Online Appendix to “The biases in applying static demand models under dynamic demand”

Takeshi Fukasawa*

A Monte Carlo Simulation

I conducted a Monte Carlo Experiment to show the biases associated with inconsistent utility parameter estimates and changing consumer expectations. We consider a market of durable goods with exogenous replacement timing, where consumers consider purchases only when they do not have any product. Here, we consider the case without persistent consumer heterogeneity.

A.1 Specifications of the Monte Carlo experiment

The Monte Carlo experiments are conducted in the following specifications and procedures.

Specifications

The synthetic data generated in this study are similar to those in Dubé et al. (2012) and Sun and Ishihara (2019),[1] except for the introduction of the replacement demand.

Let x_t be a consumer's individual-level state variables. We consider the case where consumers consider purchases only when they do not own any product ($x_t = 0$). Then, type l consumer i's present value discounted sum of utility at time t is specified as:

$$\begin{aligned} v_{ijt}(x_t = 0) &= \theta^0 + \sum_{m=1}^{2} \theta^m \chi_j^{(m)} - \alpha p_{jt} + \xi_{jt} + E_t \beta_C^L V_{t+L}^C(x_{t+L} = 0) + \epsilon_{ijt} \\ v_{i0t}(x_t = 0) &= \beta_C E_t V_{t+1}^C(x_{t+1} = 0) + \epsilon_{i0t} \end{aligned}$$

for $j = 1, ...J$, and $t = 1, ..., T$. Here, χ_j, p_{jt}, ξ_{jt} denote the product j's observed characteristics, price, and unobserved characteristics. L denotes the lifetime of products.

We assume that all the products follow the same lifetime distribution. Products follow geometric depreciation with a depreciation rate ρ. Then, $Pr(x_t)$ follows the process below:

$$Pr_{t+1}(x_{t+1} = 0) = \left(1 - Pr_t(x_t = 0) s_{0t}^{(cd)}(x_t = 0)\right) \rho + Pr_t(x_t = 0) s_{0t}^{(cd)}(x_t = 0).$$

We consider the case where only one market exists, and we let the values of T and J be $T = 100$ and $J = 50$. In addition, we assume that none of the consumers possess the products at the beginning of $t = 1$ ($Pr_{t=1}(x_{t=1} = 0) = 1$).

Observed product characteristics $\chi_j = \left(\chi_j^{(1)}, \chi_j^{(2)}\right)'$ follows log-normal distribution:

$$\chi_j \equiv \begin{pmatrix} x_j^1 \\ x_j^2 \end{pmatrix} \sim LN\left(\begin{pmatrix} 1.5 \\ 1.5 \end{pmatrix}, \begin{pmatrix} 0.5^2 & \\ & 0.5^2 \end{pmatrix}\right).$$

*Graduate School of Economics, The University of Tokyo. 7-3-1 Hongo, Tokyo, Japan. E-mail: fukasawa3431@gmail.com.

[1] These studies considered alternative estimation procedures other than the method relying on the nested fixed-point algorithm.

Unobserved product characteristics ξ_{jt} follows i.i.d. normal $N(0, 0.5^2)$.

Product price is generated by:

$$p_{jt} = \gamma_z^0 + \gamma_x \chi_{jt} + \gamma_z z_{jt} + \gamma_w w_{jt} + \gamma_\xi \xi_{jt} - \gamma_p \frac{\sum_{k \neq j} \chi_k}{J-1} + u_{jt}^p.$$

where $u_{jt}^p \sim N(0, 0.01^2)$. We consider the environment where product prices decline over time, but finally converge to stable levels.

w_{jt} and z_{jt} represent cost shifters, and w_{jt} follows standard normal distribution $N(0, 1^2)$. z_{jt} follows $AR(1)$ process $z_{jt} = \lambda_0^z + \lambda_1^z z_{jt-1} + u_{jt}^z$, where $u_t^z \sim N(0, 0.01^2)$.

The values of the parameters are set as follows: $z_{j0} = 6$, $[\lambda_0^z, \lambda_1^z] = [0.1, 0.9]$, $[\gamma_z^0, \gamma_{x_1}, \gamma_{x_2}, \gamma_z, \gamma_w, \gamma_\xi] = [1, 0.2, 0.2, 1, 0.2, 0.7]$, $\gamma_p = [0.05, 0.05]$, $[\theta^0, \theta^1, \theta^2, \alpha] = [2, 1.5, 1, 2]$.

