November 2021

Koohyun Kwon

Address: Department of Economics
Yale University
New Haven, CT 06520-8268

Telephone: (+1) 203-500-9607

E-mail: koohyun.kwon@yale.edu

Web page: koohyunkwon.com

Citizenship: South Korea, J-1 Visa (no residence requirement)

Fields of Concentration:
Econometrics

Desired Teaching:
Econometrics
Applied Econometrics
Data Science

Comprehensive Examinations Completed:
2017 (Oral): Econometrics (*with distinction)*, Industrial Organization
2016 (Written): Microeconomics, Macroeconomics

Dissertation Title: *Essays in Inference for Nonparametric Regression Models*

Committee:
Professor Donald Andrews (Chair)
Professor Timothy Armstrong
Professor Yuichi Kitamura

Expected Completion Date: May 2022

Degrees:
Ph.D., Economics, Yale University, 2022 (expected)
M.Phil., Economics, Yale University, 2018
M.A., Economics, Yale University, 2017
B.A., Business Administration (*Summa cum laude*), Seoul National University, 2013

Fellowships, Honors and Awards:
University Dissertation Fellowship, 2020–
University Fellowship, Yale University, 2015–2020
Cowles Foundation Scholarship, 2015–2019

Samsung Scholarship, 2015–2020
Yangyoung Foundation Scholarship, 2013–2015
Social Sciences Korea Research Assistant Scholarship, National Research Foundation of Korea, 2013–2014

Teaching Experience

Yale University:

Summer 2021, Residential College Math/Science Tutor (Economics)
Spring 2019, Teaching Assistant to Prof. Xu Cheng, Econometrics II (Graduate)
Spring 2018, Teaching Assistant to Prof. Timothy Armstrong, Econometrics II (Graduate)

Seoul National University:

Spring 2015, Teaching Assistant to Prof. Sokbae Lee, Advanced Econometrics

Research and Work Experience:

Research Assistant, to Prof. Timothy Armstrong, Yale University, 2018–2019
Research Assistant, to Prof. Donald Andrews, Yale University, 2016–2018

Publications:

"The Identification Power of Smoothness Assumptions in Models with Counterfactual Outcomes" (2018), with Wooyoung Kim, Soonwoo Kwon, and Sokbae Lee, *Quantitative Economics* 9.2, 617–642.

"An Empirical Analysis on the WTO Safeguard Actions" (2018), with Dukgeun Ahn, Jihong Lee, and Jee-Hyeong Park, *Journal of World Trade* 52.3, 415–459.

"Discussion of "Local Quantile Regression" by Spokoiny, Wang, and Härdle" (2013), with Sokbae Lee, *Journal of Statistical Planning and Inference* 143.7, 1136–1138.

Working Papers:

"Bias-Aware Inference for Conditional Average Treatment Effect Functions" (November 2021), *Job Market Paper.*

"Inference in Regression Discontinuity Designs under Monotonicity," with Soonwoo Kwon, (November 2020), *arXiv:2011.14216*.

"Adaptive Inference in Multivariate Nonparametric Regression Models Under Monotonicity," with Soonwoo Kwon, (November 2020), *arXiv:2011.14219.*

Seminar and Conference Presentations:

2014: Econometric Study Group Conference (University of Bristol)

Languages:

English (fluent), Korean (native)

November 2021

References

Prof. Donald Andrews
Yale University
Department of Economics
New Haven, CT 06520
Phone: (+1) 203-432-3698
donald.andrews@yale.edu

Prof. Timothy Armstrong
University of Southern California
Department of Economics
Los Angeles, CA 90089
Phone: (+1) 213-740-3511
timothy.armstrong@usc.edu

Prof. Yuichi Kitamura
Yale University
Department of Economics
New Haven, CT 06520
Phone: (+1) 203-432-3699
yuichi.kitamura@yale.edu

Dissertation Abstract

Bias-Aware Inference for Conditional Average Treatment Effect Functions
[Job Market Paper]

In randomized controlled trials (RCTs), researchers are often interested in analyzing heterogeneous treatment effects with respect to observed covariates. If one is interested in heterogeneity with respect to a continuous covariate, a complete pattern of heterogeneity can be captured by considering the conditional average treatment effect (CATE) function, which characterizes how the average treatment effect changes conditional on different values of the covariate. Continuous covariates are prevalent in empirical research with RCTs, and some of the examples are income, age, pre-treatment outcome, and test score. Given the growing interest in analyzing heterogeneous treatment effects and the prevalence of continuous covariates, it is useful to have a credible and efficient inference method for the CATE function.

