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Education

Ph.D. in Economics, Stanford University — 2026 (Expected)
B.A. in Mathematics (*Honors)*, New York University — 2019
B.S. in Business (*Honors*), NYU Stern — 2019

References

Guido Imbens (Primary)
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Jann Spiess
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Alessandra Voena
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Research Fields

Econometrics, Applied Econometrics, and Labor Economics

Working Papers

Causal Attribution Bounds: Decomposing the Effects of Multiple Causes
Job Market Paper
Abstract: When faced with multiple causes, researchers often ask, "How much did each cause contribute to their combined effect?" For instance, advertisers want to attribute the effect of an ad campaign to each ad, while economists want to *decompose* the effect of a policy bundle. This seemingly simple question hides a fundamental problem: there is no single, agreed-upon estimand, so competing methods naturally yield contradictory results. This paper confronts this challenge by developing a novel framework for causal attribution. I characterize a causal decomposition, establishing that it attributes to each cause its individual effect plus some convex share of its jointly-produced effects (e.g., interaction or indirect effects). The result is not a single causal decomposition, but rather a set, formally capturing the fundamental ambiguity of attribution. While standard practice masks this ambiguity by reporting a single point estimate, I propose embracing it by reporting a new estimand: attribution bounds. These bounds transparently communicate the minimum and maximum attributable to a cause across all causal decompositions, collapsing to a single point when there are no joint effects. To make the bounds practical, I provide design-based and observational methods for identification and estimation. Finally, I demonstrate the bounds utility in two applications: one where wide bounds underscore the limitations of reporting a single point estimate, and another where tight bounds indicate minimal ambiguity.

How Disability Benefits in Early Life Affect Adult Outcomes (with M. Deshpande & A. Voena) *Submitted*
Abstract: We exploit three sources of variation in childhood SSI receipt to examine how receiving Supplemental Security Income (SSI) in childhood influences adult outcomes. Across quasi-experiments, we find that the program has heterogeneous effects that vary with the parental earnings response to SSI benefits: SSI has positive effects on children when parents do not adjust their labor supply in response to SSI income (meaning household income increases), but zero or negative effects on children when parents maintain their earnings or reduce them (meaning household income remains constant or falls). These results suggest that, relative to parent non-work time, consumption is crucial in the human capital production of low-income children with disabilities. We estimate a model of maternal labor supply and child human capital formation to quantify the relative importance of these channels. Our findings indicate that 1) the income effects of SSI on children's human capital are substantial, with a limited role for perverse incentive effects from conditioning benefits on disability status, and 2) parental work on net improves

children's outcomes by increasing household resources, despite the potential decrease in parental time.

Work in Progress

A Prediction Approach to Structural Identification

Abstract: Determining which data identifies a structural model can be cumbersome if not infeasible, leading researchers to rely on heuristic arguments regularly. This paper proposes an intuitive, computational alternative in two steps. First, I embed identification questions within a more general decision problem: What data (e.g., moments) should be collected to inform an economic quantity of interest (e.g., a policy counterfactual)? Second, I translate the decision problem into an algorithmic prediction exercise by showing that the value of a particular type of data corresponds to how well it predicts the quantity of interest. I provide a simulation-based algorithm that uses machine learning to assess the predictive ability of the data and, thus, its value. When using population data, the resulting metric reflects a decision-relevant notion of the size of the identified set; when using sample data, the metric also addresses finite-sample concerns. By conditioning on existing data, our framework also yields a natural analog to local identification measures, and I provide a simple algorithm for efficiently computing it. Leveraging these core algorithms, I show how one can systematically choose which (additional) moments to collect. I illustrate the practical utility of our approach through simulation experiments and an application to the life-cycle savings model in Gourinchas and Parker (2002).

Unbiased Covariate Adjustments in Clustered Experiments (with L. Bottmer, J. Spiess, and D. Watt)

Abstract: Recent work has demonstrated the value of flexibly incorporating covariates when analyzing experiments with many experimental units. It is less clear how, or even if, we should incorporate covariate information in settings with few experimental units, like clustered experiments. For this case, we propose a Leave One (or Two) Cluster Out (LOCO) estimator that leverages the cluster-level randomization to guarantee an unbiased estimate, while simultaneously incorporating individual-level information in a flexible way to reduce variance. While clustered experiments tend to have few experimental units (e.g., villages), we often observe outcome data and covariates for a much larger number of individuals (e.g., people living in those villages). In practice, researchers often choose between leveraging this more granular data in individual-level linear regressions that control for covariates and a simple difference in means that ignores the covariates. While the former reduces variance, it comes at the expense of the latter's unbiasedness guarantee. Our proposed estimator aims to combine the best of both strategies.

Task Allocation and Labor Market Decisions among Couples (with A. Blattner, M. Guido, and S. Subramanyam)

Other

An Undergraduate Course in Causality (with L. Bottmer, G. Imbens, & M. Wootters) *Forthcoming*, Harvard Data Science Review

Abstract: In the Fall quarter of 2024 we (a computer scientist and an economist as the faculty in charge of the course, with two economics graduate students as course assistants) taught an undergraduate course with the title "Causality, Decision Making, and Data Science," cross-listed in the Economics Department, the Data Science Major, the Computer Science Department and the Graduate School of Business undergraduate program. The course was primarily intended for freshmen and sophomores, but because it was the first time we offered it, we also admitted juniors and a few seniors. We restricted enrollment to forty students to make the course interactive. The course was case-based, with minimal statistics requirements. It was successful from our perspective, and student evaluations reflected a similarly positive view. We would like to share here some of what we learned. The materials we put together, including an extensive set of slides, problem sets, and data sets, are available on this website (https://stanford-causal-inference-class.github.io/).

Fellowships & Awards	Stanford Data Science Scholar	2024-2026
	Stanford King Center, GRSF	2024
	George P. Shultz Dissertation Fund at SIEPR	2023
	Sean Buckley Memorial Award - Second Year Paper Prize	2021
	Award for Academic Excellence in Economics, NYU Stern	2019
	Rosenwald Fellow, NYU Stern	2018-2019
Research Experience	Stanford University, Economics Department	
	Research Assistant to Professor Guido Imbens	2021-2025
	Research Assistant to Professor Alessandra Voena	2020-2025
	NYU Stern, Economics Department	
	Research Assistant to Professor Petra Moser	2016-2019
Teaching Experience	Stanford University, Economics Department	
	TA: Causality, Decisions, and Data Science *(Undergrad)*	2024
	TA: Decision Modeling and Information *(Undergrad)*	2022
	NYU Stern, Technology, Operations & Statistics Department	
	TA: Introduction to The Theory of Probability *(Undergrad/MBA)*	2017
Professional Activities	PhD Econometrics Tutor, Stanford Economics Department	2022-2024
	Applied Lunch Seminar Organizer, Stanford Economics Department	2022–2023
	Graduate Recruitment Organizer, Stanford Economics Department	2021
	Graduate Student Assoc. Organizer, Stanford Economics Department	2020–2021
Languages	English (native)	