Week 10: Price Discrimination / Dynamics

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Logistics

Week 10

- Ref report presentations next week
- Keep working on research proposalour own reference soon
- Problem set solutions posted very soon

Overview

Hendel & Nevo (2006)

- Canonical product market analyses study static demand, rather than dynamic demand
  - In dynamic setting, consumers buy more when prices low, substituting away from purchases where prices are high
  - Requires that goods are storable
- Dynamic behavior by consumers has the potential to bias static demand estimates
- Temporary price reductions are common for many goods, resulting in increased quantities sold
  - True even without marginal cost shocks
  - A form of second-degree price discrimination (inter-temporally)

Overview

Hendel & Nevo (2006)

- Authors develop dynamic model of consumer behavior; no supply side but complicated enough with just demand
- People aware of issues with consumer dynamics, but finding parsimonious way to model/estimate this difficult
- Under specific assumptions separating how brand preferences relate to dynamic inventory choice, authors develop clever way to estimate dynamic behavior specification
- Use panel data with 218 households buying laundry detergent, a lot of depth on panel
  - Illustrates limitations of approach, even with simplicity
  - Methodology applies to many settings

Overview

Hendel & Nevo (2006)

- Results show improvements to static framework, with implications for studies of pricing and mergers (e.g. Bresnahan, BLP, Nevo):
  - Static demand overestimates own-price elasticities by 30%
  - Static demand underestimates cross-price elasticities by up to a factor of five
  - Overestimate substitution to outside option in static setup
- Though no explicit supply side, implications for price cost margins are inversely proportional to elasticity, implying 30% higher markups with dynamic estimates
- Bias even larger for multi-product firms because of cross-price elasticities
- Static models will underpredict effects of mergers

Dynamic Models

Hendel & Nevo (2006)

- When should you estimate a dynamic model?
- Answer is not just 'when dynamics could be important in environment'
- Things to consider:
  - Is it likely adding dynamics will substantially alter conclusions?
  - Trade-off between incremental model complexity and incremental economic results
  - Can you see dynamic phenomenon clearly in the data?
  - Can your dynamic model incorporate rich enough data structures?
  - Are you writing a methodological paper?

Data

Hendel & Nevo (2006)

- IRI Scanner data from 1991-1993 with store and household level data
- Store level data:
  - For each brand-size combo the price charged, quantity sold, and promotional activities
- Household level data:
  - Purchases at household level over two years
  - Know when they visit supermarket
  - Purchases of 24 products, how much paid

Purchase Data

Hendel & Nevo (2006)

TABLE I

SUMMARY STATISTICS OF HOUSEHOLD-LEVEL DATA[a]

	Mean	Median	Std	Min	Max
Demographics					
Income (000's)	35.4	30.0	21.2	<10	>75
Size of household	2.6	2.0	1.4	1	6
Live in suburb	0.53	—	—	0	1
Purchase of laundry detergents					
Price ($)	4.38	3.89	2.17	0.91	16.59
Size (oz.)	80.8	64	37.8	32	256
Quantity	1.07	1	0.29	1.00	4
Duration (days)	43.7	28	47.3	1	300
Number of brands bought over the 2 years	4.1	3	2.7	1	15
Brand HHI	0.53	0.47	0.28	0.10	1.00
Store visits					
Number of stores visited over the 2 years	2.38	2	1.02	1	5
Store HHI	0.77	0.82	0.21	0.27	1.00

[a]For Demographics, Store visits, Number of brands, and Brand HHI, an observation is a household. For all other statistics, an observation is a purchase instance. Brand HHI is the sum of the square of the volume share of the brands bought by each household. Similarly, Store HHI is the sum of the square of the expenditure share spent in each store by each household.