For this purpose, I propose a new method to construct a confidence band for the CATE function, a collection of intervals that covers the function-valued parameter with a specified probability. I consider a class of bias-aware confidence bands, taking into account the maximum smoothing bias of a nonparametric estimator given a bound on the derivatives of regression functions. Such a confidence band maintains correct coverage under minimal asymptotic arguments. Then, I investigate how to construct a confidence band with the shortest length under this bias-aware structure. Minimizing the length of a confidence band is practically important since shorter confidence bands provide more information regarding the CATE parameter. Compared to previous methods, my confidence band is the first to solve an explicit length minimization problem while accounting for the maximum smoothing bias.

My main theoretical result is that it is possible to construct a confidence band whose length is asymptotically the shortest at every evaluation point in the domain of the CATE function. In deriving this result, I focus on the class of confidence bands that are based on either local constant or local linear regression estimators. I impose regularity conditions on the bandwidths, which in particular require that the size of the bandwidth used at different evaluation points varies in a smooth way. Then, I derive the form of the bandwidths that yields the asymptotically shortest confidence band in this class. The optimal bandwidths are obtained by solving a two-dimensional minimization problem at each evaluation point, leading to a computationally simple

procedure to construct a confidence band with an optimal length. These results rely on a novel extension of the conventional extreme value theory, which is necessary because different sized bandwidths are used at different evaluation points. By allowing for different sized bandwidths, I fully optimize the local bias-variance tradeoff, thus obtaining a shorter confidence band.

I compare the performance of the bias-aware confidence bands to that of the confidence bands proposed by Cheng and Chen (2019). Their procedure is based on the debiased estimator of Calonico, Cattaneo and Farrell (2018), and was shown to outperform other confidence bands. I consider a simulation design mimicking some features of the randomized controlled trial in Bryan, Choi and Karlan (2021), and find that the bias-aware confidence bands perform well in terms of the coverage and the length over different smoothness bounds on the regression functions. On the other hand, the debiased confidence bands undercover under a large value of the smoothness bound, and alternative choices of bandwidths lead to either poor coverage or a considerably larger length relative to the bias-aware confidence bands. Additional Monte Carlo simulation results also support this finding.

Inference in Regression Discontinuity Designs under Monotonicity, with Soonwoo Kwon

We provide an inference procedure for the sharp regression discontinuity design (RDD) under monotonicity, with possibly multiple running variables. Specifically, we consider the case where the true regression function is monotone with respect to (all or some of) the running variables and assumed to lie in a Lipschitz smoothness class. Such a monotonicity condition is natural in many empirical contexts, and the Lipschitz constant has an intuitive interpretation. We propose a minimax two-sided confidence interval (CI) and an adaptive one-sided CI. For the two-sided CI, the researcher is required to choose the Lipschitz constant for the set of functions that contains the true regression function. This is the only tuning parameter, and the resulting CI has uniform coverage and obtains the minimax optimal length. The one-sided CI can be constructed to maintain coverage over all monotone functions, providing maximum credibility in terms of the choice of the Lipschitz constant. Moreover, the monotonicity makes it possible for the (excess) length of the CI to adapt to the true Lipschitz constant of the unknown regression function. Overall, the proposed procedures make it easy to see under what conditions on the underlying regression function the given estimates are significant, which can add more transparency to research using RDD methods.

Adaptive Inference in Multivariate Nonparametric Regression Models Under Monotonicity, with Soonwoo Kwon

We consider the problem of adaptive inference on a regression function at a point under a multivariate nonparametric regression setting. The regression function belongs to a Hölder class and is assumed to be monotone with respect to some or all of the arguments. We derive the minimax rate of convergence for confidence intervals (CIs) that adapt to the underlying smoothness, and provide an adaptive inference procedure that obtains this minimax rate. The procedure differs from that of Cai and Low (2004), and our procedure is designed to yield shorter CIs under more practically relevant specifications. The proposed method applies to general linear functionals of the regression function, and is shown to have favorable performance compared to existing inference procedures.