discrete choice, so in this model stockpiling is achieved by buying larger sizes rather than by buying a larger quantity as in the homogeneous good case.

The consumer also has to decide how much to consume each period.[62] To reduce the state space Hendel and Nevo assume that the per period utility consumer i obtains from consuming in t is the same as in equation (6.1). This assumption implies that there is no differentiation in consumption: consumers care only about the quantity they consume but not the brand.[63] They further assume that inventory cost depends only on total inventory, hence $C(i_t)$ for inventory i_t. They introduce differentiation by assuming an instantaneous utility associated with preference for the purchased brand. At period $t = 1$, the purchase and consumption decisions, $\{c, j, q\}$, are made to maximize

$$\begin{aligned} &\textstyle\sum_{t=1}^{\infty} \delta^{t-1} \mathbb{E}\left[u_i(c_t + \nu_t) - C_i(i_t) + x_{jqt}\beta_i + \alpha_i p_{jqt} + \xi_{jqt} + \varepsilon_{ijqt} \mid \mathbf{s}_1\right] \\ &s.t. \quad 0 \leq i_t, \quad 0 \leq c_t \quad \textstyle\sum_{j,q} d_{jqt} = 1, \quad i_{t+1} = i_t + \sum_x d_{jqt} q_t - c_{jt} \quad j = 1, ..., J \end{aligned} \tag{6.3}$$

where s_t is the information set at time t, p_{jqt} is the price of purchasing quantity q of brand j, ξ_{jqt} is an unobserved (to the researcher) brand-specific quality, x_{jqt} are observed product characteristics and ε_{ijqt} is a random shock. They allow ξ_{jqt} to vary by brand in order to capture differentiation across products, and across sizes.

The expectation $\mathbb{E}(.)$ is taken with respect to the uncertainty regarding future shocks in ν_t and $\boldsymbol{\varepsilon}_t$, and future prices (and other time-varying characteristics). They assume that ε_{ijqt} is i.i.d. type-1 extreme value, and as before that ν_t is i.i.d. over time and across consumers. Prices (and observed characteristics) evolve according to a first-order Markov process.

Let $V_i(\boldsymbol{s}_t)$ be the value function of consumer i. Given the above assumptions $\boldsymbol{s}_t$ consists of inventory, i_t, a vector of current prices (and observed characteristics), which we will denote (slightly abusing notation) by $\boldsymbol{x}_t$, the scalar shock ν_t and the vector of extreme value shocks $\boldsymbol{\varepsilon}_{it}$. As usual in a dynamic programming problem, this value function can

[62] Alternatively, one can assume that consumption is constant over time, but varying across households, and not a decision variable. A slightly more general model, than constant consumption, allows for random shocks, that determine consumption. Both these models are nested within the above model and in principle can be tested. The results in Hendel and Nevo (2006a) suggest that consumption is mostly constant, but when inventory runs low consumers reduce consumption. This behavior is required to explain long periods of no purchase followed by periods of frequent purchases observed in the data. Indeed, it is this variation in inter-purchase time that identifies the utility from consumption.

[63] For the product they study, laundry detergents, this assumption makes sense. This of course raises the question of why products are differentiated. Hendel and Nevo propose an interpretation that allows differentiation in the linear part of the utility.

be obtained as the unique solution of a Bellman equation:

$$V_i(\mathbf{s}_t) = \max_{\{c,j,q\}} \{u_i(c_t + \nu_t) - C_i(i_t) + x_{jqt}\beta_i + \alpha_i p_{jqt} + \xi_{jqt} + \varepsilon_{ijqt} + \delta \int V_i(\mathbf{s}_{t+1}) dF_s(\mathbf{s}_{t+1} \mid \mathbf{s}_t, c, j, q)\}, \quad (6.4)$$