Industry Structure

Hendel & Nevo (2006)

- 70% liquid detergent (focus of paper)
- Modal price 71% of time, sale 5% below modal
- Median sale discount \$0.40, mean \$0.67 (8%-12%)
- Variation across brands in quantity sold on sale
- 97% of volume of detergent sold in five size categories
  - Product choice will be split into brand and size choice
- Data records two types of promotional activities used in mode:
  - Feature: Correlation with sale 0.38
  - Display: Correlation with sale 0.23
  - Conditional on feature/display sale % is (93%/50%)

Industry Structure

Hendel & Nevo (2006)

TABLE II

BRAND VOLUME SHARES AND FRACTION SOLD ON SALE[a]

	Liquid					Powder				
	Brand	Firm	Share	Cumulative	% on Sale	Brand	Firm	Share	Cumulative	% on Sale
1	Tide	P & G	21.4	21	32.5	Tide	P & G	40	40	25.1
2	All	Unilever	15	36	47.4	Cheer	P & G	14.7	55	9.2
3	Wisk	Unilever	11.5	48	50.2	A & H	C & D	10.5	65	28
4	Solo	P & G	10.1	58	7.2	Dutch	Dial	5.3	70	37.6
5	Purex	Dial	9	67	63.1	Wisk	Unilever	3.7	74	41.2
6	Cheer	P & G	4.6	72	23.6	Oxydol	P & G	3.6	78	59.3
7	A & H	C & D	4.5	76	21.5	Surf	Unilever	3.2	81	11.6
8	Ajax	Colgate	4.4	80	59.4	All	Unilever	2.3	83	
9	Yes	Dow Chemical	4.1	85	33.1	Dreft	P & G	2.2	86	15.2
10	Surf	Unilever	4	89	42.5	Gain	P & G	1.9	87	16.7
11	Era	P & G	3.7	92	40.5	Bold	P & G	1.6	89	1.1
12	Generic	—	0.9	93	0.6	Generic	—	0.7	90	16.6
13	Other	—	0.2	93	0.9	Other	—	0.6	90	19.9

[a]Columns labeled Share are shares of volume (of liquid or powder) sold in our sample, columns labeled Cumulative are the cumulative shares, and columns labeled % on Sale are the percent of the volume, for that brand, sold on sale. A sale is defined as any price at least 5 percent below the modal price, for each UPC in each store. A & H = Arm & Hammer; P & G = Procter and Gamble; C & D = Church and Dwight.

Quantity Discounts

Hendel & Nevo (2006)

TABLE III

QUANTITY DISCOUNTS AND SALES[a]

	Quantity Discount (%)	Quantity Sold on Sale (%)	Weeks on Sale (%)	Average Sale Discount (%)	Quantity Share (%)
Liquid					
32 oz.	—	2.6	2.0	11.0	1.6
64 oz.	18.1	27.6	11.5	15.7	30.9
96 oz.	22.5	16.3	7.6	14.4	7.8
128 oz.	22.8	45.6	16.6	18.1	54.7
256 oz.	29.0	20.0	9.3	11.8	1.6
Powder					
32 oz.	—	16.0	7.7	14.5	10.1
64 oz.	10.0	30.5	16.6	12.9	20.3
96 oz.	14.9	17.1	11.5	11.7	14.4
128 oz.	30.0	36.1	20.8	15.1	23.2
256 oz.	48.7	12.9	10.8	10.3	17.3

[a] All cells are based on data from all brands in all stores. The column labeled Discount presents percent quantity discount (per unit) for the larger sizes, after correcting for differences across stores and brands (see text for details). The columns labeled Quantity Sold on Sale, Weeks on Sale, and Average Sale Discount present, respectively, the percent quantity sold on sale, percent of weeks a sale was offered, and average percent discount during a sale, for each size. A sale is defined as any price at least 5 percent below the modal. The column labeled Quantity Share is the share of the total quantity (measured in ounces) sold in each size.

Preliminary Analysis

Hendel & Nevo (2006)

- Initial analysis of data showing that dynamics matter
- Duration since previous sale has positive effect on aggregate quantity purchase, during sale and non-sale periods
- Indirect measures of storage costs correlated negatively with tendency to buy on sale
- Households more likely to buy during a sale conditional on inventory/time to previous purchase (and buy more)
- Variation in storage costs across categories consistent with patterns of purchases during sales

Model

Hendel & Nevo (2006)

