

Structural Econometrics

Assignment 2

Question 1

- Table 1 from Arcidiacono Miller (2011) as a reference point.
- Q1.1 - Replicate columns 2-3 (there is a typo in the question, s is *observed*, not ignored) and 5-6.
 - Change parameter, whichever you want, and run the Monte-Carlo (simulate data and use it to estimate the parameters).
- Q1.2 – Change N or T, check how s.e. change
- Q1.3 – As you carry out 1 or 2, record the replacement rate or similar (average mileage on bus, average time since replacement). Something that summarizes the agent's behavior and that can be policy relevant.
- Q1.4 –

Question 1.4

- Counterfactual: answers the question “How does the Data Generating Process and its moments change if the fundamental parameters were different?”
- I.e. “what if” experiments involving fundamental parameters, focusing on features of the DGP that are policy relevant.
- Ex. of moments of interest: distribution of agents across choices, distribution of agents across the state space: x and d .
- Monte Carlo experiments => you control the DGP. You generate the data.
- In research, can only do counterfactuals while sitting on your *estimated* parameters, not the true ones.

Question 1.4

1. Take column 3: estimation with CCPs with s observed.
2. Take your estimates obtained from Q1.2/Q1.3 and substitute those in the DGP, as in enter those values in the data simulation part of the code.
3. Now we pretend we are doing research on buses. We obtained some *estimates* about the process (not the true parameters) and we want to carry out a counterfactual analysis. You have to change parameters once more, this time starting from your *estimates* as a baseline (of course if you change them all and preserve none of the estimated values then it's kind of pointless).
4. Describe and discuss your counterfactual experiment. E.g. Did the replacement rate change the way you expected?

Question 2

- Arcidiacono and Miller 2011 propose three different ways to update the CCPs, but they really boil down to two.
- “using the model” (The logit expression is analogous to 2.8 for the bus problem)

$$(5.8) \quad p_{jt}^{(m+1)}(x, s) = l_{jt}(x, s, \theta^{(m)}, \pi^{(m)}, p^{(m)}).$$

$$p_{1t}^{(i,m+1)}(x, s) = \frac{1}{1 + \exp[v_{2t}^{(i)}(x, s, p^{(m)}, \theta^{(m)}, \pi^{(m+1)})]}.$$

- Empirical likelihood / “using the data”

$$(5.9) \quad p_{jt}^{(m+1)}(x, s) = \frac{\sum_{n=1}^{\mathcal{N}} d_{njt} q_{nst}^{(m+1)} I(x_{nt} = x)}{\sum_{n=1}^{\mathcal{N}} q_{nst}^{(m+1)} I(x_{nt} = x)}.$$

In the application, this is approximated with a logit (“reduced form”).

(Notice that 5.9 is the analogous to the bin estimator you can find in footnote 10 in the paper. The difference is that 5.9 refers to a nonstationary environment, so you cannot sum across time as well because decisions made at different times are assumed to stem from different CCPs: notice the time subscript.)

Question 2

- Repeat points 2-4 like in Q1.
- Run only one of the CCP updating methods: "using the data" or "using the model".
 - Column 4: Analytical expression for the likelihood
 - Column 5: Using the data, logit approximation
 - Column 6: Two-stage.
 - Column 7: Using the model

The two-stage estimator is just a modification of the estimation algorithm allowed by updating the CCPs using the data. That's why I said

In the two-stage estimator, π , $q_{s',s}$, $f(x'|x, \theta_1)$ and $p(x, s)$ are obtained first by iterating the expectation step (Section 5.1. of the paper) until convergence, and *then* the likelihood is maximized to obtain the profit and price parameters.

This is permitted by the fact that the profit parameters are not needed to update the CCPs if you update using the data.

Question 2

- Q2.5: Replicate the column of table 2 that you chose in Q2.2, by reducing the number of players to 2. But use the original DGP parameters that Arcidiacono and Miller (2011) used.

About the code

- For each specification/column, there is a folder
- Each folder contains a Matlab script (.m) which name begins with ***shell*** (busprograms) or ***montecarlo*** (entry/exit). Start from there.
- All of the DGP controls are at the beginning of each shell file. Except for Q1.3 and Q2.3, this is all you need to modify.
- **PARFOR: parallelization using Matlab's Parallel Computing Toolbox (you probably have to install it)**
- You have to inject at some point in the code some lines to record the moment/statistic of the data you are interested in.
- Don't hesitate to reach out if you get stuck.

