ECON-L1350 - Empirical Industrial Organization PhD I: Static Models

Lecture 11

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Outline: Previously

- Discrete choice demand models
  - Logit and nested logit
  - BLP
  - Variations (e.g. micromoments)
- Supply: price setting

Standard Discrete Choice

- The utility specification in the standard discrete choice framework (e.g., BLP):

$$u_{ijt} = x_{jt}\beta_{it} - \alpha p_{jt} + \xi_{jt} + e_{ijt} \quad (1)$$

  - Rely on observing demand using revealed preference
  - Assume that consumers have complete information about p_{jt}, ξ_{jt}, the availability of products $j \in \{1, ..., J\}$ etc.
  - Product availability observed, no uncertainty, no risk aversion, no mistakes in choices etc.
  - Is this realistic?
  - How does it matter for estimating demand and welfare?

Outline

- Additional topics to consider in welfare analysis:
  - What if we abandon complete information? And what if firm could affect available information through advertising?
  - What if consumers have misperceptions about product value?
  - How can we estimate demand/welfare if choices no longer reveal true valuations?

Revealed Preference Approach

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  - Choices are made after some information is revealed
    - E.g. buy insurance after the health risk is realized (adverse selection)
    - Observed demand tells little about value from ex-ante perspective (prior to demand is measured)
    - Welfare conclusions based on observed choices vary with the information that individuals have while making those choices

Revealed Preference Approach

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    - E.g. buy insurance after the health risk is realized (adverse selection)
    - Observed demand tells little about value from ex-ante perspective (prior to demand is measured)
    - Welfare conclusions based on observed choices vary with the information that individuals have while making those choices
  - Behavioral constraints or choice frictions
    - E.g., limited information, effects of advertising, misperceptions, inattention, inertia, cognitive limitations $\rightarrow$ perceived value differs from true value

Why Do We Care?

- Choice frictions appear in many markets and sectors of the economy
- Consumers make often seemingly bad choices
- For example, patients buy branded drugs, instead of cheaper generics, despite the fact that they are bioequivalent (work in the same way)
- Consumers lose money by not switching away from expensive electricity contracts
  - Because they lack information or are unaware of cheaper alternatives?
  - Because they have misperceptions about generics?
  - Because they have inertia or switching costs?

Why Do We Care?

- Policy question: should we use laws, defaults etc to reduce choice frictions?
- Are behavioral constraints/choice frictions welfare relevant or not?

Choice Frictions: True vs. Perceived Value (Handel et al., 2019)

- Individuals vary on willingness to pay w_i (say, for health insurance)
- Choice frictions enter the model as a distortion to an individual's willingness to pay
- The friction, denoted by f_i, results from, for example, limited information about risks or coverage, or decision biases at the time of purchase

Choice Frictions: True vs. Perceived Value (Handel et al., 2019)

- w_i: perceived value of product (determines demand)
- $v_i = w_i - f_i$: true value of product (welfare relevant)
- So f_i determines the difference between true value v_i and perceived value w_i, affecting individuals differently
- Even if true and perceived value are equal on average, true and perceived value may differ conditional on choice (since demand depends only on perceived value)

Demand with Choice Frictions (Handel et al., 2019)

- Demand: buy if perceived value exceeds price: $w_i \geq P$

$$D_w(P) = 1 - F_w(P).$$

- The demand curve shows what individuals are willing to pay at a given price P based on the perceived value w_i
- However, true utility is maximized by buying if $v_i = w_i - f_i \geq P$

Estimation and Identification

- How do we estimate true valuations?
- What the demand would be in absence of all choice frictions?
- How do we identify choice frictions?

Modeling Assumptions

- We need to modeling assumptions to identify departures from the standard demand model of complete information (e.g., BLP)
- E.g. specify a particular source of frictions
  - Uncertainty
  - Switching costs
  - Other behavior constrains
- Modeling choices motivated by institutional features / descriptive evidence

Current Best Practice

- Using data and institutional information, identify possible choice frictions and departures from the standard demand model.
  - Start with descriptive results
  - Add assumptions as needed, progress on this
  - Can even exploit quasi-experimental variation to affect choice frictions (laws, defaults etc.)