The values of the product depreciation rate and consumers' discount factor are set to 0.03 and 0.99.

For estimation, we use the weight matrix $W = (Z'Z)^{-1}$, where Z is the matrix of instrumental variables. As instrumental variables, we use polynomial expansions of $[\chi_j, z_{jt}, w_{jt}, \sum_{k \neq j} \chi_k]$. There are 35 instrumental variables.

Solution of the model

I solved the model by the following procedure:

1. Generate product price, characteristics, and other variables
2. Solve $V_t^C(x_t = 0)$ and $s_{jt}^{(cd)}(x_t = 0)$

   To solve these values, we assume the following AR(1) transition process of inclusive value $V_t^C(x_t = 0)$:[2]

   $$V_{t+1}^C(x_{t+1} = 0) = \gamma_0^\delta + \gamma_1^\delta V_t^C(x_t = 0) + u_t^\delta \quad (Eu_t^\delta = 0)$$
3. Calculate the path of stock ($Pr_t(x_t = 0)$) and market share (s_{jt})

Using the generated data, I conducted the following numerical experiments:

1. Parameter estimates:

   Estimate parameters by assuming a static demand model and applying the BLP method. Static BLP estimation was implemented by using PyBLP (Conlon and Gortmaker, 2020).
2. Long-run price elasticities:

   Assuming the knowledge of true dynamic demand structure and true parameter values, compare the values of short-run and long-run own price elasticities.

A.2 Results

Before looking at the results of the biases, we look at the market environment generated in the simulation.

The left panel of Figure 1 shows the fraction of consumers who do not possess any product at the beginning of each period. As time passes, more and more consumers possess the products in the earlier periods. In contrast, in the later periods, the fraction is mostly stable over time. In the later periods, most of the demand comes from the replacement demand, rather than new purchases. Hence, the demand structure is largely different between the two ranges of periods.

The right panel of the figure shows the time trend of average price($\frac{1}{J}\sum_j p_{jt}$) and demand($\sum_j s_{jt}$). First, the price declines gradually, and finally it reaches a stable level. In contrast, demand increases from time 1 to

[2] In this study, inclusive value δ_t is defined as follows: $\delta_t = E_\epsilon \left[\max_{a_t \in \mathcal{J} \cup \{0\}} v_{it}(x_t, a_t)\right]$. On the other hand, most of the literature has used the alternative specification of inclusive value equivalent to $\delta_t = E_\epsilon \left[\max_{a_t \in \mathcal{J}} v_{it}(x_t, a_t)\right]$. When using the latter specification, we need to specify the distribution of u_{lt}^δ and calculate expectations based on the distribution of u_{lt}^δ. In this case, the computation gets more complicated. Hence, I use the former specification.

time 10, and declines from time 10 to time 25. From time 25, the demand is at a stable level, even though it fluctuates over time. Then, we can observe negative correlations between price and demand in time 1–10 and positive correlations between price and demand in time 10–25. The positive correlation may seem strange, but it is mainly caused by the declining fraction of no-stock consumers as shown in the left panel.

