THE UNIVERSITY OF GEORGIA
DEPARTMENT OF STATISTICS

Colloquium Series

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3:30pm in room 204, Caldwell Hall

Regularization Adjusted Local Average Treatment Estimation for Regression Discontinuity Designs

The regression discontinuity design is one of the most popular and credible methods available for causal inference with observational data.

Estimation of local average treatment effects in RDDs are typically based on local linear regressions using the outcome variable, a treatment assignment variable, and a continuous running variable. In political science research, treatment effects using RDDs are often estimated with a small number of observations and when the correct functional form of local regressions are unknown. Covariates are typically added to increase the efficiency of treatment effect estimates or to adjust for known imbalances, but model selection can lead to instability in treatment effect estimates when few observations are available for estimation. In this paper, I propose regularization adjusted local average treatment effect estimation (RALATE), a machine learning approach to treatment effect estimation for regression discontinuity designs for circumstances in which covariates are included in treatment effect estimation. Simulation studies demonstrate that treatment effect point estimates and intervals produced by this approach outperform robust estimation alone, particularly when treatment effect estimation is conducted with few observations. An illustrative example demonstrating how this method can be incorporated into treatment effect estimation for regression discontinuity designs is then conducted through estimation of the gender penalty in congressional elections using House primary vote share. A *R* Package will be available for implementing the RALATE method.