Literature: Role of Behavior Biases / Consumer Mistakes

Abaluck, Jason, and Jonathan Gruber. 2011. "Choice Inconsistencies among the Elderly: Evidence from Plan Choice in the Medicare Part D Program." American Economic Review, 101 (4): 1180-1210.

Big Question

- Are individuals making choices that are inconsistent with optimization under full information?
- Is it beneficial for individuals' welfare to allow them to choose across a wide variety of options that meet their needs ("more is better"), as suggested by standard economic theory?
- Should we constraint them to a limited (and possibly better) set of choices being made by the government?
- Setting: the choices of elders across a large number of health insurance options in the U.S.

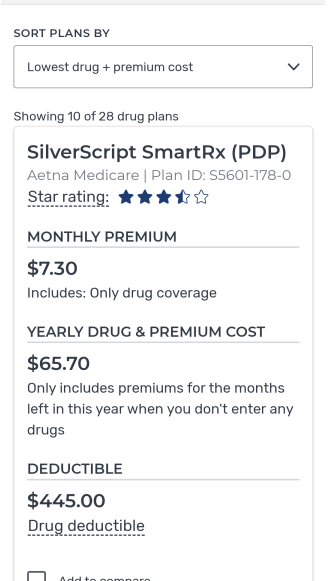
Setting: Medicare Part D

- The Medicare Modernization Act of 2003 added the Part D prescription drug benefit to the Medicare program
  - One of the most significant expansions of public insurance programs in the U.S.
  - Available for elderly (age 65 or older) and disabled individuals
- Dozens of private insurers were allowed to offer a wide range of products with varying prices and product features

Setting: Medicare Part D

- Complex choice situation
- The typical elder in the data faces a choice of over 40 stand-alone drugs plans
- The potential for cognitive failures rises at older ages, which may affect their ability to make choices

Medicare Plan Comparison



Plan Details

Below, swipe left and right to view more info.

Tiers	Initial coverage phase	Gap coverage phase	Catastrophic coverage phase
Preferred Generic	$0.00 copay	Generic drugs: 25% Brand-name drugs: 25%	Generic drugs: $3.70 copay or 5% (whichever costs more) Brand-name drugs: $9.20 copay or 5% (whichever costs more)
Generic	$19.00 copay		
Preferred Brand	$46.00 copay		
Non-Preferred Drug	49%		
Specialty Tier	25%		

- To lower costs, many plans place drugs into different "tiers"
- Generally, a drug in a lower tier will cost a patient less than a drug in a higher tier
- Three stages: deductible (if applicable), initial coverage, coverage gap ("donut hole"), and catastrophic coverage (low copayment amount set by Medicare)

Data

- Information on almost one-third of all third-party prescription drug transactions in the U.S. from the Wolters Kluwer (WK) Company
- Focus on transactions for individuals aged over age 65 during 2005–2006
- Linked to a comprehensive set of information from the Centers for Medicare and Medicaid Services (CMS) on the Part D plans available to each person in the dataset

Construction of Cost Variables

- The total enrollee costs of Part D can be decomposed into:
  - Premiums: known for certain at the time of plan choice
  - The distribution of out-of-pocket costs given the information available at the time when plans are chosen

Estimating Distribution of Out-of-Pocket Costs

- However, challenging to estimate the distribution:
  - observe only realized out-of-pocket costs for the chosen plan
  - observe only a single realization of out-of-pocket costs for each individual, making it impossible to estimate the variance

Estimating Distribution of Out-of-Pocket Costs

- To determine what each individual's realized costs would be for each plan in their choice set, assume that the set of 2006 claims is fixed and would remain constant had the individual in question chosen a different plan
- That is, assume no moral hazard
- To estimate the distribution (e.g., variance), sample realized costs from individuals who are "identical" to the individual in question at the time when the plan choice is made