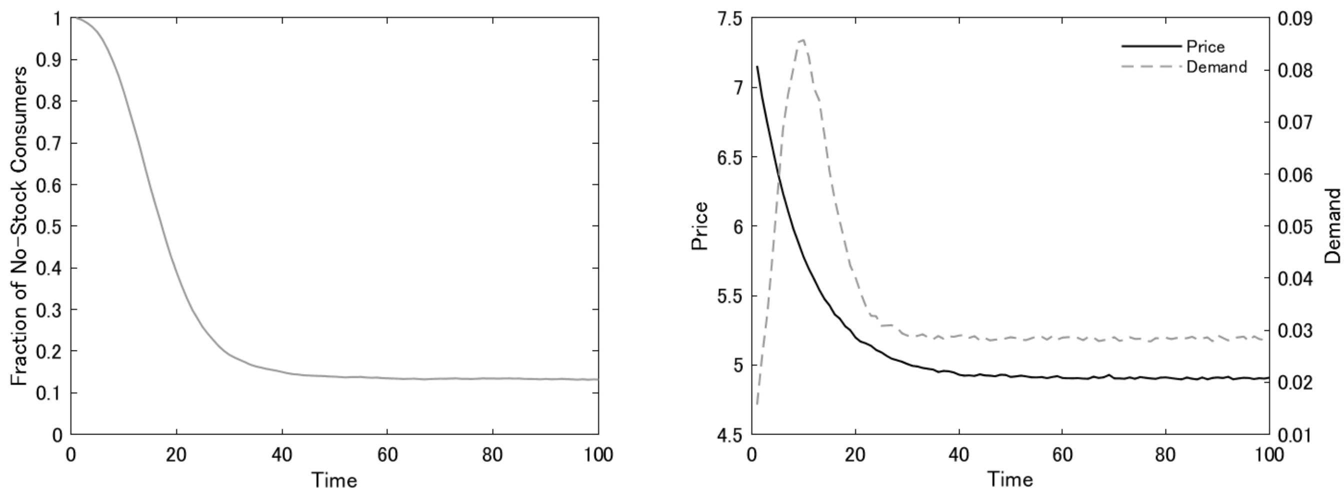

Figure 1: Environment of the simulated market

Notes: Fraction of no-stock consumers is defined as $Pr_{lt}(x_t = 0)$. Price is defined as $\frac{1}{J}\sum_j p_{jt}$. Demand is defined as $\sum_j s_{jt}$. Averages of 20 simulated data are shown.

A.2.1 Parameter estimates

The estimation results are shown in Table 1. Since the environment is largely different between the earlier periods and the later periods, I divide the data into two parts (t =1–50 and t =51–100), and estimate parameters in each case. Here, I also show the estimation results where time dummies are introduced. Note that in the model, all the products share the same continuation values, and the introduction of time dummies yields consistent utility parameter estimates under the nonexistence of persistent consumer heterogeneity, as discussed in Section 3.3.

The first and second columns of Table 1 show the estimation results using the data of the nonstationary market (t =1–50). In the case of the nonstationary market, estimated parameters are largely different from the true values when fixed effect terms are not introduced. For instance, the average estimated value of α is -0.308, though the true value is 2.0. On the other hand, when fixed effect terms are introduced, estimated values are closer to the true values.

Similarly, the third and fourth columns of Table 1 show the estimation results using the data of the stationary market (t =51–100). In this case, both specifications yield parameter estimates close to the true values. From time 51 to time 100, the market is in a stationary environment: consumers' expectations and product stock are mostly stable over time. Hence, the role of controlling the fixed effect terms is limited. Even when estimating parameters with the static model without controlling fixed effect terms, the biases are relatively small.[3]

[3]Similar insight was also discussed in Melnikov (2000).

Parameters	True value	Nonstationary (t =1–50) without FE	with FE	Stationary (t =51–100) without FE	with FE
θ^1	1.5	1.171	1.493	1.491	1.496
		(0.023)	(0.007)	(0.010)	(0.008)
θ^2	1.0	0.668	0.996	0.992	0.997
		(0.027)	(0.007)	(0.009)	(0.008)
α	2.0	-0.308	1.970	1.959	1.987
		(0.085)	(0.035)	(0.041)	(0.033)

Table 1: Results of the Monte Carlo Experiment (No persistent consumer heterogeneity)

Notes:
Based on 20 simulated data and 5 initial parameter values. Root mean squared errors are shown inside parenthesis.

A.2.2 Difference between long-run and short-run price own elasticities

Next, we compare the values of long-run and short-run price own elasticities, whose differences correspond to the bias associated with changing expectations of consumers. I choose one sample of 20 simulated data used in the estimation, and consider the environment where prices of each product are expected to be raised by 1% permanently from time 51. Here, we assume that the price increase is not expected by the consumers until time 50. Under the setting, we compare the short-run and long-run own elasticities at time 51.

Table 2 shows the summary statistics of the long-run own price elasticities computed from the true dynamic model. Figure 2 compares the values of long-run and short-run own price elasticities. To understand when the bias is large, I present the scatter diagrams between products' CCPs and biases in elasticities measured by percentage.

As the figure shows, the biases are very large especially for large CCP products. For instance, the bias of the product whose CCP value is roughly 0.2 is about -100%, as shown by the point located at the lower right in the figure.[4] In contrast, the biases are small for small CCP products, as shown by the points located at the upper left in the figure.

