# Brett Gordon Marketing Science (2008): A Dynamic Model of Consumer Replacement Cycles in the PC Processor Industry

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Main question: In mature high-tech markets (e.g. computers, cell phones, etc.) replacement purchases are the dominant proportion of sales. Little work separates out the problem of replacement sales versus initial adoption, an analysis complicated by dynamics.

- What do replacement cycles look like?
- How does a big innovation effect replacement?

Basic idea: augment basic logit model with evolving outside option. Match model prediction against a rich set of data.

#### 1 Data

- Looking at the PC processor industry dominated by Intel and AMD.
- Intel is the leader. AMD used to be low-price low-quality competitor, role has changed over time (see figure 2)
- Data available:

- 1. Shipments of processors. Because of just-in-time inventory, little time delay between shipment of processor and purchase of a PC.
- 2. Portion of sales for replacement machines (i.e. households purchasing a computer who already have a computer) (figure 5).
- 3. Survey data: information on consumer PC ownership and penetration rates (figures 1 and 4). See how long consumers hold onto computers (Pentium vs Pentium II).
- 4. Prices (of processors)
- 5. Quality CPU Scorecard benchmark rating for processors.
- 6. Underlying assumption: Processor is what people care about when buying a computer

### 2 Model

- Model only of consumers. Consumers buy only one computer at a time (more of a data limitation)
- No used-market for computers.
- No maintenance costs computers maintain their quality (i.e. CPU Scorecard rating)
- Only looking at consumers firms' behavior is taken as exogenous.
- Products are represented by a scale quality attribute  $q_{jk} \in Q = \{1, 2, ..., \bar{q}\}$  for product  $j \in J$  of firm  $k \in K$ .
- $\mathbf{q}_t$  vector of products available in period t,  $\mathbf{p}_t$  is the associated vector of prices.
- Product quality and price evolve according to an exogenous stochastic process.

• Consumers have different outside options (their current computer). Outside option is  $\tilde{q}_{kt}$ , element in the set of

$$\tilde{Q}_t = \left\{ \tilde{q}_k : \tilde{q}_k \in \{\cup_{\tau=1}^t \mathbf{q}_\tau\} \cup \{0\} \right\}$$
(1)

where  $\tilde{q} = 0$  represents a consumer without a computer.

• Consumer of type i's indirect utility function

$$u_{ijk} = \gamma_i q_{jk} - \alpha_i p_{jk} + \xi_{ik} + \epsilon_{ijk} \tag{2}$$

where  $\gamma$  is taste for quality and  $\xi$  is a firm fixed-effect.

- note this is a simple logit without an unobserved characteristic presumably quality measure in the data is very good.
- Indirect utility from outside option is

$$\underline{\mathbf{u}}_{i,\tilde{q}_{k}} = \begin{cases} \gamma_{i}\tilde{q}_{k} + \xi_{ik} + \epsilon_{ik} & \text{if } \tilde{q}_{k} > 0\\ \epsilon_{i0} & \text{if } \tilde{q}_{k} = 0 \end{cases}$$
(3)

- Important the outside option will as consumers upgrade their computers!
- Consumer problem:

$$V_i(\tilde{q}_k, \mathbf{q}_t, \mathbf{p}_t, \epsilon) = \max\left\{\underline{u}_i(\tilde{q}_k, \epsilon) + \beta E[V_i(\tilde{q}_k, \mathbf{q}'_t, \mathbf{p}'_t, \epsilon')|\mathbf{q}_t, \mathbf{p}_t],$$
(4)

$$\max_{q' \in \mathbf{q}} \{ u_i(q', \mathbf{q}_t, \mathbf{p}_t, \epsilon) + \beta E[V_i(q', \mathbf{q}'_t, \mathbf{p}'_t, \epsilon') | \mathbf{q}_t, \mathbf{p}_t] \}$$
(5)

#### **3** Implementation

- Simplify, simplify, simplify!
- Intel and AMD each only offer 2 products: frontier and non-frontier composite products. Split product into 2 groups using median product.

- 2 types of consumers (kept adding types until results did not change)
- Price expectations: VAR

$$\log(p_t) = A_0 + A_1 \log(p_{t-1}) + z_t$$
, where  $z \sim N(0, \Sigma)$  (6)

- Quality expectations: Make quality measure discrete. Let  $\phi(q_{jkt}) = q_{jkt} q_{jk,t-1}$  denote change in quality.
- Probability of *no* quality change

$$\Pr(\phi(q_{jkt}) = 0 | q_{jk,t-1}) = \kappa_0 + \kappa_1 q_{jk,t-1} + \epsilon_q,$$
(7)

where  $\epsilon$  is normally distributed.