- Consumer h obtains per period utility:

$$u(c_{ht} + v_{ht}; \theta_h) + \alpha_h m_{ht}$$

- c is quantity consumed, v is a shock that changes marginal utility of consumption
- θ vector of consumer-specific taste parameters
- m is outside good consumption, α is marginal utility of outside good
- J different brands, $c_{ht} = \Sigma_j c_{jht}$
- Consumers face random and potentially non-linear prices each period

Model

Hendel & Nevo (2006)

- In each period consumers decide:
  - Brand to buy if they buy
  - How much to buy
  - How much to consume
- Assumptions make it so that consumption not affected by brands in storage
- x_{ht} choice of size, doesn't matter how you get there. Price is p_{jxt}
- Assume purchase 1 per period at most: $\Sigma_{j,x} d_{hjxt} = 1$

Value Function

Hendel & Nevo (2006)

$$
\begin{aligned}
(1) \qquad & V(s_1) \\
& = \max_{\{c_h(s_t), d_{hjx}(s_t)\}} \sum_{t=1}^{\infty} \delta^{t-1} E\Big[u(c_{ht}, \nu_{ht}; \boldsymbol{\theta}_h) - C_h(i_{h,t+1}; \boldsymbol{\theta}_h) \\
& \qquad + \sum_j d_{hjxt}(\alpha_h p_{jxt} + \xi_{hjx} + \beta_h a_{jxt} + \varepsilon_{hjxt}) \Big| s_1 \Big] \\
& \text{s.t.} \quad 0 \le i_{ht}, \quad 0 \le c_{ht}, \quad 0 \le x_{ht}, \quad \sum_{j,x} d_{hjxt} = 1, \\
& \qquad i_{h,t+1} = i_{ht} + x_{ht} - c_{ht},
\end{aligned}
$$

- $C_h(i; \theta_h)$ cost of storage, ξ_{hjx} idiosyncratic taste, a_{jxt} is advertising, idiosyncratic shock ϵ_{hjxt}
- s_t state at t is composed of i_t, p, v_t, and ϵ. Consumers face future uncertainty about future utility shocks and future prices

Model Assumptions

Hendel & Nevo (2006)

- **Assumption 1:** v_t is independently distributed over time and across consumers
  - Serial correlation leads to high computational burden
- **Assumption 2:** Prices (and advertising) follow an exogenous first order Markov process
  - What happened to the supply side?
  - Are they effectively controlling for things like seasonality?
  - Exogenous process, process is independent of unobserved random components (things not modeled explicitly here). This is an advantage of household level data
- **Assumption 3:** ϵ_{jxt} is i.i.d. logit
  - Model persistence based on observed variables
- Product differentiation at time of choice, not for consumption, under several assumptions is valid

Econometrics

Hendel & Nevo (2006)

- Dynamic estimation procedure takes substantially longer than static
- Algorithm nests dynamic programming solution (computed numerically) within parameter search
- Assuming distribution of unobserved shocks, derive likelihood of observing each consumer's decision conditional on prices and inventory
  - Search over parameters to match with observed data
- **Problem 1:** Don't observe initial inventory or consumption
  - Start at arbitrary initial inventory and use 'pre-period' in data to generate inventory implied by model
  - Conditional on initial inventory, solve sequential problem subject to other parameters

Econometrics

Hendel & Nevo (2006)

- For given value of parameters, probability of observing sequence of purchase decisions $d_1....d_T$ is a function of the observed state variables $p_1....p_T$:

$$\text{(2)} \qquad \Pr(d_1 \cdots d_T | p_1 \cdots p_T) = \int \prod_{t=1}^{T} \Pr\big(d_t | p_t, i_t(d_{t-1}, \ldots, d_1, \nu_{t-1}, \ldots, \nu_1, i_1), \nu_t\big)\, dF(\nu_1, \ldots, \nu_T)\, dF(i_1).$$

$$\text{(3)} \qquad \Pr(d_{jx} | p_t, i_t, \nu_t) = \frac{\exp(\alpha p_{jxt} + \xi_{jx} + \beta a_{jxt} + M(s_t, j, x))}{\sum_{k,y} \exp(\alpha p_{kyt} + \xi_{ky} + \beta a_{kyt} + M(s_t, k, y))},$$