Obs	Median	Mean	s.d.	Min	Max
50	9.16	9.05	0.88	5.15	10.88

Table 2: Summary statistics of long-run own price elasticities

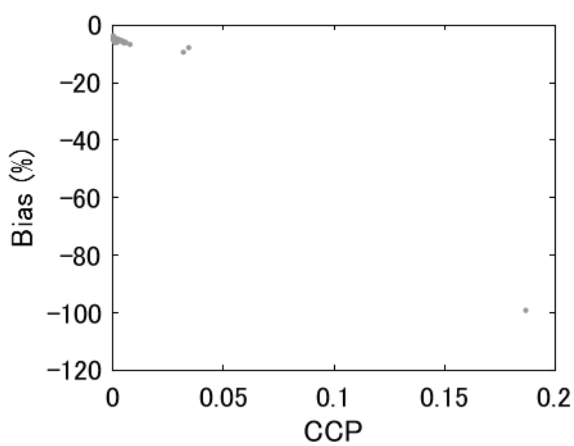

Figure 2: Biases in long-run own price elasticities

Notes:
Bias is calculated by: $\frac{\text{(long run own elasticity)}-\text{(short run own elasticity)}}{\text{(long run own elasticity)}} \times 100$. CCP is defined as $s_{jt}^{(ccp)}(x_t = 0)$.

[4] As shown in Table 2, long-run price elasticities are not necessarily close to zero. Hence, we cannot attribute the large biases to small values of true price elasticities.

B Literature on the biases in static demand models

In this section, I show the source of the information of each article's estimates summarized in Table 1. In addition, for some articles I provide additional interpretation of the results based on the discussion in this article.

B.1 Durable goods

Chen et al. (2008)

Chen et al. (2008) specified both dynamic demand-side model and dynamic supply-side model, and generated data on the automobile market given calibrated parameter values. Besides, both new and used goods exist in the market, and no persistent consumer heterogeneity exists.

- Price coefficient: Table 3 ($N = 3$, δ=0.11, $\rho = 0.10$, β_1=0.96, $\beta_2 = 0.96$)

  $\widehat{\gamma}$ represents the static estimates of the price coefficient (marginal utility of money), and γ represents the true marginal utility of money based on the dynamic model.

- Own elasticity: Table 3 ($N = 3$, δ=0.11, $\rho = 0.10$, β_1=0.96, $\beta_2 = 0.96$)

  $\widehat{\eta}$ represents the static estimate of the price elasticity (of the new product). e represents the true price elasticity of the new product based on the dynamic model. Note that η considers the effect of temporary price change on the current demand, yet it includes the changing future expectations of consumers after the temporary price change. In contrast to e, η abstracts away the changing price of used car prices under market clearing conditions of the secondary market.

Prince (2008)

- Price coefficient: Table V ("1999 Full Data Estimate") (dynamic), Table VII ("1999 Myopic Model Estimate") (myopic) and Table VII ("No Stock Model #1 Estimate") (static)

  We look at the row of "Marginal utility of Money" in the tables. Note that the "Myopic" model corresponds to the case where state variables (product holdings) are correctly specified, but setting the consumers' discount factor to zero. "No Stock Model #1" corresponds to the case where state variables are not specified (researchers assume that consumers do not possess anything). This model corresponds to the "static model", in our terminology.

- Own elasticity: Table IX (1999)

Gordon (2009)

- Price coefficient: Table 2

  Estimates of Price coefficients under "Myopic"(myopic) model and "Two Segment"(dynamic; Segment 1) are shown in Table 1 of the current article.

- Own elasticity: Table 5

  Estimates of Intel and AMD's own elasticities of demand under dynamic and static models are presented.

- Cross elasticity: Table 5

  Estimates of Intel and AMD's cross elasticities of demand under dynamic and static models are presented.

Schiraldi (2011)

Schiraldi (2011) introduced the existence of used goods in the model.

- Price coefficient: Table 4 ("Dynamic Model with Micromoments" / "Static Model")
- Own elasticity: Table 5 ("Dynamic Model with Transaction Costs and Micromoments, Short run", "Static Model"; Small Car)
- Cross elasticity: Table 6 ("Full dynamic model (Short-run)", "Static Model"; Small Car, New)