- Given there is quality change, the probability of quality change follows a standard Poisson process.
- Assume the innovation process is *independent* across products (can there be innovation on non-frontier product?)
- Implicitly no dependence between price and quality evolution (which is odd in appendix has a specification which allows for dependence).
- Demand
  - market size evolves deterministically,  $M_t$ .
  - Assume  $\epsilon_{jkt}$  is iid and type 1 extreme value
  - demand for product (jk) by consumer  $(i, \tilde{q}_l)$  is

$$d_{jkt}(\tilde{q}_l, i) = \frac{\exp[V_i(q_{jk}, \tilde{q}_l, \mathbf{q}_t, \mathbf{p}_t)]}{\sum_{q' \in \mathbf{q}_t \cup \tilde{q}_l} \exp[\bar{V}_i(q', \tilde{q}_l, \mathbf{q}_t, \mathbf{p}_t)]}$$
(8)

• Choice-specific value function  $\bar{V}_i$  is equal to

$$\bar{V}_{i}(q_{jk}, \tilde{q}_{l}, \mathbf{q}_{t}, \mathbf{p}_{t}) = u_{i}(q_{jk}, \tilde{q}_{l}, \mathbf{q}_{t}, \mathbf{p}_{t}) + \beta \int_{\mathbf{p}_{t+1}} \int_{\mathbf{q}_{t+1}} \log \left( \sum_{q' \in \mathbf{q}_{t} \cup \tilde{q}_{l}} \exp[\bar{V}_{i}(q_{jk}, \mathbf{q}_{t+1}, \mathbf{p}_{t+1})] \right) \Pi_{q}(\mathbf{q}_{t+1} | \mathbf{q}_{t}) \Pi_{p}(\mathbf{p}_{t+1} | \mathbf{p}_{t}) \quad (9)$$

- Aggregating across consumers and their choices, to get market share prediction, is a little complicated
  - note  $d_{jkt}$  is sales, NOT predicted market share. Need to include those that "stay"
  - Total new demand is

$$x_{jkt} = M_t \sum_{\tilde{q}_l \in \tilde{Q}_t, \tilde{q}_l \neq q_{jk}} \Delta_{lt} \sum_{i \in I} d_{jkt}(\tilde{q}_l, i) \Delta_{it|l}$$
(10)

where  $\Delta_{lt}$  is the fraction of consumers who own l in period t, and  $\Delta_{it|l}$  is the fraction of consumers who own l in period t that are type i.

- To get the stock correct next period, need to account for those who stay.
- Just accounting tricky to track, but not hard conceptually
- As in Rust, big hurdle is solving for the value function. Use the same contraction mapping approach, where you guess an initial value to the value function and then iterate according to equation 4
- Need to computationally integrate over integral for next period's prices and qualities. Gordon forms grids of price and quantity, ends up taking a weighted mean (usual approach).
- Uses GMM moments are
  - 1. demand shares
  - 2. ownership shares; matching share of owners of a particular product and the penetration rate (i.e. 1 households who do not buy a computer)

- Need to instrument for price –usual BLP instruments of characteristics and averages of other product's characteristics.
- discount rate is fixed,  $\beta = 0.98$ .

## 4 results and implications

- Spends a lot time in working paper comparing dynamic model to more simple alternatives (e.g. myopic). See table 4
- High price elasticities from a permanent price change (which seem sensible) Table 5 and Table 6.
- Focus on replacement cycles. Average is 3.3 years (matches industry results), but segments differ (table 7 and figure 8).
- Table 9 shows that larger innovations have less an effect on replacement cycle over time (or that the replacement cycle is slowing). Curvature on quality in the indirect utility would strengthen this.
- Figure 10,11 is highlighting why replacement is slowing.
- Slowing replacement due to low types dominating the market figure 7 and figure 12
- Managerial implications may be able to discriminate across types of consumers b/c they are different replacement cycles.

#### **General Comments**

- Nice empirical paper integrates a number of different data sources.
- Careful selection of moments for the paper to match.
- Model itself is fairly straightforward, but well-tailored for the application.

- Could use a richer model, but to what end? For the questions asked, seems fine. Look at all the alternative specifications to see on what dimensions Gordon added richness.
- Could have done more with the joint price and quality innovations. Should that not be crucial for replacement cycles? Though hard to model.
- Adding in unobservable characteristic is not that easy. See Gowrisankaran and Rysman (2008) working paper.