effect on the treated (ATT) if treatment probabilities are uncorrelated with the potential outcomes in a finite population sense. We further derive expressions for the variance of the SDIM estimator and a central limit theorem under sequences of finite populations with growing sample size. We then show how our results can be applied to analyze the distribution and estimand of difference-in-differences (DiD) and two-stage least squares (2SLS) from a design-based perspective when treatment is not completely randomly assigned.