  Average price elasticities weighted by market shares are shown in the article. Note that Schiraldi (2011) also considered "long-run price elasticity" ("Dynamic Model with Transaction Costs and Micromoments, Long run" in Table 5 (own elasticity) and "Full dynamic model (Long run)" in Table 6 (cross elasticity)). Nevertheless, the elasticity is different from ours, in that Schiraldi (2011) allowed changing used car prices. For example, the author mentioned in footnote 28 that "I increase the price of a new FIAT compact in 2000, the 1-year-old FIAT compact in 2001, the 2-year-old Fiat compact in 2002, and so on" for computing long-run elasticities. Under the specification, "price changes" not only affect consumers' expectations on future new car prices but also resell values of the cars already owned by consumers. In contrast to the discussion of the current article, Schiraldi (2011) showed the case where long-run cross price elasticity is smaller than short-run cross elasticity (0.1558 (long-run, New, Small car) / 0.2564 (short-run, New, Small car)) in Table 6[5].

Gowrisankaran and Rysman (2012)

- Price coefficient: Table 1 ("Dynamic Model with Micro Moment", "Static Model")

  Mean coefficients of "Log price" are reported in Table 1 of the current article.

- Own elasticity: Figure 13

  Figure 13 shows the own price elasticity for the product "Sony DCRTRV250", which had the largest market share in the median period, and the values of the elasticities are mentioned on page 1206 (2.59 for long-run elasticity and 2.41 for short-run elasticity). Note that industrywide elasticities are reported to be 2.55 (long-run) and 1.23 (short-run), which is mentioned on page 1206 and plotted in Figure 12. Besides, the price elasticity derived from the static model are based on the information in footnote 29 of the article.

Lou et al. (2012)

- Price coefficient: Table 3 ("BLP model"(static), "GR model"(dynamic))
- Own and cross elasticity: Table 5 ("BLP model"(static), "GR model"(dynamic))

  In addition to the static and dynamic models, Lou et al. (2012) compared "BLPWP" model proposed in the article.

B.2 Storable goods

Erdem et al. (2003)

- Own elasticity:

  Own elasticities of quantity demanded with respect to Heinz's price cut are shown. The values of 3.6(long-run) and 4.9(short-run) are shown in Table 11 (short-run; "Heinz", "Fixed") and Table 12 (long-run; "Heinz", "Permanent 10% drop in mean offer price of Heinz" "Purchase quantity", "Heinz").

[5] For larger cars, he showed that long-run cross price elasticity is larger than short-run cross elasticity (0.0797 (long-run, New) / 0.0691 (short-run, New))

- Cross elasticity:

  Cross elasticities of several products are reported. The values of 0.2(short-run) and 0.75∼1(long-run) are shown in Table 11 (short-run; “Hunts / Del Monte / Store Brand”, “Fixed”) and Table 12 (long-run; “Hunts / Del Monte / Store Brand”, “Permanent 10% drop in mean offer price of Heinz, “, “Purchase quantity”, “Heinz”).

In Erdem et al. (2003), “short-run price elasticity” is defined as the current demand change in response to the current price change allowing for changing future expectations of consumers. In contrast, in the current article, “short-run price elasticity” is defined as the current demand change in response to the current price change given fixed consumers’ future expectations.

Sun et al. (2003)

- Price coefficient: (“Logit with No-Purchase Alternative”(static) and “Dynamic Structural Model”(dynamic))

  “Logit with No-Purchase Alternative” model corresponds to the static model in our setting. Note that “Logit” model in Table 4 does not include an outside option (buy nothing) as a choice, and it does not coincide with the “static model” in our setting.

- Own elasticity: Table 5 (“Logit with No-Purchase Alternative”(static) and “Dynamic Structural Model”(dynamic))

  Based on the results in Table 5, under “Logit with No-Purchase Alternative” (static) specification, “short-run switching elasticity” is 0.346, and its ratio to “short-run promotion effect” is 77%. Then, the short-run promotion effect is $\frac{0.346}{0.77} = 0.449$ in this case.

  Similarly, under “Dynamic Structural Model” (dynamic) specification, “short-run switching elasticity” is 0.242, and its ratio to “short-run promotion effect” is 56%. Then, the short-run promotion effect is $\frac{0.242}{0.56} = 0.432$ in this case.

  Hence, the ratio of static estimates of price elasticity to short-run price elasticity based on the dynamic model is $\frac{0.449}{0.432} = 1.039$.

Hendel and Nevo (2006)

Hendel and Nevo (2006) allowed household level heterogeneity, but they did not introduce persistent unobserved consumer heterogeneity.