- Notice the footnote! The reported results are mean and standard deviations of the point estimates over 100 iterations of **Table 1**

TABLE I
MONTE CARLO FOR THE OPTIMAL STOPPING PROBLEM^a

	DGP (1)	nohetero s Observed		noheterowrong Ignoring s CCP (4)	intcondat s Unobserved		nohet10nsTime Effectshetero10ns s Observed s Unobserved	
		FIML (2)	CCP (3)		FIML (5)	CCP (6)	CCP (7)	CCP (8)
θ_0 (intercept)	2	2.0100 (0.0405)	1.9911 (0.0399)	2.4330 (0.0363)	2.0186 (0.1185)	2.0280 (0.1374)		
θ_1 (mileage)	-0.15	-0.1488 (0.0074)	-0.1441 (0.0098)	-0.1339 (0.0102)	-0.1504 (0.0091)	-0.1484 (0.0111)	-0.1440 (0.0121)	-0.1514 (0.0136)
θ_2 (unobs. state)	1	0.9945 (0.0611)	0.9726 (0.0668)		1.0073 (0.0919)	0.9953 (0.0985)	0.9683 (0.0636)	1.0067 (0.1417)
β (discount factor)	0.9	0.9102 (0.0411)	0.9099 (0.0554)	0.9115 (0.0591)	0.9004 (0.0473)	0.8979 (0.0585)	0.9172 (0.0639)	0.8870 (0.0752)
Time (minutes)		130.29 (19.73)	0.078 (0.0041)	0.033 (0.0020)	275.01 (15.23)	6.59 (2.52)	0.079 (0.0047)	11.31 (5.71)

^aMean and standard deviations for 50 simulations. For columns 1–6, the observed data consist of 1000 buses for 20 periods. For columns 7 and 8, the intercept (θ_0) is allowed to vary over time and the data consist of 2000 buses for 10 periods. See the text and the Supplemental Material for additional details.

Table 2

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TABLE II
MONTE CARLO FOR THE ENTRY/EXIT GAME^a

	DGP (1)	<i>s_t</i> Observed (2)	Ignore <i>s_t</i> (3)	CCP Model (4)	CCP Data (5)	Two-Stage (6)	No Prices (7)
Profit parameters							
θ_0 (intercept)	0	0.0207 (0.0779)	-0.8627 (0.0511)	0.0073 (0.0812)	0.0126 (0.0997)	-0.0251 (0.1013)	-0.0086 (0.1083)
θ_1 (obs. state)	0.05	-0.0505 (0.0028)	-0.0118 (0.0014)	-0.0500 (0.0029)	-0.0502 (0.0041)	-0.0487 (0.0039)	-0.0495 (0.0038)
θ_2 (unobs. state)	0.25	0.2529 (0.0080)		0.2502 (0.0123)	0.2503 (0.0148)	0.2456 (0.0148)	0.2477 (0.0158)
θ_3 (no. of competitors)	-0.2	-0.2061 (0.0207)	0.1081 (0.0115)	-0.2019 (0.0218)	-0.2029 (0.0278)	-0.1926 (0.0270)	-0.1971 (0.0294)
θ_4 (entry cost)	-1.5	-1.4992 (0.0131)	-1.5715 (0.0133)	-1.5014 (0.0116)	-1.4992 (0.0133)	-1.4995 (0.0133)	-1.5007 (0.0139)
Price parameters							
α_0 (intercept)	7	6.9973 (0.0296)	6.6571 (0.0281)	6.9991 (0.0369)	6.9952 (0.0333)	6.9946 (0.0335)	
α_1 (obs. state)	-0.1	-0.0998 (0.0023)	-0.0754 (0.0025)	-0.0995 (0.0028)	-0.0996 (0.0028)	-0.0996 (0.0028)	
α_2 (unobs. state)	0.3	0.2996 (0.0045)		0.2982 (0.0119)	0.2993 (0.0117)	0.2987 (0.0116)	
α_3 (no. of competitors)	-0.4	-0.3995 (0.0061)	-0.2211 (0.0051)	-0.3994 (0.0087)	-0.3989 (0.0088)	-0.3984 (0.0089)	
π (persistence of unobs. state)	0.7			0.7002 (0.0122)	0.7030 (0.0146)	0.7032 (0.0146)	0.7007 (0.0184)
Time (minutes)		0.1354 (0.0047)	0.1078 (0.0010)	21.54 (1.5278)	27.30 (1.9160)	15.37 (0.8003)	16.92 (1.6467)

^aMean and standard deviations for 100 simulations. Observed data consist of 3000 markets for 10 periods with 6 firms in each market. In column 7, the CCP's are updated with the model. See the text and the Supplemental Material for additional details.

sim6f5sCom

sim6f5sUpmodinit

sim6f5s2noY

sim6f5s2stage

sim6f5sWrong

sim6f5sUpdatainit