Facts on Plan Choice

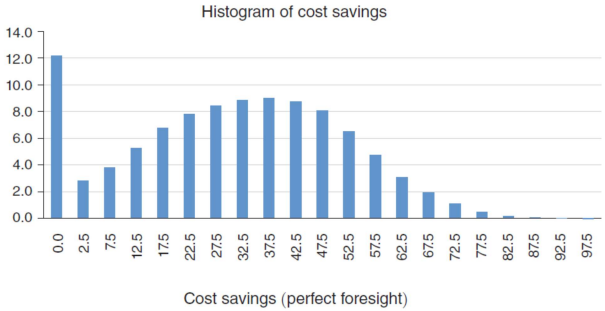


FIGURE 1. HISTOGRAM OF COST SAVINGS FROM SWITCHING TO LOWEST-COST PLAN (*Percents*)

- Only 12.2 percent of individuals choose the lowest-cost plan
- On average, individuals could save 30.9 percent of their total Part D spending by choosing the lowest-cost plan rather than the plan they chose

Part D Plan Choice with Testable Restrictions

A conditional logit model of plan choice where the utility of individual i from choosing plan j is given by:

$$u_{ij} = \pi_j \beta_0 + \mu^*_{ij} \beta_1 + \sigma^2_{ij} \beta_2 + x_j \lambda + q_{b(j)} \delta + e_{ij}$$

- $\beta_0 = \beta_1$, i.e. the coef. of premiums (π_j) = the coef. of the average out-of-pocket costs (μ^*_{ij})
  - Individuals should be willing to pay exactly one dollar in additional premiums for coverage, which reduces expected out-of-pocket costs by one dollar
  - Otherwise, they could switch to alternative plans with comparable risk (σ^2_{ij}) but lower total costs

Part D Plan Choice with Testable Restrictions

$$u_{ij} = \pi_j \beta_0 + \mu^*_{ij} \beta_1 + \sigma^2_{ij} \beta_2 + x_j \lambda + q_{b(j)} \delta + e_{ij}$$

- $\lambda = 0$: Individuals should not care about other financial characteristics x_j (e.g, cost sharing) per se; they should care only about these factors to the extent that they affect the distribution of out-of-pocket costs (μ^*_{ij} and σ^2_{ij})

Part D Plan Choice with Testable Restrictions

$$u_{ij} = \pi_j \beta_0 + \mu_{ij}^* \beta_1 + \sigma_{ij}^2 \beta_2 + x_j \lambda + q_{b(j)} \delta + e_{ij}$$

- $\lambda = 0$: Individuals should not care about other financial characteristics x_j (e.g, cost sharing) per se; they should care only about these factors to the extent that they affect the distribution of out-of-pocket costs (μ_{ij}^* and σ_{ij}^2)
- The coefficients on the variance of costs $\beta_2 < 0$: holds if individuals are risk averse

Conditional Logit

TABLE 1—CONDITIONAL LOGIT RESULTS

	(1)	(2)	(3)	(4)
Premium (hundreds)	−0.4330*** (0.0029)	−0.7663*** (0.0038)	−0.4990*** (0.0061)	−0.5218*** (0.0069)
OOP costs (realized) (hundreds)	−0.2127*** (0.1520)	−0.1172*** (0.0015)	−0.0961*** (0.0015)	−0.0967*** (0.0016)
Variance (times 10^6)	−0.0189*** (0.0027)	−0.0004 (0.0007)	−0.0006 (0.0007)	−0.0005 (0.0007)
Deductible (hundreds)	x	−0.2899*** (0.0049)	−0.1628*** (0.0067)	−0.1674*** (0.0072)
Donut hole	x	3.023*** (0.0181)	1.762*** (0.0277)	1.865*** (0.0303)
Generic coverage	x	0.4203*** (0.0140)	0.3004*** (0.0175)	0.2700*** (0.0177)
Cost sharing	x	3.282*** (0.0538)	1.189*** (0.0741)	1.057*** (0.0778)
Number of top 100 on form	x	0.0937*** (0.0007)	0.0587*** (0.0017)	0.0644*** (0.0018)
Average quality	0.4091*** (0.0032)	0.7398*** (0.0039)	x	x
Brand dummies	No	No	Yes	No