- Price coefficient

  On page 1665, the authors mentioned that “The price coefficient estimated in the static model is roughly 15 percent higher than that estimated in the first stage of the dynamic model”.

- Own elasticity

  The information of “overestimate own-price elasticities by 30 percent” is based on the description of the results by the authors in the abstract of the article. The result is based on Table VIII.

- Cross elasticity

  In the abstract of this article, the authors mention that “underestimate cross-price elasticities by up to a factor of 5”. The result is based on Table VIII.

Hendel and Nevo (2013)

Hendel and Nevo (2013) considered the model and estimation procedures where utility parameters are not explicitly estimated. The estimation procedure of price elasticity is largely different from the articles applying standard discrete choice models.

- Own elasticity

  The authors mentioned on page 2741 of the article that "The own-price elasticity implied by the estimates from the dynamic model, evaluated at the quantity-weighted price, is 2.16 for Coke and 2.78 for Pepsi. The elasticities implied by the static estimates are 2.46 and 2.94, respectively. As expected, neglecting dynamics in the estimation overstates own-price elasticities".

Wang (2015)

- Own elasticity

  The author mentioned in the abstract and introduction of the article that "static analyses overestimate the long-run own-price elasticity of regular soda by 60.8%".

Perrone (2017)

Perrone (2017) considered the model where only one product exists. The estimation procedure of price elasticity is largely different from the articles applying standard discrete choice models.

- Own elasticity: Table 3 ($\epsilon^{sr0}/\epsilon^{lr0}$)

Li (2021)

Li (2021) theoretically investigated the biases in price elasticities under the existence of consumer stockpiling. Nevertheless, he compared "elasticity of demand for immediate consumption" and "elasticity of demand for sum of immediate consumption and stockpiling". Even though the latter elasticity corresponds to either "short-run elasticity" or "long-run elasticity" discussed in the current article, the former elasticity is different from neither "short-run elasticity" nor "long-run elasticity" in our terminology.

B.3 Goods with switching costs

Ho (2015)

- Price Coefficient: Table 2 ("Dynamic-1" (dynamic) and "Myopia" (static))

- Own Elasticity

  Inequality in the absolute values of the three elasticities (Static<Short<Long) is obtained by comparing the results in Table 4 and Table 6 of the article.

- Cross Elasticity

  Inequality on the absolute values of the three elasticities (Static<Short<Long) is obtained by comparing the results in Table 4 and Table 6 of the article.

Shcherbakov (2016)

Shcherbakov (2016) did not introduce persistent consumer heterogeneity in the baseline model. The results in Table 1 are based on the specification. Note that he also showed the results with persistent consumer heterogeneity as robustness checks.

- Price Coefficient: Table 3 ("Static" and "Dynamic(1)")

- Own Elasticity: Table 4 ("Dynamic short run" and "Dynamic long run")

  Price elasticities of cable and satellite are shown. Note that Shcherbakov (2016) also showed static estimates of own price elasticities for cable and satellite. Nevertheless, since the results (inequalities with other elasticities) are largely different between the two alternatives, I did not show the result in Table 1 of the current article.

Yeo and Miller (2018)

Yeo and Miller (2018) introduced random coefficients for static models, but they did not introduce them for a dynamic model.

- Price Coefficient: Table 6 ((1); dynamic) and Table 7 ((1); static)
- Own Elasticity: Table 9 Panel A ("Myopic"(myopic), "Dyn-1"(short-run), "Dyn-3"(long-run), $t = 2006$)

  Median of the own elasticities are shown in Table 1 of the current article.
- Cross Elasticity: Table 9 Panel C ("Myopic"(myopic), "Forward-looking"(long-run), $t = 2006$)

  The means of the cross elasticities are shown in Table 1 of the current article.

Note that static estimates of own and cross elasticities are shown in Table 9 of the article. Nevertheless, since (inequalities with other elasticities) are largely different between the $t = 2006$ and $t \geq 2007$, I did not show the result in Table 1 of the current article.

B.4 Others

Hartmann (2006)

Even though Hartmann (2006) focused on consumption capital, the basic structure of the model is close to the one for durable goods.

- Price Coefficient: Table 4 ("Static logit Random coefficients" and "Dynamic logit Random coefficients")
- Own Elasticity:

  The value of 2.7789 (long-run elasticity) is mentioned on page 345. The value of 3.0550 (short-run elasticity) appears in Table 5 of the article.

