Zheng (Lucas) Zhang

Bates White Economic Consulting, Washington DC

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Education

Ph.D. in Economics, University of California, Los Angeles — June 2024

- Fields: Econometrics, Applied Microeconomics, Empirical IO
- Advisors: Andres Santos (co-chair), Denis Chetverikov (co-chair), Rosa Matzkin

B.A. in Economics, University of California, Berkeley — May 2017

- Highest Honor in Economics (honor thesis advised by Joseph Farrell)
- Highest Distinction in General Scholarship

Experience

Economist — *Bates White Economic Consulting*, 2024 – Present

- Conducted economic and econometric analyses in support of testifying experts across multiple antitrust matters, including market definition, competitive effects, and damages estimation.
- Supported expert report drafting and exhibit preparation in close coordination with team members and attorneys, addressing case-specific requests.
- Participated in PhD recruiting, including candidate evaluation. Mentored new junior staff as part of the on-boarding and development program.
- Contributed to the development and refinement of internal Python tools to streamline routine documentation workflows, improving efficiency and reducing administrative burden.

Instructor — *University of California, Los Angeles*, 2020 – 2023

- Instructor of undergraduate econometrics courses during summer sessions and regular academic quarter. Topics covered including various regression concepts and basic programming.

Teaching Assistant — *University of California, Los Angeles*, 2018 – 2024

- Teaching assistant of various undergraduate and PhD-level economics and econometrics courses.
- Co-facilitated with the vice chair on the development and training of new TAs as the teaching assistant consultant.

Research

"Continuous Difference-in-Differences with Double/Debiased Machine Learning," *The Econometrics Journal* (accepted). [Link]

Abstract: This paper extends difference-in-differences to settings with continuous treatments. Specifically, the average treatment effect on the treated (ATT) at any level of treatment intensity is identified under a conditional parallel trends assumption. Estimating the ATT in this framework requires first estimating infinite-dimensional nuisance parameters, particularly the conditional density of the continuous treatment, which can introduce substantial bias. To address this challenge, we propose estimators for the causal parameters under the double/debiased machine learning framework and establish their asymptotic normality. Additionally, we provide consistent variance estimators and construct uniform confidence bands based on a multiplier bootstrap procedure. To demonstrate the effectiveness of our approach, we apply our estimators to the 1983 Medicare Prospective Payment System (PPS) reform studied by Acemoglu and Finkelstein (2008), reframing it as a DiD with continuous treatment and nonparametrically estimating its effects.

“Difference-in-Differences with Time-Varying Continuous Treatments Using Double/Debiased Machine Learning,” (joint with Michel F. C. Haddad and Martin Huber). [Link]

Abstract: We propose a difference-in-differences (DiD) method for a time-varying continuous treatment and multiple time periods. Our framework assesses the average treatment effect on the treated (ATET) when comparing two non-zero treatment doses. The identification is based on a conditional parallel trend assumption imposed on the mean potential outcome under the lower dose, given observed covariates and past treatment histories. We employ kernel-based ATET estimators for repeated cross-sections and panel data adopting the double/debiased machine learning framework to control for covariates and past treatment histories in a data-adaptive manner. We also demonstrate the asymptotic normality of our estimation approach under specific regularity conditions. In a simulation study, we find a compelling finite sample performance of undersmoothed versions of our estimators in setups with several thousand observations.

“Data-Driven High-Dimensional Conditional Density Estimation,” (forthcoming).

Abstract: Conditional density enjoys a series representation, with each term being a known function multiplied by its conditional expectation. This structure is especially beneficial in high-dimensional settings, where these conditional expectations can be flexibly estimated using various machine learning methods. However, choosing the right series terms is challenging. We introduce a data-driven estimator using a cross-validation procedure and demonstrate its optimality through an oracle inequality that bounds the estimation error. Beyond our theory-backed estimation strategy, we underscore the extensive role of conditional density in economics, especially as the generalized propensity score in causal inference with continuous treatment.

“Approximate Sparsity Class and Minimax Estimation,” (available upon request).

Abstract: Motivated by the orthogonal series estimation for densities in $L^2([0,1],\mu)$, in this project we consider a new class of functions that we call the approximate sparsity class. This new class is characterized by the rate of decay of the individual Fourier coefficients for a given orthonormal basis. We establish bounds on the $L^2([0,1],\mu)$ metric entropy of such class, with which we establish the minimax rate of convergence. For the density subset in this class, we propose an adaptive density estimator based on hard-thresholding that achieves this minimax rate up to a log term.

Honors and Awards

UCLA

- Proseminar Award, Econometrics, 2022
- Dissertation Year Fellowship, 2022-2023
- Distinguished TA Award, 2018, 2020, 2021, 2022
- Graduate Summer Research Mentorship (GSRM), 2019
- University Fellowship, 2017-2018

UC Berkeley

- Phi Beta Kappa, 2017
- Berkeley Club of Hong Kong Scholarship, 2017
- International Student Tuition Grant, 2017
- URAP Summer Research Award, 2016

Others

Technical: Python, R, MATLAB, Stata, LaTeX

Languages: English, Mandarin Chinese

Work Authorization: STEM OPT