Testable Restrictions

- $\beta_0 \neq \beta_1$: the coefficient on premium is an order of magnitude larger than the coefficient on out-of-pocket expenditures
- $\lambda \neq 0$: generalized plan characteristics enter the model highly significantly, even conditional on individual out-of-pocket risk
- $\beta_2 \approx 0$: individuals are not willing to pay more for plans with lower variance in expected spending

Counterfactual

- What if premiums and out-of-pocket costs were equally weighted?
- Evaluate welfare in conditional logit models when positive and normative utility functions fail to coincide
- The normative (welfare-relevant) utility function sets restrictions on preferences ($\beta_0 = \beta_1$, $\lambda = 0$), unlike the positive utility function u_{ij}
  - Also assumes that e_{ij} do not matter for welfare
  - True, if e_{ij} are a result of optimization mistakes

Counterfactual

The welfare of consumer i in plan j:

$$W_{ij} = \frac{1}{\beta_0}(\beta_0(\pi_j + \mu_{ij}^*) + \sigma_{ij}^2\beta_2 + q_{b(j)}\delta).$$

- This metric omits from welfare other plan financial characteristics, non-financial brand characteristics, and the error term
- Appropriate if π_j, μ_{ij}^*, σ_{ij}^2 and $q_{b(j)}$ capture all welfare relevant factors of plans
- Other factors could matter only heuristically because consumers are unable to calculate, or unwilling to spend the time to calculate, the welfare metric above

Counterfactual

- The foregone welfare for individual i at time in plan j (chosen according to the maximization of the positive utility function) is given by

$$FW_i = W_{ijt} - W_i^*$$

  where $W_i^* = \max_j W_{jt}$ is the welfare for the best plan.
- Consumer mistakes led to a welfare loss equivalent to 27 percent of out-of-pocket expenditures on plan premiums and prescription drugs in 2006
- If there were some intervention that would make individuals fully informed and fully rational, this is the amount by which their utility could be improved (in partial equilibrium)

Policy Implications

- Policies that could realize some of these gains:
  - Information about costs
  - Increase doctors' or pharmacists' role in plan choice
- How about restricting choice set?
  - If restricted to the plans on the "efficient frontier", there are sizeable welfare gains for seniors (in partial equilibrium)
  - If smaller choice set, individuals may be better able to compare alternatives
  - However, restricting the size of the choice set may lower competitive pressure on the supply side (in general equilibrium)

Additional Considerations

- The results have raised further questions
- Do violations of the restrictions reflect:
  - optimization mistakes made by consumers,
  - a rejection of the parametric model for utility,
  - some combination of the two?
- Later (non-parametric) evidence suggest that welfare-reducing mistakes may be smaller as previously suggested (Ketcham et al., 2016)
- Yet, robust to alternative normative assumptions highlighting the role of brand fixed effects and unobservable characteristics (Abaluck and Gruber, 2016)

Literature: Limited information and advertising

Sovinsky Goeree, M., 2008. "Limited Information and Advertising in the U.S. Personal Computer Industry." Econometrica, 76, 5, 1017 - 1074.

Sovinsky Goeree, Econometrica 2008

- Following key ingredients:
  1. Extend BLP
     - Limited consumer information about product offerings or choice sets
     - Advertising influences the set of products from which consumer i chooses to purchase from, $\mathcal{C}_i$
     - Firms choose both advertising and prices
  2. Use estimated model to quantify the effects of limited information and of advertising in the U.S. home PC computer market
     - effects on demand
     - effects on markups

Data

- Market data + Microdata to supplement

1. Product level prices and sales (U.S. shipments, "home market")
   - quarterly, 1996-98
   - $product = brand \times form\ factor \times cpu \times type \times cpuspeed$ (2 112 models)
   - Source: Gartner
2. Advertising
   - quarterly ad expenditure by product, 10 media.
   - source: industry consultant.

