Online Appendix: Not for Publication

A Recursive Formulation and Solution Accuracy

A.1 Recursive Formulation

We discretize the state spaces and the evolution processes for aggregate government spending, along with aggregate and idiosyncratic productivity using the discretization method by Tauchen (1986). We next proceed as follows:

1. Generate a set of random samples of both idiosyncratic and aggregate shocks.

2. Initiate a set of aggregate law of motion for prices μ_P and back out the policy function via fixed point iterations

   (a) Update the aggregate law of motion (ALM) for all intermediate firms μ_P.

   (b) Given the ALM, we conduct a fixed point iteration to back out the policy function.

   (c) Given the policy function obtained in the previous step, we simulate the model using the shocks generated in step 1 and update the aggregate variables.

   (d) I follow Maliar, Maliar and Valli (2010) in updating the next optimal guess μ_P for such a distribution using the following process:

   $$\mu_P = \lambda^s \mu_P' + (1 - \lambda^s)\, \mu_P'',$$

   in which λ^s is a smoothing parameter.[23]

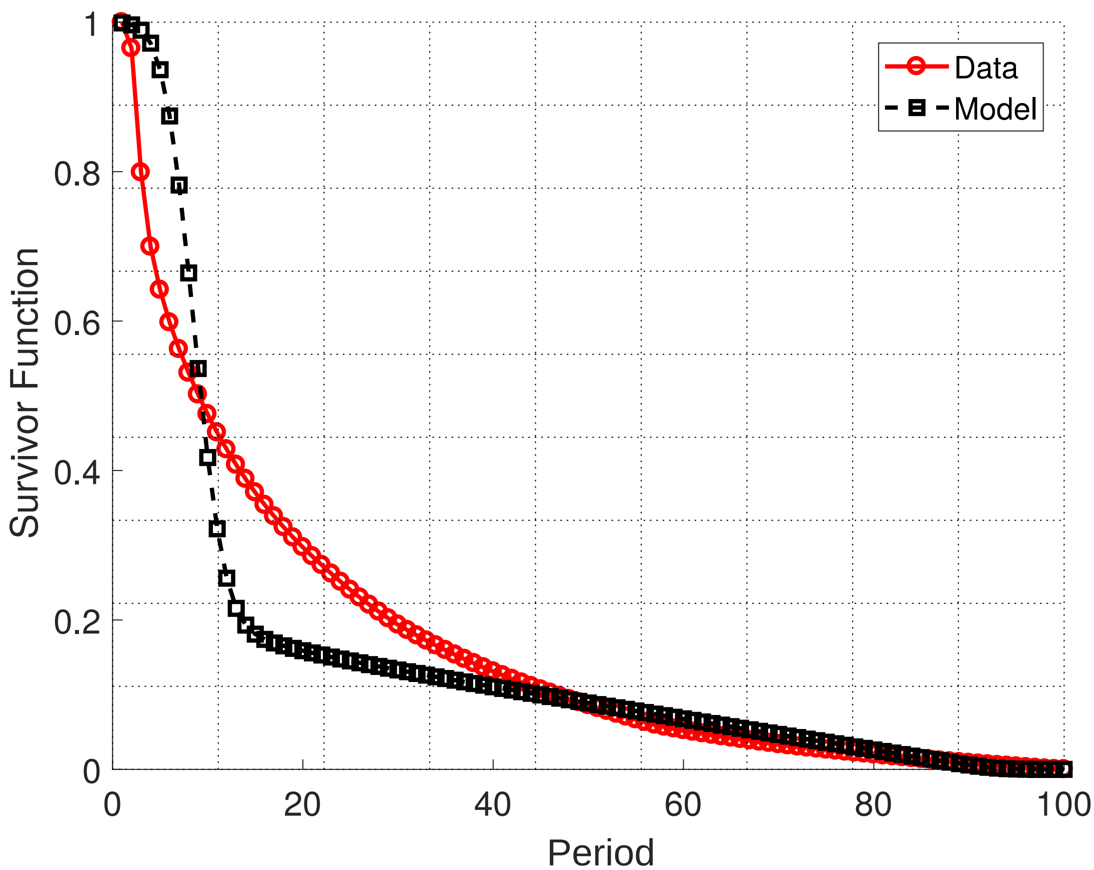
3. Given the updated aggregate variable, we obtain an update on the aggregate law of motions μ_P. Repeat until convergence of the aggregate laws of motion.