- $M(s, j, x)$ is complete discounted utility value implied by the optimal choice of c_t, conditional on purchase d_{jxt}

Econometrics

Hendel & Nevo (2006)

- **Problem 2:** Dimensionality of state space in general model is huge
  - Individual inventories, shocks, prices of all brands and sizes, promotional activities
  - Computationally infeasible

Econometrics

Hendel & Nevo (2006)

- So they propose three step procedure to reduce computational burden without giving up too much in terms of credibility:
  - Step 1: Maximizing observed brand choice likelihood *conditional on size bought* (to recover non-dynamic parameters)
  - Step 2: Compute inclusive values associated with each size and transition probabilities from period to period
  - Step 3: Apply nested algorithm with dynamic program to simplified maximization problem. This maximization is for sequence of quantities only, with single ‘price’ or inclusive value for each category
  - Time indepedent shocks makes this possible

Algorithm Part I

Estimating Static Parameters

- Probability of choosing brand j and size x:

$$Pr(d_{jt} = 1, x_t | p_t, i_t, v_t) = Pr(d_{jt} = 1 | p_t, x_t, i_t, v_t) Pr(x_t | p_t, i_t, v_t)$$
$$Pr(d_{jt} = 1 | p_t, x_t, i_t, v_t) = Pr(d_{jt} = 1 | x_t, p_t) =$$
$$\frac{exp(\alpha p_{jxt} + \xi_{jx} + \beta a_{jxt})}{\Sigma_k exp(\alpha p_{kxt} + \xi_{kx} + \beta a_{kxt})}$$

- In general, need dynamic programming to find above, but here can be found statically:
  - Optimal consumption, conditional on quantity purchased, is not brand specific
  - Conditional distribution of ϵ not a function of x
- Maximize product over time wrt parameters (static model conditional on size)

Algorithm Part II

Inclusive Quantity Values

- State variables of simplified dynamic problem are inclusive values of each quantity, i.e. quality adjusted price index for all brands of size x:

$$\omega_{xt} = log[\Sigma_k exp(\alpha p_{kxt} + \xi_{kx} + \beta a_{kxt})]$$

- Inclusive value is utility expected by consumer from brands of size x before ϵ realized
- **Assumption 4:** $F(\omega_t | s_{t-1})$ is summarized by $F(\omega_t | \omega_{t-1})$
- If marginal income utility and income are household specific, problem needs to be solved for each household (they group into six types)
- Inclusive prices represent all prices in parsimonious space (what is loss?)

Algorithm Part III

Dynamic Param. Search

- Flow utility of x is $\omega_{xt} + \epsilon_{xt}$
- Simplified dynamic problem:

$$
\begin{aligned}
& V(i_t, \omega_t, \varepsilon_t, \nu_t) \\
& \quad = \operatorname*{Max}_{\{c,x\}} \{ u(c + \nu_t) - C(i_{t+1}) + \omega_{xt} + \varepsilon_{xt} \\
& \qquad\qquad + \delta E[V(i_{t+1}, \omega_{t+1}, \varepsilon_{t+1}, \nu_{t+1}) | i_t, \omega_t, \varepsilon_t, \nu_t, c, x] \}.
\end{aligned}
$$

- Use estimated inclusive values and transition probabilities to estimate utility and storage cost
- **Claim 1:** Prices for all products can be replaced by inclusive values of observed prices in computation of $Pr(x_t)$
- Claim 1 is not obvious, Assumptions 3 and 4 imply that expected value of choice is same under both regimes
- Complex numerical value function optimization

Identification

Hendel & Nevo (2006)

- **Static parameters:** variation over time in prices and advertising identify coefficients using variations in shares across products.
- Heterogeneity identified by sensitivity conditional on demogaphics, household specific brand FE

Identification

Hendel & Nevo (2006)

- **Dynamic Parameters:** Inventory and consumption are unobserved, identified from patterns in prices, purchases now, previous purchases
    - Probability of purchase with current prices conditional on past purchases
    - Storage costs: Same price process, same aggregate purchase amount, one purchases more frequently implies higher storage costs
    - Given storage costs, preferences determine level of demand
    - Given demand, storage costs imply interpurchase duration and able to leverage sales

