Penalized LIML

Zhentao Shi

June 11, 2015

I am interested to explore uncharted water with you. If you choose this project, you will be working on a new estimator that no one has ever experimented with. Though I have some conjectures about the theoretical results, they must be verified by simulations. If the outcomes turn out as expected, we have the potential to push this programming project into a paper.

1 Motivation

In a linear IV model, it is well known among econometricians that 2SLS exhibits large finite-sample bias when the number of IVs is non-trivial relative to the sample size. This problem becomes even worse in GMM-Lasso, as Shi (2015)'s simulations show.

Another well-known fact about the linear IV model is that the limited information maximum likelihood (LIML) enjoys small bias but suffers from enormous variance, because LIML's moments do not exist for any finite sample size (Phillips, 1983, 1984).

I am interested to check the finite sample performance of an l_1-penalized LIML. This will be a new estimator never seen in the literature.

2 Computing LIML

Hayashi (2000, pp. 538-541) covers LIML. Though we can obtain the standard LIML in closed-form (Hayashi 2000, p. 541, Eq. 8.6.9), we have to go back to the likelihood function (Hayashi 2000, p. 539, Eq. 8.6.6) to construct the l_1-penalized LIML. Fortunately the optimization problem is straightforward.

3 Tasks

Below is a brief summary of the tasks. I will meet you in person for more detailed instructions.

1. Simulate artificial data as in Shi (2015, p. 12)'s Experiment 1. I will provide the R code for this.

2. Estimate the parameter by standard LIML. I will provide the R code for this.

3. Estimate the parameter by the l_1-penalized LIML. You will write an R function for this.

4. Calculate the empirical bias and variance of the standard LIML and the l_1-penalized LIML in simulations.