A.2 Model Fits: Micro Price

One key advantage of menu cost models lies in its ability to remain consistent with features of micro-price data (as noted by, for example, Golosov and Lucas (2007)). In this section, we assess how the model fits with micro-price data for Japan. The key metric that we rely on - beyond

[23]I select this parameter to be 0.1. Changing the parameter only affects the speed of convergence, but not any quantitative and/or qualitative result of the model.

Figure A.1: Micro-price evidence: Model Prediction versus Data

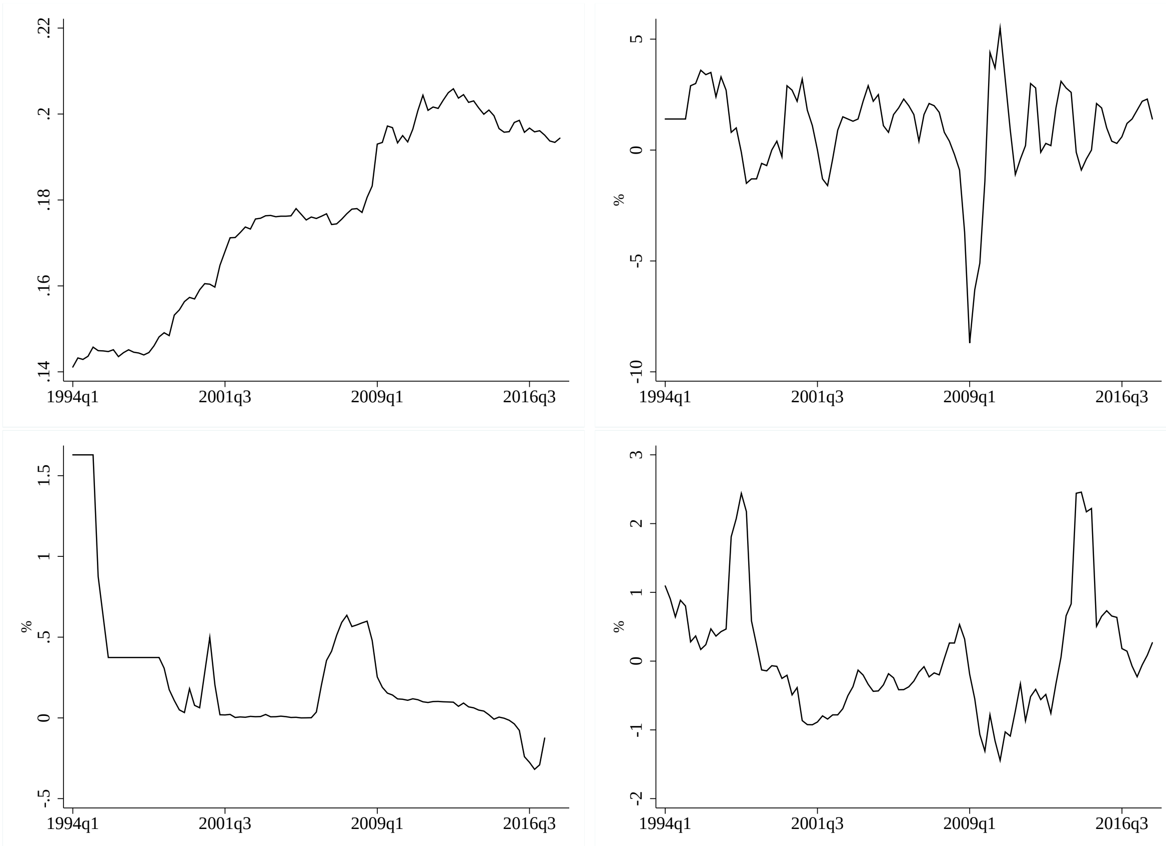


Note: This figure compares the survivor function generated by the data and the one generated by the model under our baseline specification. We simulate the model for 1,000 periods with 1,000 firms. We repeat this procedure for 100 and take the average across these samples.

the size and the median frequency of price changes - is the duration of a particular price change. To that end, we compare the survivor functions for price changes generated from the data to the ones generated by model simulation under the baseline calibration strategy presented in Section 3. These survivor functions represent the probability of a price change to survive beyond a t number of months.