Table I

TABLE I

SUMMARY STATISTICS FOR MARKET SHARES, ADVERTISING, PRICES, AND MARKUPS[a]

	Percentage Dollar Home Market Share			Average Annual			Median Percentage Markup, Home Sector	
Manufacturer	1996	1997	1998	Ad Expend	Ad-to-Sales Ratio	Median Price Home Sector	Over Marginal Costs	Including Ad Costs
Industry					3.4%	$2239	15%	10%
Top 6 firms	65.67	68.31	75.26	$469	9.1%	$2172	17%	12%
Acer	6.20	6.02	4.37	$117	5.4%	$1708	11%	9%
Apple	6.66	5.79	9.16	$161	5.3%	$1859	16%	9%
AST	3.08	1.53					13%	
Compaq	11.89	16.29	16.43	$208	2.4%	$2070	23%	16%
Dell	2.46	2.87	2.57	$150	2.1%	$2297	10%	
Gateway	8.94	11.77	16.43	$277	5.6%	$2767	12%	10%
Hewlett–Packard	4.02	5.52	10.05	$651	17.7%	$2203	16%	10%
IBM	8.49	7.42	6.85	$1189	20.1%	$2565	16%	10%
Micron	3.26	4.05	1.68				7%	
NEC	3.22							
Packard–Bell	23.48							
Packard–Bell NEC		21.02	16.33	$327	7.2%	$2075	16%	11%
Texas Instruments	1.40						7%	
15 included	83.11	82.27	83.88					

- Market size: the number of U.S. households in a given period from the Census Bureau
- Market shares: unit sales of each model divided by market size

Data

3 Additional microdata

- HH media exposure
- HH income
- HH consumer PC purchase and the manufacture
- Source: the Survey of Media and Markets from Simmons

4 U.S. consumer demographics (Consumer Population Survey, CPS)

Table II

DESCRIPTIVE STATISTICS FOR SIMMONS DATA[a]

	Sample		Population	
Variable Description	Mean	Std. Dev.	Mean	Std. Dev.
Male	0.663	0.474	0.661	0.473
White	0.881	0.324	0.881	0.324
Age (years)	47.38	15.68	46.87	15.13
30 to 50 (= 1 if 30 < age < 50)	0.443	0.497	0.449	0.497
Education (years)	13.98	2.54	14.00	2.35
Married	0.564	0.496	0.572	0.495
Household size	2.633	1.429	2.631	1.428
Employed	0.695	0.460	0.693	0.461
Income ($)	56,745	45,246	56,340	44,465
Inclow (= 1 if income < $60,000)	0.667	0.471	0.669	0.471
Inchigh (= 1 if income > $100,000)	0.107	0.309	0.106	0.308
Own PC (= 1 if own a PC)	0.466	0.499	0.470	0.499
PCnew (= 1 if PC bought in last 12 months)	0.113	0.317	0.112	0.316
Media Exposure	Mean	Std. Dev.	Min	Max
Cable (= 1 if receive cable)	0.749	0.434	0	1
Hours cable (per week) cable (per week)	3.607	2.201	0	7
Hours noncable (per week)	3.003	2.105	0	6.2
Hours radio (per day)	2.554	2.244	0	6.5
Magazine (= 1 if read last quarter)	0.954	0.170	0	1
Number magazines (read last quarter)	6.870	6.141	0	95
Weekend newspaper (= 1 if read last quarter)	0.819	0.318	0	1
Weekday newspaper (= 1 if read last quarter)	0.574	0.346	0	1

Preferences

$$u_{ijt} = \alpha \ln(y_{it} - p_{it}) + x_j \beta_{it} + \xi_{jt} + \epsilon_{ijt}$$

$$\beta_{it} = \beta + \Omega D_i + \Sigma \nu_{it}$$

$$\nu_{it} \sim N(0, 1)$$

$u_{i0} = \alpha \ln(y_{it}) + \epsilon_{i0t}$ (utility from outside good).

$\epsilon_{ijt} \sim$ i.i.d. type 1 EV

$D_i =$ observed consumer attributes

- Advertising a does not enter utility directly (this is an assumption!).

