Fixed Effects Quantile Regression via Deconvolutional Differencing in Short Panels

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Abstract :
This paper provides sufficient conditions for the point identification of a quantile regression model with fixed effects. Instead of typical high-level conditions for nonlinear measurement error models, or covariates with dense or large support, I consider a low-level shape restriction: conditional symmetry. Conditional symmetry is testable and allows for fixed effects with unrestricted distribution. I show how "deconvolutional differencing'' can be applied when only two periods are available. In the first step, time-differenced outcomes of the population of *stayers* (whose covariates values do not change across periods) identify all quantile effects up to a location shifter. In the second step, an OLS regression in the population of *movers* (whose covariates values change across periods) identifies the location shifter. A lagged outcome can be included on the right-hand side if four periods are available. Under standard conditions, computationally simple plug-in estimators are sup-norm consistent and conjectured to be pointwise asymptotically normal as n diverges while T is fixed. Monte Carlo simulations suggest reasonable finite-sample performance. I apply the new method to measure the effect of smoking during pregnancy on birth weight.