Identification

Hendel & Nevo (2006)

- Procedure allows for heterogeneity as function as observed household attributes and past behavior
  - Cannot allow for persistent unobserved heterogeneity
  - Need to compute brand choice probability conditional on size integrating over types conditional on size purchased! Need to solve dynamic problem to do this
- Household brand dummies included, do not substantially impact computational costs
- Only need to estimate brand preferences for brands actually purchased, pretty interesting

Paramaterization & Final Data

Hendel & Nevo (2006)

- Assume $u(c+v) = \gamma log(c_t + v_t)$ and $C(i) = \beta_1 i_t + \beta_2 i_t^2$
- v distributed log-normal
- For inclusive value evolution, assume ω_{st} distributed normal with mean $\gamma_{s0} + \gamma_{s1}\omega_{1,t-1} + ...\gamma_{s4}\omega_{4,t-1}$ and σ_s
- Dynamic programming solved by parametric polynomial policy apporximation
- Estimation performed with sample of 218 households:
    - More than 10, less than 59 detergent purchases
    - 75% liquid purchases
    - 45-103 supermarket visits, with 3,772 liquid detergenet purchases
    - Third stage with visits 11-35, 1-10 used for initial inventory, avoid right censoring

Results

Hendel & Nevo (2006)

- Static Model:
  - Feature and display matter a lot, cutting price coefficient in half
  - Highlight how approach here can easily control for observed variables
  - Family size, race, and suburbs are important
- Price Process:
  - Inclusive values estimated vary by household, grouped in this specification
  - Internally consistent treatment of advertising: predict future impact of it
  - Lagged own-inclusive values matter most
  - Explore alternatives to first-order Markov

Static Parameter Estimates

Hendel & Nevo (2006)

TABLE IV

FIRST STEP: BRAND CHOICE CONDITIONAL ON SIZE[a]

	(i)	(ii)	(iii)	(iv)	(v)	(vi)	(vii)	(viii)	(ix)	(x)
Price	−0.51	−1.06	−0.49	−0.26	−0.27	−0.38	−0.38	−0.57	−1.41	−0.75
	(0.022)	(0.038)	(0.043)	(0.050)	(0.052)	(0.055)	(0.056)	(0.085)	(0.092)	(0.098)
*Suburban dummy				−0.33	−0.30	−0.34	−0.33	−0.25	−0.45	−0.19
				(0.055)	(0.061)	(0.055)	(0.056)	(0.113)	(0.127)	(0.127)
*Nonwhite dummy				−0.34	−0.39	−0.38	−0.33	−0.34	−0.33	−0.26
				(0.075)	(0.083)	(0.076)	(0.076)	(0.152)	(0.166)	(0.168)
Large family				−0.23	−0.13	−0.21	−0.22	−0.46	−0.38	−0.43
				(0.080)	(0.107)	(0.080)	(0.082)	(0.181)	(0.192)	(0.195)
Feature			1.06	1.05	1.08	0.92	0.93	1.08		1.05
			(0.095)	(0.096)	(0.097)	(0.099)	(0.100)	(0.123)		(0.126)
Display			1.19	1.17	1.20	1.14	1.15	1.55		1.52
			(0.069)	(0.070)	(0.071)	(0.071)	(0.072)	(0.093)		(0.093)
Brand dummy variable		✓	✓	✓	✓					
*Demographics					✓					
*Size						✓				
Brand–size dummy variable							✓			
Brand-HH dummy variable								✓		
*Size									✓	✓

[a] Estimates of a conditional logit model. An observation is a purchase instance by a household. Options include only products of the same size as the product actually purchased. Asymptotic standard errors are shown in parentheses.

