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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
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Teaching and Research Fields

Primary fields: Econometrics

Secondary fields: Public Economics, Labor 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

2021 Econometric Society – North American Winter Meeting; Brookings Institution's Artificial Intelligence Conference; ETH Online Seminar in

Economics + Data Science; ZEW Conference on the Economics of Information and Communication Technologies; NBER Summer Institute (Forecasting and Empirical Methods).

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 Econometrics, 35th Conference on Neural Information Processing Systems (NeurIPS 2021).*

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 judges and doctors, make consequential choices based on predictions of unknown outcomes. Do these decision makers make systematic prediction mistakes based on the available information? In empirical settings, the preferences and information sets of decision makers are unknown to researchers, which makes uncovering systematic prediction mistakes a difficult identification problem. I develop an econometric framework to tackle this challenge and provide conditions under which systematic prediction mistakes can be identified. I show that exclusion restrictions on which observable characteristics of decisions may directly affect the decision maker's preferences and quasi-experimental variation together are sufficient to identify systematic prediction mistakes. Based on these identification results, I develop a tractable test for whether a decision maker makes systematic prediction mistakes that is applicable to empirical settings such as pretrial release, medical testing, and many others. Future drafts will apply the theory to empirically analyze pretrial release decisions in the criminal justice system.

Publications

"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

"Characterizing Fairness over the Set of Good Models under Selective Labels" (with Amanda Coston and Alexandra Chouldechova). 2021. *Accepted for publication, International Conference on Machine Learning (ICML) 2021.*

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.

"Panel Experiments and Dynamic Causal Effects: A Finite Population Perspective" (with Iavor Bojinov and Neil Shephard). 2020. *Accepted for publication, Quantitative Economics.*

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.

"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.

"Econometric Analysis of Potential Outcome Time Series: Instruments, Shocks, Linearity and the Causal Response Function" (with Neil Shephard). 2020.

Bojinov and Shephard (2019) defined potential outcome time series to nonparametrically measure dynamic causal effects in time series experiments. Four innovations are developed in this paper: "instrumental paths," treatments which are "shocks," "linear potential outcomes" and the "causal response function." Potential outcome time series are then used to provide a nonparametric causal interpretation of impulse response functions, generalized impulse response functions, local projections and LP-IV.

"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.