Consideration (Choice) Set

- $\mathcal{C}_i \subseteq \mathcal{J}$, $0 \in \mathcal{C}_i \ \forall i$
- A possible model of consideration sets:

$$\Pr(\mathcal{C}_i = c_i) = \prod_{l \in c} \phi \prod_{k \notin c} (1 - \phi)$$

- Sovinsky Goeree makes ϕ (the probability i is informed about j at time t) a function of observables as follows:

$$\phi_{ijt} = \frac{\exp(\gamma_{jt} + \lambda_{ijt})}{1 + \sum_l \exp(\gamma_{jt} + \lambda_{ijt})}$$

Information Technology

$$\phi_{ijt} = \frac{\exp(\gamma_{jt} + \lambda_{ijt})}{1 + \sum_l \exp(\gamma_{jt} + \lambda_{ijt})}$$

- γ_{jt} = common to all consumers, a function of adverting a_j, for example
- Consumer info heterogeneity: λ_{ijt}. Depends on consumer demographics, unobservables/random coef. (κ_i) and ad exposure measured through Simmons survey data.

Market Shares

- Now, with usual notation $u_{ijt} = \delta_{jt} + \mu_{ijt} + \epsilon_{ijt}$, market shares depend on $\mathcal{C}_i$:

$$s_{ijt}|\delta, \mu, \mathcal{C}_i = \frac{\exp(\delta_{jt} + \mu_{ijt})}{y_{it}^{\alpha} + \sum_{r \in \mathcal{C}_i \setminus \{0\}} \exp(\delta_{rt} + \mu_{irt})}$$

$$\Rightarrow s_{ijt}|\delta, \mu, a, \kappa = \sum_{c \in 2^{\mathcal{J}}} (\mathcal{C}_i = c|a, \kappa) \times s_{ijt}|\delta, \mu, \mathcal{C}_i$$

$$s_{jt}(\delta, a) = \int [s_{jt}|\delta, \mu, a, \kappa] \, dF(y, D) dG(\nu) \underbrace{dH(\kappa)}_{lognormal}$$

$dF(y, D)$ = joint density of income, ad exposure and demographics. This is observed, affects μ.

Market Shares

- Consumer i's consideration set and ad exposure are just two more components of the consumer's "type" - what we usually define by random coefficients.
- Choice probabilities are always derived by integrating conditional choice probabilities (conditional on type) over the distribution of types:

$$s_{ijt} = \int_{type} s_j(observables, type_i) dF(type_i)$$

- This is an(other) example of a mixture model: the outcomes we observe are mixtures (= weighted averages) of outcomes conditional on latent states (e.g., random coefficients, consideration sets, demographics). This is why random coefficients logit is sometimes called "mixed logit".

Supply

Profits of firm f with products $\mathcal{J}_f \in \mathcal{J}$:

$$\sum_{j \in \mathcal{J}_f} (p_j - mc_j)\mathcal{M}s_j(p, a) + \sum_{j \in \mathcal{J}_f} \Pi_j^{nh}(p^{nh}) - \sum_m mc_{jm}^{ad}(\sum_{j \in \mathcal{J}_f} a_{jm}) - \mathcal{C}_f$$

where

- s_j is the home market share
- Π_j^{nh} is is gross profit from the non-home sector and p^{nh} is the price in this sector
- mc_{jm}^{ad} is the marginal cost of advertising in medium m
- $\mathcal{C}_f$ is the fixed cost of production

Supply

- Use FOCs for prices and advertising.
- Marginal costs:
  $\ln mc_j = w_{jt}\eta + \omega_{jt}$
  $\ln mc^{ad}_{jtm} = w_{jtm}\psi + \tau_{jtm}$ for each ad medium m
  $\tau \sim MVN(0, I)$

Macro Moments

1 Modified BLP

- demand (match the predicted market shares to observed shares)
- price FOC
- advertising FOC
  BLP instruments + time trend as proxy for cost shifters (exclusion restriction?).

The ad FOC (nh = non-household sector):

$$\mathcal{M} \sum_{r \in \mathcal{J}_f} (p_r - mc_r) \frac{\partial s_r(p, a)}{\partial a_{jm}} + mr_j^{nh} = mc_{jm}^{ad}$$

where by assumption $mr_j^{nh} = \theta_p^{nh} p_j^{nh} + x_j^{nh\prime} \theta_x^{nh}$

Moment Conditions (Macro+Micro)