Price Process Estimates

Hendel & Nevo (2006)

TABLE V

SECOND STEP: ESTIMATES OF THE PRICE PROCESS[a]

	Same Process for All Types				Different Process for Each Type			
	ω_{2t}	ω_{4t}	ω_{2t}	ω_{4t}	ω_{2t}	ω_{4t}	ω_{2t}	ω_{4t}
$\omega_{1,t-1}$	0.003	−0.014	0.005	0.014	−0.023	−0.005	−0.019	0.007
	(0.012)	(0.011)	(0.014)	(0.014)	(0.017)	(0.014)	(0.019)	(0.015)
$\omega_{2,t-1}$	0.413	0.033	0.295	0.025	0.575	−0.003	0.520	0.011
	(0.007)	(0.010)	(0.008)	(0.007)	(0.013)	(0.010)	(0.016)	(0.013)
$\omega_{3,t-1}$	0.003	−0.034	0.041	−0.006	0.027	−0.072	0.051	−0.018
	(0.007)	(0.007)	(0.009)	(0.009)	(0.020)	(0.016)	(0.025)	(0.020)
$\omega_{4,t-1}$	0.029	0.249	0.026	0.236	−0.018	0.336	−0.018	0.274
	(0.008)	(0.008)	(0.008)	(0.017)	(0.020)	(0.016)	(0.021)	(0.017)
$\sum_{\tau=2}^{5} \omega_{1,t-\tau}$			−0.003	−0.012			−0.008	−0.003
			(0.005)	(0.004)			(0.006)	(0.005)
$\sum_{\tau=2}^{5} \omega_{2,t-\tau}$			0.089	0.006			0.073	−0.004
			(0.003)	(0.002)			(0.005)	(0.004)
$\sum_{\tau=2}^{5} \omega_{3,t-\tau}$			−0.008	−0.009			−0.004	−0.016
			(0.003)	(0.003)			(0.008)	(0.006)
$\sum_{\tau=2}^{5} \omega_{4,t-\tau}$			−0.013	0.018			−0.008	0.056
			(0.003)	(0.003)			(0.007)	(0.005)

[a]Each column represents the regression of the inclusive value for a size (32, 64, 96, and 128 ounces, respectively) on lagged values of all sizes. The inclusive values were computed using the results in column (x) of Table IV. The four left columns impose the same process for each household type; the four right columns allow for a different process for each type. Reported results are only for households of type 3, that is, households in market 1 with large families. Results for other types are available from the authors.

Results

Hendel & Nevo (2006)

- Dynamic Parameters:
  - Six types each with different storage utility parameters and size fixed effects
  - With 30oz inventory, buying 128oz relative to 64oz increases storage cost by $.20 to $.75 depending on household type
  - With $.40 per unit savings from non-linear pricing, stratifies purchasing
  - 27-33oz is estimated median inventory held
  - Mean consumption between 22-36 oz
- Model Fit:
  - Hazard rate probability of purchase since last duration
  - If not duration dependent, equal to 0.25 and constant
  - Model fits data quite well, better than static

Dynamic Parameter Estimates

Hendel & Nevo (2006)

TABLE VI

THIRD STEP: ESTIMATES OF DYNAMIC PARAMETERS[a]

Household Type:	1	2	3	4	5	6
		Urban Market			Suburban Market	
Household Size:	1–2	3–4	5+	1–2	3–4	5+
Cost of inventory						
Linear	9.24	6.49	21.96	4.24	4.13	11.75
	(0.01)	(0.02)	(0.09)	(0.01)	(0.17)	(5.3)
Quadratic	−3.82	1.80	−35.86	−8.20	−6.14	−0.73
	(29.8)	(1.77)	(0.19)	(0.03)	(1.69)	(1.53)
Utility from consumption	1.31	0.75	0.51	0.08	0.92	3.80
	(0.02)	(0.09)	(0.21)	(0.03)	(0.18)	(0.38)
Log likelihood	365.6	926.8	1,530.1	1,037.1	543.6	1,086.1

[a] Asymptotic standard errors are shown in parentheses. Also included are size fixed effects, which are allowed to vary by household type.