where F_s represents the transition probability of the vector of state variables. Given that the state variables $(\nu_t, \boldsymbol{\varepsilon}_{it})$ are independently distributed over time, it is convenient to reduce the dimensionality of this dynamic programming problem by using a value function that is integrated over these i.i.d. random variables. The integrated value function, sometimes also called the ex-ante value function, is defined as $EV_i(i_t, \boldsymbol{x}_t) \equiv \int V_i(\boldsymbol{s}_t) dF_\varepsilon(\boldsymbol{\varepsilon}_t) dF_\nu(\nu)$, where $F_{\boldsymbol{\varepsilon}}$ and F_ν represent the CDFs of $\boldsymbol{\varepsilon}_t$ and ν_t, respectively. The value function EV_i is the unique solution of the integrated Bellman equation. Given the distributional assumptions on the shocks $\boldsymbol{\varepsilon}_t$ and ν_t, the integrated Bellman equation is:

$$EV_i(i_t, \boldsymbol{x}_t) = \max_{c,q} \int \ln \left(\sum_j \exp \left\{ \begin{array}{l} u_i(c_t + \nu_t) - C_i(i_t) + x_{jqt}\beta_i + \alpha_i p_{jqt} + \xi_{jqt} \\ \\ +\delta\, \mathbb{E}\left[EV_i(i_{t+1}, \boldsymbol{x}_{t+1}) \mid i_t, \boldsymbol{x}_t, c, j, q\right] \end{array} \right\} \right) dF_\nu(\nu_t). \quad (6.5)$$

Despite the significant reduction in size, the state space is still high dimensional. Therefore, to reduce the dimension further, they note that the assumptions imply that the optimal consumption does not depend on which brand is purchased. Formally, let $c^*(\boldsymbol{s}_t; q, k)$ be the optimal consumption conditional on state $\boldsymbol{s}_t$ and on purchase of size q. Lemma 1 in the appendix of Hendel and Nevo (2006a) shows that $c^*(\boldsymbol{s}_t; q, k) = c^*(\boldsymbol{s}_t; q, j) = c^*(\boldsymbol{s}_t; q)$. In words, the optimal consumption does not depend on the brand purchased, only on the size.

This result implies that the (integrated) Bellman equation in (6.5) can be written as

$$EV_i(i_t, \boldsymbol{x}_t) = \max_{c,q} \int \ln \left(\sum_q \exp\left\{u_i(c_t + v_t) - C_i(i_t) + \omega_{iqt} + \delta\, \mathbb{E}\left[EV_i(i_{t+1}, \boldsymbol{x}_{t+1}) \mid i_t, \boldsymbol{x}_t, c, q\right]\right\} \right) dF_\nu(\nu_t), \quad (6.6)$$

where ω_{iqt} is the inclusive value from all brands of size q, as defined by equation (3.10), i.e., $\omega_{iqt} = \ln\left(\sum_j \exp(x_{jqt}\beta_i - \alpha_i p_{jqt} + \xi_{jqt})\right)$. In words, the problem can now be seen as a choice between sizes, each with a utility given by the size-specific inclusive value (and extreme value shock). The dimension of the state space is still large and includes all characteristics and prices, because we need all the prices to compute the evolution of the inclusive value.

To further reduce the state space Hendel and Nevo assume

$$F(\boldsymbol{\omega}_{i,t+1} \mid \boldsymbol{s}_t) = F(\boldsymbol{\omega}_{i,t+1} \mid \boldsymbol{\omega}_{it}(\boldsymbol{x}_t)), \tag{6.7}$$

where $\boldsymbol{\omega}_{it}$ is a vector of inclusive values for the different sizes. In words, the vector $\boldsymbol{\omega}_{it}$ contains all the relevant information in $\boldsymbol{s}_t$ to obtain the probability distribution of $\boldsymbol{\omega}_{i,t+1}$ conditional on $\boldsymbol{s}_t$. Instead of all the prices (and characteristics) we only need a single index for each size. Two vectors of prices (and characteristics) that yield the same (vector of) current inclusive values imply the same distribution of future inclusive values. This assumption is violated if individual prices have predictive power above and beyond the predictive power of $\boldsymbol{\omega}_{it}$. Therefore, if the inclusive values can be estimated outside the dynamic demand model, the assumption can be tested and somewhat relaxed by including additional statistics of prices (and characteristics) in the state space. Note, that $\boldsymbol{\omega}_{it}$ is consumer-specific: different consumers value a given set of products differently and therefore this assumption does not further restrict the distribution of heterogeneity.

