Assignment

August 4, 2016

1. Bootstrap method is commonly used by applied economists. Use the panel data provided, do the following estimations. Note a constant is included in all x

   (a) Load data1a_1b, estimate $y_{i1} = \beta x_{i1} + \varepsilon_{i1}$

   (b) $y_{it} = \beta x_{it} + \lambda_i + \varepsilon_{it}$ (you can use difference in means method or treat λ_i as a separate control)

   (c) Load data1c. Let's restrict to y_{i1} and x_{i1} only, so we can treat them as y_i and x_i. Think of y_i as income of people. Suppose y_i is only observed if the person is employed ($e_i = 1$). Assume $e_i = \gamma_0 + \gamma z_i + \xi_i > 0$, where $\xi_i \sim N(0,1)$. And also assume $\xi_i = \varepsilon_i$. If $y_i = \beta x_i + \varepsilon_i$, use Heckit method to make inference of β.

      i. use b = glmfit(z,e,'binomial','link','probit','constant','off') for probit estimation of e on z.

      ii. use glmval(b,z_x,'probit','constant','off') for fitting value from probit estimation.

      iii. Make sure when you do resampling, you are resampling on the person level (i.e. y, e, x, and z should remain the same for each individual)

      iv. z corresponds to the whole sample, z_x corresponds to the subsample for which we have observations on y, z_nx corresponds to the subsample for which we do not have observations on y.

(d) Load data1d. Again consider y_i and x_i only, and $y_i = \beta x_i + \varepsilon_i$, if x_i is correlated to ε_i, and w_i is the instrument, use IV method to make inference of β.

2. Create your own function that generate LaTeX table. It should be able to have the same basic functionality as commands commonly used in STATA, and should be as autonomous as possible. Test it on question 1.

   (a) It should be able to allow users to add texts before and after the table. And the main script should include this text.

   (b) Significance level: *10%, ** 5%, *** 1%

   (c) Note that some special characteristics (e.g. /) needs / in front to be recognized as special characteristics (e.g. //).

3. There is one type of camera sold in a market over time. Time is discrete with infinite horizon, $t = 0, 1, 2, ...$ In each period, m cameras are supplied to the market. The market participants consist of two types: the incumbents who stay on after losing in previous auctions with probability ρ, and n entrants who newly enter the market. Incumbent buyers and new entrants has equal chance to be assigned to one of the m auctions, so there is a chance that some of the auctions are empty. Bidders do not know which auction they are in and how many people are bidding against them. But they do know the distribution of bidder's types which follows a normal distribution with mean μ and standard error σ. If no bidders enters a particular auction, the auction is canceled. Alternatively, if only one bidder is in an auction, the auction is canceled as well (you can treat the bidder as losing in the auction). After the auction, the winners exit with certainty, and the losers stay with probability ρ.

   (a) Suppose $m = 10$, $\rho = 0.8$, $n = 15$, bidder's valuation follows normal distribution with $\mu = 200$ and $\sigma = 10$. Model this virtual auction economy, and plot the equilibrium bidding strategy

      i. The overall structure is the following:

         A. Assume each individual bids his valuation (standard second price auction)

B. Simulate Economy and collect bidding information

C. Update optimal bidding information for each bidder

D. Repeat Step B and C until bidding strategy converge

ii. Use linspace(mu-5*sigma,mu+5*sigma,1000) to generate 1000 equally spaced grid points of bidder valuations for bids comparison in i.D

iii. When you update optimal bidding information, instead of finding optimal bidding strategy for each individual, you should use contraction mapping to find optimal strategy. Note that $b = v - v_c$, that is, optimal bid is equal to valuation minus continuation value in a second price type auction. For any v, start with a given b, you should be able to calculate v_c through state value, then you can update b.

iv. For contraction mapping within each iteration, use maximal distance as the measure. For contraction mapping in step i.D, use average distance as the measure

(b) Now, suppose you as the camera producer, is interested in the distribution of bidder's valuation, and would like to estimate μ and σ. Using method of moments to make point estimate of parameters mentioned in the question.

i. The moments you can use are average of winning bids and second bids, standard deviation of wining and second bids. Assume identity weight matrix

ii. You should use 10000 period with 500 burn-in period for this question

iii. A simple way of estimation is to simulate an economy with $\hat{\mu} = \text{avg(winning bid)}$ and $\hat{\sigma} = \text{std(winning bid)}$, calculating moments, then you can scale up and scale down. The more conservative way is to re-simulate the economy every time you feed in a new pair of parameters.

(c) Now the producer would like to know $p(\mu > 198)$, the probability that the valuation of an average person is higher than the cost of camera, and $p(\sigma < 9.5)$, the tightness of the distribution. In addition, the producer is also concerned with the data requirement for this task. Using bootstrap method for the question and generate a table with both estimates and significance level (like the table found in economic journals), for 1000,. 2000, 3000 period for the analysis. You have to use cluster to obtain the result.