Model Fit

Hendel & Nevo (2006)

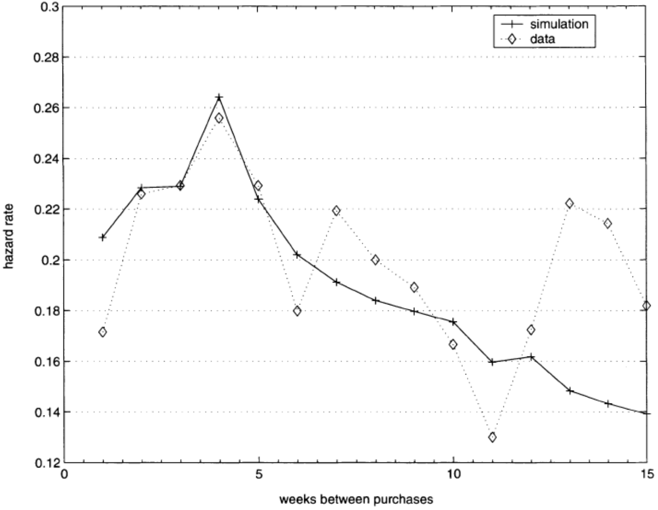

FIGURE 1.—Hazard rate of purchases.

Implications

Hendel & Nevo (2006)

- Elasticities:
  - Substitution to other products of same brands or sizes is higher (implied by fixed effects)
  - Substitution to outside option is pretty low
- Comparison to Static Model:
  - Static elasticities upward bias because of omitted inventories and expectations
  - Dynamic model needed to separate short-run inventory responses to long-run consumption and brand substitution effects
  - Static own-price elasticities overestimate by 30%
  - Cross-price elasticities are smaller in static setup (except for outside option). Intuition: substitution conditional on inventory in static short-run case

Implications

Hendel & Nevo (2006)

- With own price effect, and outside option effect, econometric bias and difference between short and long run effects are in same direction
- For cross-price elasticities, works in opposite directions
- PCM and mergers:
  - PCM roughly 30% higher for single product firms in dynamic model
  - Bias is even larger for multi-product firms
  - Static models will tend to find evidence of collusion when there is none, because PCM will be low
  - Static model underestimates impact of merger, because it underestimates substitution among products
  - Market definition and substitution to outside market

Long Run Elasticities

Hendel & Nevo (2006)

TABLE VII

LONG-RUN OWN- AND CROSS-PRICE ELASTICITIES[a]

Brand	Size (oz.)	All[b]	Wisk	Surf	Cheer	Tide	Private Label
All[b]	32	0.418	0.129	0.041	0.053	0.131	0.000
	64	0.482	0.093	0.052	0.033	0.085	0.006
	96	0.725	0.092	0.036	0.035	0.100	0.002
	128	−2.536	0.154	0.088	0.059	0.115	0.007
Wisk	32	0.088	0.702	0.046	0.012	0.143	0.006
	64	0.078	0.620	0.045	0.014	0.116	0.004
	96	0.066	0.725	0.051	0.022	0.135	0.009
	128	0.126	−2.916	0.083	0.026	0.147	0.005
Surf	32	0.047	0.061	0.977	0.024	0.369	0.003
	64	0.146	0.086	0.905	0.023	0.158	0.005
	96	0.160	0.101	0.915	0.016	0.214	0.001
	128	0.202	0.149	−3.447	0.039	0.229	0.008
Cheer	64	0.168	0.049	0.027	0.831	0.293	0.001
	96	0.167	0.015	0.008	0.982	0.470	0.001
	128	0.250	0.090	0.058	−4.341	0.456	0.003
Tide	32	0.071	0.085	0.050	0.022	1.007	0.002
	64	0.048	0.055	0.024	0.025	0.924	0.001
	96	0.045	0.063	0.016	0.026	1.086	0.001
	128	0.072	0.093	0.039	0.045	−2.683	0.001
Solo	64	0.066	0.070	0.027	0.021	0.150	0.002
	96	0.219	0.032	0.023	0.033	0.075	0.000
	128	0.127	0.125	0.060	0.043	0.302	0.001
Era	32	0.035	0.155	0.039	0.022	0.425	0.000
	64	0.030	0.103	0.039	0.018	0.304	0.008
	96	0.035	0.168	0.033	0.027	0.352	0.001
	128	0.054	0.192	0.061	0.029	0.513	0.014
Private	64	0.123	0.119	0.066	0.039	0.081	0.248
label	128	0.174	0.266	0.100	0.019	0.072	−2.682
No purchase		0.007	0.002	0.004	0.000	0.013	0.000

[a]Cell entries i and j, where i indexes row and j indexes column, give the percent change in market share of brand i with a 1 percent change in the price of j. All columns are for a 128 oz. product, the most popular size. The results are based on Tables IV–VI.