Given these assumptions Hendel and Nevo (2006a) show that

$$EV_i(i_t, \boldsymbol{p}_t) = EV_i(i_t, \boldsymbol{\omega}_{it}(\boldsymbol{p}_t)) \tag{6.8}$$

In words, the expected future value only depends on a lower dimensional statistic of the full state vector.

Hendel and Nevo estimate the model using consumer level data and using a three-step procedure. First they estimate many of the parameters (including various fixed effects) with a static conditional Logit model where they use the probability of choosing a brand *conditional* on the size being purchased (i.e. they consider only options that have the same size as the size purchased). They show that for this conditional probability they do not need to solve the dynamic programming problem.[64] Next, they use the first-stage

[64]The intuition for the result is similar to the result in Chamberlain (1980) who proposes to estimate a fixed effects Logit model by conditioning such that the fixed effects drop out. The same happens here, but with the expected value function, instead of a fixed effect.

estimates to compute the transition process of the inclusive values. Finally, they estimate a nested fixed point as in Rust (1987) to estimate the remaining parameters.[65]

They find that estimates that do not account for dynamics overestimate own-price elasticities by roughly 30 percent and underestimate cross-price elasticities by as much as a factor of 5. They also find that static estimates overstate the substitution to the outside option by over 200 percent. Together these suggest that static estimates, like the ones discussed above, might underestimate price–cost margins and be downward biased in predicting the effects of mergers (i.e., static estimates will predict effects that are lower compared to the dynamic model). The models has implications for other policy debates as well. For example, Wang (2015) finds that a static model will overestimate the effect of a soda tax, by as much as 60%.

6.2.2 Durable Products

Many of the papers we discussed above involve estimation of demand for durable goods (Bresnahan, 1987; Berry et al., 1995). Static models miss two important dynamic effects. First, whether a product is owned (and which one) is likely to impact purchases. For example, a consumer who more recently purchased a cell phone might be less likely to buy a new phone than a consumer who owns an older model. Second, purchase decisions will depend on expectations about future prices and quality. Expectation about the future are especially important when nominal prices are declining and quality increasing, as is the case in many durable good industries. The decline in quality-adjusted prices creates a trade off for consumers between purchasing today, and getting the benefits of usage earlier, or delaying purchase and paying a lower price (or getting higher quality).

Initially, the literature separated the modeling between two cases: with and without repeat purchase, as far as we can tell mostly because the no repeat purchase was easier to deal with. More recently the literature has focused on the repeat purchase case, which seems to better fit reality, and that is the one we mostly focus on here. With repeat purchases the main issues with the static model are the ones discussed in the previous paragraph. It is difficult to theoretically sign the direction of the bias in a static model, but empirically it seems like static estimates are lower in absolute value.[66]

[65] They need to modify the Rust estimation algorithm to account for the fact that inventory, a state variable, is unobserved.

[66] Without repeat purchase the issues with the static model are a bit different. First, after consumers purchase they leave the market, and if consumers are heterogeneous then the distribution of the remaining consumers changes over time in a way that is not accounted for by the static model. Second, if consumers

Gowrisankaran and Rysman (2012) offer a framework that extends the static BLP model and allows for dynamics. Interestingly, their model in several ways is similar to the inventory model we presented in the previous section, where the role of inventory is equivalent to the role of the quality of the product owned, in the model below. In the durable good model ”stockpiling” means buying a higher quality product, i.e., ”stockpiling” quality rather than quantity. The real difference between the two models is in the pricing patterns and therefore the trade-off faced by consumers. In storable goods markets, consumers face temporary price reductions that create an incentive to purchase today for future consumption. In durable goods markets the typical pattern is a decreasing quality-adjusted price, which creates an incentive to delay purchase, either by not buying today or by buying a lower quality product, with the intention of replacing it soon, or renting/leasing.[67]