1. demand (market shares)
2. supply (pricing decisions)
3. modified FOC for advertising
4. firm choice micro moments using Simmons data (connect consumers to firms, thus associating consumer and average product attributes)
   - let θ denote all model parameters
   - let $b_{if} = 1$ {consumer i buys from manufacturer f}
   - let $G_i(\delta, \theta) = \mathbb{E}[b_{if}|D_i, \delta, \theta] = \sum_{j \in \mathcal{J}_f} s_{ij}(\delta, a, \theta)$
   - if model correctly specified, $b_{if} - G_i(\delta, \theta)$ represents sampling error in micro data

$$\Rightarrow \mathbb{E}[Z'(b_{if} - G_i(\delta, \theta))] = 0$$

5. media exposure micro moments: creates variation in ad exposure across households (as related to observables)

Results - Table III

TABLE III

STRUCTURAL ESTIMATES OF UTILITY AND COST PARAMETERS[a]

					Interactions With Demographics			
Variable	Coefficient	Std. Error	Standard Deviation	Std. Error	Household size	Income > $100,000	Age 30 to 50	White Male
Utility Coefficients								
Constant	−12.026**	(0.796)	0.044	(0.558)				
CPU speed (MHz)	9.288**	(1.599)	0.156**	(0.017)	4.049**			
					(0.674)			
Pentium	1.236*	(0.890)	0.209	(0.886)		0.016		
						(0.489)		
Laptop	2.974**	(0.525)	0.953	(4.619)			2.048	4.099
							(8.870)	(9.192)
ln(income − price)	1.211**	(0.057)						
Acer	2.624	(4.900)						
Apple	3.070**	(1.032)						
Compaq	2.662	(18.009)						
Dell	2.658**	(0.301)						
Gateway	7.411	(14.615)						
Hewlett–Packard	1.309	(3.905)						
IBM	2.514**	(0.712)						
Micron	−1.159	(6.011)						
Packard–Bell	4.372*	(4.002)						

Results - Table III

Cost Side Parameters		
In marginal cost of production		
Constant	7.427**	(0.212)
ln(CPU speed)	0.462**	(0.044)
Pentium	−0.250**	(0.007)
Laptop	1.204**	(0.071)
Quarterly trend	−0.156**	(0.027)
In marginal cost of advertising		
Constant	2.631	(7.087)
Price of advertising	1.051**	(0.074)
Non-Home Sector Marginal Revenue		
Constant	11.085	(278.374)
Non-home sector price	1.815**	(0.354)
CPU speed	0.010**	(0.004)
Non-PC sales	3.688*	(1.881)

[a]Notes: ** indicates t-stat > 2; * indicates t-stat > 1. Standard errors are given in parentheses.

Results - Table IV

TABLE IV

STRUCTURAL ESTIMATES OF INFORMATION TECHNOLOGY PARAMETERS[a]

			Coefficient Estimates for Interactions With Media							
			Magazine (mag)		Newspaper (np)		Television (TV)		Radio	
Variable	Coefficient	Std. Error	Coefficient	Std. Error	Coefficient	Std. Error	Coefficient	Std. Error	Coefficient	Std. Error
Consumer Information Heterogeneity Coefficients										
Media and demographic interactions (Y)										
Constant			−1.032**	(0.040)	−0.973**	(0.040)	−1.032**	(0.041)	−1.000**	(0.043)
30 to 50 (= 1 if 30 < age < 50)			−0.042*	(0.025)	0.207**	(0.025)	0.019	(0.025)	−0.030*	(0.025)
50 plus (= 1 if age > 50)			0.005	(0.025)	0.541**	(0.025)	0.193**	(0.025)	−0.245**	(0.025)
Married (= 1 if married)			−0.022*	(0.018)	0.187**	(0.018)	0.075**	(0.018)	−0.011	(0.018)
hh size (household size)			0.040**	(0.006)	−0.038**	(0.006)	0.018**	(0.006)	0.012*	(0.006)
inclow (= 1 if income < $60,000)			−0.194**	(0.021)	−0.251**	(0.021)	0.114**	(0.021)	−0.117**	(0.022)
inchigh (= 1 if income > $100,000)			0.153**	(0.029)	0.127**	(0.028)	−0.025	(0.030)	0.069**	(0.030)
malewh (= 1 if male and white)			−0.078**	(0.018)	0.002	(0.018)	−0.019*	(0.018)	0.006	(0.018)
eduhs (= 1 if highest edu 12 years)			−0.102**	(0.026)	−0.338**	(0.026)	0.296**	(0.027)	0.076**	(0.027)
eduad (= 1 if highest edu 1–3 college)			0.032*	(0.028)	−0.166**	(0.027)	0.278**	(0.028)	0.115**	(0.029)
edubs (= 1 if highest edu college grad)			−0.024	(0.025)	−0.063**	(0.024)	0.145**	(0.025)	0.081**	(0.026)
edusp (education if <11)			−0.028**	(0.003)	−0.069**	(0.003)	0.034**	(0.003)	−0.014**	(0.003)
Advertising media exposure (ξ)										
media exposure* advertising	0.948**	(0.059)								
Demographics (λ)										
Constant	0.104**	(0.004)								
High school graduate	0.834**	(0.028)								
Income < $60,000	0.687**	(0.009)								
Income > $100,000	0.139	(0.318)								