[b]Note that "All" is the name of a detergent produced by Unilever.

Comparison to Static Model

Hendel & Nevo (2006)

TABLE VIII

AVERAGE RATIOS OF ELASTICITIES COMPUTED FROM A STATIC MODEL TO LONG-RUN ELASTICITIES COMPUTED FROM THE DYNAMIC MODEL[a]

		64 oz.						128 oz.					
Brand	Size (oz.)	All[b]	Wisk	Surf	Cheer	Tide	Private Label	All[b]	Wisk	Surf	Cheer	Tide	Private Label
All[b]	64	1.03	0.13	0.14	0.12	0.13	0.15	0.14	0.17	0.17	0.18	0.21	0.34
	128	0.17	0.24	0.26	0.20	0.28	0.35	1.23	0.09	0.11	0.09	0.15	0.22
Wisk	64	0.14	1.20	0.13	0.17	0.12	0.13	0.16	0.22	0.14	0.22	0.25	0.20
	128	0.25	0.27	0.23	0.31	0.26	0.28	0.08	1.42	0.08	0.13	0.18	0.11
Surf	64	0.14	0.13	0.93	0.16	0.13	0.14	0.18	0.18	0.12	0.18	0.22	0.28
	128	0.25	0.22	0.18	0.27	0.25	0.18	0.12	0.11	1.20	0.08	0.15	0.14
Cheer	64	0.12	0.17	0.16	0.84	0.09	0.13	0.14	0.24	0.16	0.14	0.22	0.24
	128	0.25	0.26	0.26	0.12	0.23	0.22	0.09	0.12	0.06	0.89	0.15	0.07
Tide	64	0.16	0.17	0.13	0.13	1.26	0.15	0.22	0.28	0.16	0.26	0.22	0.37
	128	0.25	0.31	0.22	0.24	0.22	0.31	0.11	0.16	0.08	0.13	1.44	0.31
Solo	64	0.15	0.12	0.15	0.14	0.12	0.14	0.17	0.15	0.15	0.30	0.30	0.28
	128	0.23	0.20	0.24	0.21	0.21	0.25	0.07	0.07	0.06	0.16	0.17	0.21
Era	64	0.21	0.12	0.13	0.13	0.10	0.19	0.43	0.17	0.15	0.22	0.19	0.35
	128	0.31	0.22	0.24	0.25	0.17	0.38	0.19	0.08	0.09	0.11	0.10	0.22
Private	64	0.19	0.15	0.14	0.17	0.17	1.02	0.32	0.22	0.15	0.26	0.31	0.25
label	128	0.29	0.28	0.34	0.30	0.39	0.29	0.16	0.12	0.13	0.10	0.27	1.29
No purchase		2.12	1.13	1.15	1.40	1.27	2.39	1.80	7.60	2.26	14.11	2.38	10.86

[a]Cell entries i and j, where i indexes row and j indexes column, give the ratio of the (short-run) elasticities computed from a static model divided by the long-run elasticities computed from the dynamic model. The elasticities for both models are the percent change in market share of brand i with a 1 percent change in the price of j. The static model is identical to the model estimated in the first step, except that brands of all sizes are included as well as a no-purchase decision, not just products of the same size as the chosen option. The results from the dynamic model are based on the results presented in Tables IV–VI.

[b]Note that "All" is the name of a detergent produced by Unilever.

Takeaways

Hendel & Nevo (2006)

- Great example of clear methodological work on an important topic
  - Even if we don't care about detergent, results show dynamics matter and how to implement
  - Should this be used elsewhere, or is it a lesson to view static models with some caution for mergers / PCM?
- Household sample small, data are strong conditional on sample size
  - Estimation is quite difficult and many simplifictions
  - Shows inherent limitations of dynamic approach
- Discussion of time aggregation, longer data duration, shortcut to take care of dynamic effects?
- What is another potential context to investigate this in?