To model these effects, let the (indirect) utility consumer i gets from product j at time t be given by:

$$u_{ijt} = x_{jt}\beta_i + \alpha_i p_{jt} + \xi_{jt} + \varepsilon_{ijt}, \tag{6.9}$$

where the notation follows the definitions of the static model in Section 3. For what follows it is convenient to define the flow utility as $\gamma^f_{ijt} = x_{jt}\beta_i + \xi_{jt}$. If the consumer does not purchase she gets the utility $u_{i0t} = \gamma^f_{i0t} + \varepsilon_{i0t}$ where

$$\gamma^f_{i0t} = \begin{cases} 0 & \text{if no previous purchase} \\ \gamma^f_{i\widehat{j}\widehat{t}} & \text{if last purchase was product } \widehat{j} \text{ at time } \widehat{t} \end{cases}. \tag{6.10}$$

This definition of the utility from the outside option is the main difference between the static model and the dynamic model. In the static model, the utility from the outside good is constant (and normalized to zero) across consumers and over time. In the dynamic model, once consumers purchase, the utility from the outside option changes. Forward-looking consumers take this into account when making current choices. Assuming that (i) the consumer holds at most a single product at any time and (ii) there is no resale market,

are forward-looking then they realize there is an option value to not purchasing today. This option value is reflected in the value of the outside option, which in the static model is assumed constant. Melnikov (2013) and Conlon (2012) offer models and empirical estimates of the no-repeat purchase model.

[67] In some cases, dynamics can also arise due to temporary price changes in durable goods markets. For example, Busse et al. (2010) study the 2005 Employee Discount Pricing, and show that its main effect was to induce consumers to purchase earlier.

then the Bellman equation of the consumer problem is given by

$$V_i(\boldsymbol{\varepsilon}_{it}, \gamma^f_{i0t}, \boldsymbol{x}_t) = \max_{j=0,\dots J} \left\{ u_{ijt} + \delta\, \mathbb{E}[EV_i(\gamma^f_{ijt+1}, \boldsymbol{x}_{t+1})|\boldsymbol{x}_t] \right\}, \tag{6.11}$$

where $EV_i(\gamma^f_{ijt}, \boldsymbol{x}_t) = \int V_i(\boldsymbol{\varepsilon}_{it}, \gamma^f_{ijt}, \boldsymbol{x}_t) dF_\varepsilon(\boldsymbol{\varepsilon}_{it})$, and $\boldsymbol{x}_t$ represents the set of prices and other product characteristics at period t. The expectation is taken with respect to the uncertainty regarding future products, prices and characteristics.

Note, that there is another similarity with the storable goods model. Here the utility carried forward is γ^f_{ijt} and not $\gamma^f_{ijt} + \varepsilon_{ijt}$. Thus, just like in the inventory model there is a separation between the utility at the time of purchase and the utility at the time of usage.

As is usually the case, it is convenient to work with the integrated value function. Even with this, the state space includes the vector of all characteristics and prices, which is still too large to practically work with. They reduce the state space in a similar way to what we saw in the storable goods model. The state space also includes the quality of the products currently held, which is equivalent to the inventory in the storable good problem. Because they assume that the consumer only holds a single product, this quality is a scalar. In more general models the consumer might purchase or hold multiple products, or multiple units of the same product, and the dimension of quality would be higher. To reduce the dimension of the state space, they rely, similar to the storable goods model, on the inclusive value. However, it will be defined slightly differently here. Specifically, define the dynamic inclusive value from the J inside alternatives as:

$$\omega_{it}(\boldsymbol{x}_t) = \ln \left(\sum_{j=1}^{J} \exp(\gamma^f_{ijt} + \alpha_i p_{jt} + \delta\, \mathbb{E}[EV_i(\gamma^f_{ijt+1}, \boldsymbol{x}_{t+1}) \mid \boldsymbol{x}_t]) \right). \tag{6.12}$$

