NENG-CHIEH CHANG

Email: nengchiehchang@g.ucla.edu ⋄ Mobile: +1-612-961-6364
Website: https://nengchiehchang.wixsite.com/mysite

EDUCATION

Ph.D. Economics, UCLA Expected Completion Date: June 2021

M.A. Economics, UCLA March 2017

B.S. Physics, National Taiwan University June 2014

REFERENCES

Professor Denis Chetverikov (Chair) chetverikov@econ.ucla.edu
Professor Rosa Matzkin matzkin@econ.ucla.edu
Professor Andres Santos andres@econ.ucla.edu

RESEARCH FIELDS

Primary fields: Econometrics, Causal Inference, Machine Learning
Secondary fields: Applied Microeconomics, Industrial Organization, International Trade and Tariff Liberalization, Labor Economics

RESEARCH PAPERS

Double/Debiased Machine Learning for Difference-in-Differences Models (Job Market Paper, accepted by *Econometrics Journal*)

This paper provides an orthogonal extension of the semiparametric difference-in-differences estimator proposed in Abadie (2005). The proposed estimator enjoys the Neyman-orthogonality (Chernozhukov et al. 2018) and thus it allows researchers to flexibly use a rich set of machine learning (ML) methods in the first-step estimation. It is particularly useful when researchers confront a high- dimensional data set when the number of potential control variables is larger than the sample size and the conventional nonparametric estimation methods, such as kernel and sieve estimators, do not apply. I apply this orthogonal difference-in-differences estimator to evaluate the effect of tariff reduction on corruption. The empirical results show that tariff reduction decreases corruption in large magnitude.

Quantile Treatment Effect Estimation with High-dimensional Data (with Liqiang Shi)

This paper provides a doubly robust extension of the semiparametric quantile treatment effect estimation discussed in Firpo (2007). This proposed estimator allows researchers to use a rich set of machine learning methods in the first-step estimation, while still obtaining valid inferences. Researchers can include as many control variables as they would consider necessary, without worrying about the over-fitting problem that frequently happens in the traditional estimation methods. This flexibility makes it much easier to achieve the conditional independence assumption in the treatment effect literature. We apply the proposed estimator to study the quantile treatment effect of the job training program discussed in LaLonde (1986). We find that our estimates are closer to the results of the randomized control trial than Firpo's estimates.

Mode Treatment Effect

Mean, median, and mode are three main measures of the centrality of probability distributions. In the treatment effect literature, the statistical properties of the average treatment effect (mean) and the quantile treatment effect (median) have been thoroughly studied in the past decades. The mode, however, has long been ignored in this literature. This paper fills the gap by proposing both kernel and machine learning methods to estimate the mode treatment effect. I derive the asymptotic properties of the proposed estimators and find that the estimators are asymptotically normal but with the rate of convergence slower than the traditional $\sqrt{N}$.

PROFESSIONAL EXPERIENCE

Research Assistant for Prof. Andres Santos on the paper:

"The econometrics of shape restrictions" (with Denis Chetverikov and Azeem M. Shaikh). 2018

TEACHING EXPERIENCE

Teaching Assistant

Introductory Microeconomics (Econ 1)	Winter 2017, Spring 2017
Microeconomics Theory I (Econ 11)	Fall 2016, Winter 2018
Microeconomics Theory II (Econ 101)	Spring 2018, Fall 2018
Introduction to Econometrics (Econ 103)	Summer 2018, Winter 2019, Spring 2019, Fall 2019

AWARDS AND HONORS

Teaching Assistant Fellowship 2016-

SKILLS

Programming: R, Python, SQL, Matlab, Stata
Language: English (fluent), Mandarin (native), Taiwanese (native)