Osborne (2011)

Osborne (2011) compared the results under the full model (with learning and switching costs) and the partial models (either with learning or with switching costs). This type of comparison is not intuitive in our model.

Seiler (2013)

Seiler (2013) compared the results under the full model (with inventory and search cost) and the partial model (with inventory but without search cost). This type of comparison is not intuitive in our model.

Pires (2016)

Pires (2016) compared four types of models: model (with/without) inventory and (with/without) consideration set. Parameter estimates are shown in Table 5 (model with inventory and consideration set) and Table 7 (other models).

References

Chen, J., Esteban, S., and Shum, M. (2008). Demand and supply estimation biases due to omission of durability. *Journal of Econometrics*, 147(2):247–257.

Conlon, C. and Gortmaker, J. (2020). Best practices for differentiated products demand estimation with pyblp. *The RAND Journal of Economics*, 51(4):1108–1161.

Dubé, J.-P., Fox, J. T., and Su, C.-L. (2012). Improving the numerical performance of static and dynamic aggregate discrete choice random coefficients demand estimation. *Econometrica*, 80(5):2231–2267.

Erdem, T., Imai, S., and Keane, M. P. (2003). Brand and quantity choice dynamics under price uncertainty. *Quantitative Marketing and Economics*, 1(1):5–64.

Gordon, B. R. (2009). A dynamic model of consumer replacement cycles in the PC processor industry. *Marketing Science*, 28(5):846–867.

Gowrisankaran, G. and Rysman, M. (2012). Dynamics of consumer demand for new durable goods. *Journal of Political Economy*, 120(6):1173–1219.

Hartmann, W. R. (2006). Intertemporal effects of consumption and their implications for demand elasticity estimates. *Quantitative Marketing and Economics*, 4(4):325–349.

Hendel, I. and Nevo, A. (2006). Measuring the implications of sales and consumer inventory behavior. *Econometrica*, 74(6):1637–1673.

Hendel, I. and Nevo, A. (2013). Intertemporal price discrimination in storable goods markets. *American Economic Review*, 103(7):2722–2751.

Ho, C. Y. (2015). Switching cost and deposit demand in China. *International Economic Review*, 56(3):723–749.

Li, R. (2021). Consumer stockpiling and demand elasticity biases: A theoretical note with applications. *The Manchester School*, 89(6):610–618.

Lou, W., Prentice, D., and Yin, X. (2012). What difference does dynamics make? The case of digital cameras. *International Journal of Industrial Organization*, 30(1):30–40.

Melnikov, O. (2000). Demand for differentiated durable products: the case of the US computer printer market. Technical report, working paper, Yale University.

Osborne, M. (2011). Consumer learning, switching costs, and heterogeneity: A structural examination. *Quantitative Marketing and Economics*, 9(1):25–70.

Perrone, H. (2017). Demand for nondurable goods: a shortcut to estimating long-run price elasticities. *The RAND Journal of Economics*, 48(3):856–873.

Pires, T. (2016). Costly search and consideration sets in storable goods markets. *Quantitative Marketing and Economics*, 14(3):157–193.

Prince, J. T. (2008). Repeat purchase amid rapid quality improvement: Structural estimation of demand for personal computers. *Journal of Economics & Management Strategy*, 17(1):1–33.

Schiraldi, P. (2011). Automobile replacement: A dynamic structural approach. *RAND Journal of Economics*, 42(2):266–291.

Seiler, S. (2013). The impact of search costs on consumer behavior: A dynamic approach. *Quantitative Marketing and Economics*, 11(2):155–203.

Shcherbakov, O. (2016). Measuring consumer switching costs in the television industry. *RAND Journal of Economics*, 47(2):366–393.

Sun, B., Neslin, S. A., and Srinivasan, K. (2003). Measuring the Impact of Promotions on Brand Switching When Consumers Are Forward Looking. *Journal of Marketing*, 40(4):389–405.

Sun, Y. and Ishihara, M. (2019). A computationally efficient fixed point approach to dynamic structural demand estimation. *Journal of Econometrics*, 208(2):563–584.

Wang, E. Y. (2015). The impact of soda taxes on consumer welfare: Implications of storability and taste heterogeneity. *RAND Journal of Economics*, 46(2):409–441.

Yeo, J. and Miller, D. P. (2018). Estimating switching costs with market share data: An application to Medicare Part D. *International Journal of Industrial Organization*, 61:459–501.