(*Continues*)

Results - Table IV

TABLE IV—*Continued*

			Coefficient Estimates for Interactions With Media							
			Magazine (mag)		Newspaper (np)		Television (TV)		Radio	
Variable	Coefficient	Std. Error	Coefficient	Std. Error	Coefficient	Std. Error	Coefficient	Std. Error	Coefficient	Std. Error
Information Technology Coefficients Common Across Consumers										
Age of PC	0.159**	(0.005)								
Media Advertising (ϕ, ρ)										
npand mag advertising	0.720*	(0.488)								
TV advertising	1.078**	(0.418)								
(np and mag advertising)^2	−0.013	(0.014)								
(TV advertising)^2	−0.049**	(0.004)								
Firm total advertising (Ψ)										
Acer	0.520	(0.042)								
Apple	0.163	(0.790)								
Compaq	0.504**	(0.077)								
Dell	0.497*	(0.460)								
Gateway	0.918**	(0.065)								
Hewlett–Packard	0.199	(11.750)								
IBM	0.926**	(0.184)								
Micron	0.029	(5.832)								
Packard–Bell	0.231*	(0.149)								
Group advertising (π)										
Group advertising	0.891**	(0.007)								
(Group advertising)^2	0.104**	(0.011)								

[a]Notes: ** indicates t-stat > 2; * indicates t-stat >1. Unless units are specified, variable is a dummy.

Results - Table VI

TABLE VI

ESTIMATED PERCENTAGE MARKUPS UNDER LIMITED AND FULL INFORMATION[a]

	Median Percentage Markup		
	Under Limited Information	Under Full Information	Change in Markups
Total industry	15%	5%	67%
Apple		2.5%	84%
iMac	22.1%	3.1%	
Power Mac	13.7%	2.0%	
PowerBook*	10.0%	1.6%	
Compaq		7.0%	69%
Armada 7xxx*	41.4%	3.5%	
Presario 2xxx	18.1%	2.6%	
Presario 1xxx*	15.2%	2.0%	
ProLinea	23.3%	7.0%	
Dell		1.8%	82%
Latitude XPI*	7.0%	1.4%	
Dimension	15.5%	2.4%	
Inspiron	9.4%	1.6%	
Gateway		1.7%	86%
Gateway Desk Series	12.8%	1.9%	
Gateway Portable Series	8.1%	1.5%	
HP		4.5%	72%
OmniBook 4xxx*	8.3%	5.7%	
Pavilion 6xxx	22.7%	3.1%	
Vectra 5xx	15.8%	6.8%	
IBM		2.0%	88%
Aptiva	16.0%	2.3%	
Thinkpad 7xxx*	7.4%	1.6%	
IBM PC 3xx	26.1%	2.1%	
Packard-Bell		3.0%	81%
NEC Versa*	11.1%	1.6%	
NEC Desk Series	17.6%	2.5%	

[a]Notes: Percentage markups are defined as (price – marginal cost)/price. Full information is the traditional model in which consumers know all products; under limited information the choice set is estimated. * indicates that computers are laptop.

Last Lecture

- More about consideration sets
- Pass-through

Questions?

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