Specifically, for both the model and the data, we construct the cumulative distribution function of the duration of price changes over different time horizons. Let T be a random variable that measures the time of price changes and let $F(t)$ be the corresponding cumulative distribution function. The survivor function $S(t)$ - i.e., the probability of a price change to last beyond t periods - is calculated as $S(t) = P(T \geq t) = 1 - F(t)$. We simulate the model with 1,000 firms and 1,000 periods. The first 100 periods are considered burn-ins and are discarded. Given the series of price changes for each firm simulated, we next estimate the equivalent of $S(t)$ using the

Figure A.1: Selected Variables for Japan (1993Q1:2015Q3)



Note: Data are from the St. Louis' FRED.

data generated from simulation.[24]

Figure $A.1$ plots the survivor function generated from Japanese micro-level data (red line) against the same function estimated from the model (black line). Overall, we find the underlying micro-price patterns generated by the model to dovetail with the ones generated from empirical data. The ability of the model to fit with micro-price evidence is not surprising, given the previous literature that features menu cost models (for example, Golosov and Lucas (2007) and Gagnon (2009)).

B Additional Tables and Figures

[24]For the underlying kernel smoothing, we use the Silverman rule of thumb for bandwidth selection criteria.

Table A.2: Japanese Prefectures used in the Micro-price Data

N	**City**	Δp	**Goods**	**N**	**City**	Δp	**Goods**
1	Akita	0.04	649	41	Miyazaki	0.04	649
2	Aomori	0.04	649	42	Moriguchi	0.06	573
3	Asahikawa	0.01	570	43	Morioka	0.04	649
4	Atsugi	0.01	570	44	Nagaika	0.01	570
5	Chiba	0.04	649	45	Nagana	0.02	538
6	Fuchu	0.04	649	46	Nagano	0.05	601
7	Fukui	0.04	649	47	Nagaoka	0.02	538
8	Fukuoka	0.04	649	48	Nagasaki	0.04	649
9	Fukushima	0.04	649	49	Nagoya	0.04	649
10	Fukuyama	0.00	570	50	Naha	0.02	648
11	Gifu	0.04	649	51	Nara	0.04	649
12	Hakodate	0.04	649	52	Niigata	0.04	649
13	Hamamatsu	0.04	649	53	Nishinomiya	0.04	649
14	Higashiosaka	0.04	649	54	Oita	0.02	535
15	Himeji	0.05	649	55	Okayama	0.04	649
16	Hirakata	0.01	570	56	Osaka	0.04	649
17	Hiroshima	0.04	649	57	Otsu	0.04	649
18	Itami	0.04	649	58	Qita	0.05	601
19	Kagoshima	0.04	648	59	Saga	0.04	649
20	Kamakura	0.01	538	60	Sakura	0.00	570
21	Kanazawa	0.04	649	61	Sapporo	0.04	649
22	Kasugai	0.04	649	62	Sasebo	0.04	649
23	Kawaguchi	0.04	649	63	Sendai	0.04	649
24	Kawasaki	0.04	649	64	Shizuoka	0.04	649
25	Kitakyushu	0.05	649	65	Tachikawa	0.00	570
26	Kobe	0.04	649	66	Takamatsu	0.04	649
27	Kochi	0.04	649	67	Tokorozawa	0.02	646
28	Kofu	0.04	649	68	Tokushima	0.04	649
29	Koriyama	0.04	649	69	Tottori	0.04	649
30	Kuarea of Tokyo	0.03	649	70	Toyama	0.04	649
31	Kumamoto	0.04	649	71	Toyohashi	0.08	337
32	Kure	0.05	649	72	Tsu	0.04	649
33	Kushiro	0.05	573	73	Ube	0.00	570
34	Kyoto	0.04	649	74	Urawa	0.04	649
35	Maebashi	0.04	649	75	Utsunomiya	0.04	649
36	Mastuyama	0.02	537	76	Wakayama	0.04	649
37	Matsue	0.04	649	77	Yamagata	0.04	649
38	Matsumoto	0.04	649	78	Yamaguchi	0.04	649
39	Matsuyama	0.05	601	79	Yokohama	0.04	649
40	Mito	0.04	649	80	Yokosuka	0.05	649