Note, that this definition is different in an important way from the definition given in equation (3.10). The above definition provides the expected value, including the future value, from the J options, while the definition in equation (3.10) provides the expected flow utility, not accounting for the future value. The difference is not just semantic. The static definition basically provides a (utility-consistent welfare) statistic that is a summary of prices and characteristics of available products. The dynamic definition also includes (endogenous) future behavior of the agent. Once we impose a particular stochastic structure on the evolution of ω_{it} a natural question is whether the imposed structure is consistent with the consumer optimization problem. Gowrisankaran and Rysman (2012) offer some discussion on whether or not this is restrictive, but generally little is known on what behavioral assumptions are consistent with the imposed structure.

Given this definition, Gowrisankaran and Rysman make a similar assumption to equation (6.7) made in the storable goods model

$$F(\omega_{i,t+1} \mid \boldsymbol{x}_t) = F(\omega_{i,t+1} \mid \omega_{it}(\boldsymbol{x}_t)). \tag{6.13}$$

As before, the assumption is that the inclusive value is sufficient to compute the transition probabilities, but now it is the dynamic inclusive value, ω_{it}. Furthermore, now there is a single inclusive value rather than a vector of size-specific inclusive values, as was the case for the stockpiling model.

Using this assumption we can now write

$$EV_i(\gamma^f_{i0t}, \boldsymbol{x}_t) = EV_i(\gamma^f_{i0t}, \omega_{it}) = \ln\left(\exp(\omega_{it}) + \exp\left(\gamma^f_{i0t} + \delta\, \mathbb{E}[EV_i(\gamma^f_{i0t+1}, \omega_{it+1}|\omega_{it}]\right)\right). \tag{6.14}$$

Several studies that have estimated demand for durable products using household level data.[68] However, Gowrisankaran and Rysman (2012) offer a way to estimate the model using aggregate data, which directly extend the methods of BLP.

If consumer level data are observed then, in principle, identification follows the standard arguments (Rust, 1994; Magnac and Thesmar, 2002).[69] With aggregate data we do not observe the purchase history of each consumer, which makes identification significantly more difficult. Intuitively, the key to identifying the model and to separating the different alternative models is the ability of the models to explain both the cross-sectional variation, across markets and products, and the time series variation.

We are unaware of a formal identification proof. Standard identification proofs for static models require some form of substitution between products (Berry et al., 2013). In static models the substitution is between products in a given period, but here the requirement is for substitution over time and across products. This need not be satisfied. For example, if the price of a high quality product falls at time t it could actually increase the demand for a low quality product at $t-1$, because some consumers might buy it for one period.

The estimation, using aggregate data, follows closely the method proposed by Berry et al. (1995), but nests a solution of the dynamic programming problem inside the inner

[68]For example, Erdem et al. (2005), or Prince (2008).

[69]The standard arguments need to be adjusted for the existence of ξ_{jt}, but with enough observations these could be controlled for and then we are back in the standard case.

loop. The idea is to follow the algorithm detailed in Section 4.3.4, but in Step 1 in order to compute the market shares we need to solve the dynamic problem for each of the simulated individuals. This is done by computing the inclusive value (using equation (6.12) and an initial guess for EV_i) for each simulated individual i. This in turn is used to compute $F(\omega_{it+1} \mid \omega_{it}(\boldsymbol{x}_t))$, which is used to update EV_i. The process is continued until it converges. If we think of the BLP algorithm as a nested fixed point, then here we have another layer of nesting in order to compute the market shares.

7 Concluding Comments

In this chapter we review the modern IO approach to modeling demand and supply in differentiated products industries. In many cases, we only scratch the surface of many of the topics we discussed and there are many topics that are left uncovered. For example, many of the applications of the models we discussed are covered in other chapters of this Handbook. The success of the methods we discuss here is reflected in their application to areas such as health, finance, taxation, housing and school choice, development, environmental policy and political economy, that historically were very different than IO. This is a positive trend that we hope will continue into the future as IO economists continue developing more flexible models and improved computational methods.

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