Assignment 3

Hema Yoganarasimhan

Course Number: MKTG 584 A
Course Name: Dynamic Structural Models

1 Overview

This assignment follows up on your previous two assignments. Assume the same optimal stopping problem (and model specifications) as in Assignments 1 and 2.

The goal of this assignment is to estimate the replacement costs and maintainence costs for a given dataset using the Two-step CCP method.

2 Inputs

Your code should take the following inputs:

- Data in following format (in columns) – BusNo., Timeperiod, DecisionNo. (0 if the line refers to continuation, 1 if it refers to replacement), Mileage, Chosen (0 if this line was chosen, 1 otherwise). Note that this is the same format as the data you generated in Assignment 1, except it doesn't have the column for the choice-specific value function. Ensure that your code can accept the data in .txt format.
- Discount factor β

3 Outputs

For a given dataset and discount factor, the code should generate the following outputs:

- Parameters $\{\theta_1, \theta_2\}$ and the standard errors for each of them.

4 Outline of the Code

There are two parts to this code – the first step and the second step. The details of how the code should look like are given below.

- In the first step you will nonparametrically estimate the CCPs for the observed states and the state-transition probabilities. If the size of the state-space is Z, then the number of CCPs to be estimated is Z (for two decisions) and the dimension of the state-transition matrix is $Z \times Z$, where you need to estimate $Z \times (Z - 1)$ parameters. Note that for certain parameter values, you will have a sparsely populated state space. This can affect the quality of your first-step estimates.

- In the second step, you will calculate the expected future value-functions, plug them into the choice probabilities. Because the Rust bus engine replacement demonstrates 'finite-dependence', use this property to simplify your value function calculation. Since mileage resets to zero after every replacement decision, if you represent the next period's value function in terms of the replacement decision, you only need to forward simulate one period ahead. See Arcidiacono & Ellickson (2011) for details.

  Once you have numerical estimates of the expected future value functions, plug them into the choice probabilitues, write out the log-likelihood and estimate it. You can use a ready-made ML estimator, like asclogit from Stata, to do this.
- Because your value function estimates are not data, your standard errors are likely to be biased downwards. So bootstrap the standard errors using 250 simulations. Details of how the bootstrap works are given in Assignment 1.

5 Evaluation

For the submission, you need to provide the following:

- Your complete code with comments. I will evaluate the correctness of your code by giving you a .txt dataset in the format described above and a discount factor. Your code should produce the correct parameters for the data.
- A pdf document with the following results:
  - Run your model on the dataset that is provided with this assignment and present the following – a) the parameter estimates and standard errors without bootstrap (run on the full data), and b) the bootstrapped parameter estimates and standard errors with at least 250 replications.
  - The probability distribution of parameters from the bootstrap process.
  - Compare the estimation time for the the Nested Fixed Point algorithm (without bootstrap, i.e., for one run) with that of the two-step method takes (also without bootstrap). Report the time differences.
  - Compare the bootstrapped standard errors with the non-bootstrapped standard errors for the two-step method.
  - Compare the efficiency of the standard errors of the two methods – Nested Fixed Point and Two-step method.