ECON-L1300 - Empirical Industrial Organization, PhD
I: Static models

Lecture 11

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About today's lecture

- Today's lecture is on modeling the consideration sets. We discuss
  1. what consideration sets are
  2. why it may or may not be important to model them
  3. the implementation in Sovinsky Goeree, M. (2008). "limited information and advertising in the u.s. personal computer industry. *Econometrica*, *76*(5), 1017–1074
  4. modeling of consideration sets more generally, following Abaluck, J. & Adams-Prassl, A. (forthcoming). What do consumers consider before they choose? identification from asymmetric demand responses. *Quarterly Journal of Economics*

Consideration sets

- Do consumers really know the existence of all products and their characteristics, as assumed by the discrete choice model? If not

  1. standard discrete choice framework misspecified: failure to buy cheap product could just be lack of awareness
  2. choice set: $\mathcal{J} = 1, ..., J$, the set of all products
  3. consideration set: $\mathcal{C}_i \subseteq J$, the set from which consumer i chooses
  4. various reasons could affect awareness, i.e., which products in $\mathcal{C}_i$

Does this type of mis-specification matter?

- All models are "unrealistic", so being slightly more or less so does not necessarily allow us to discriminate between models.
- Varying consideration sets could help explain why consumers are not responding to some price changes.
- Question is, is this relevant for the research question at hand?
- The answer will be yes for some research questions (e.g. welfare) and no for others (what are firm markups, how would a merger affect them).

Does this type of mis-specification matter?

- Remember that the discrete choice model is primarily a way to produce a parsimonious empirical model of demand. For measuring demand elasticities, e.g., full vs. partial consideration sets are just different functional forms for the demand function.
- A more realistic model may help find a good parsimonious specification, but if there are compromises necessary to add realism, this may or may not yield a functional with finite sample approximations/estimates of the quantities of interest. And this may depend on what those quantities of interest are.

What could give rise to consideration sets being less than the full set of products?

- Inattention
- Bounded rationality
- Search costs
- Unobserved consumer specific constraints

Sovinsky Goeree, Econometrica 2008

- Following key ingredients:

  1. Extend BLP
     - allow $\mathcal{C}_i \neq \mathcal{J}$, with advertising affecting $\mathcal{C}_i$.
     - Firms choose both advertising and prices (uniqueness of eqm.?)
  2. Use estimated model to quantify the effects of limited consideration sets 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* × *form factor* × *cpu* × *type* × *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]

Manufacturer	Percentage Dollar Home Market Share 1996	1997	1998	Average Annual Ad Expend	Ad-to-Sales Ratio	Median Price Home Sector	Median Percentage Markup, 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					

Data

3. Market data + Microdata to supplement
   - limited consumer micro data
   - HH media exposure "binned"
   - HH income
   - HH consumer purchase in the previous 12 months? brand?
4. U.S. consumer demographics (CPS)

Table II

DESCRIPTIVE STATISTICS FOR SIMMONS DATA[a]

Variable Description	Sample Mean	Sample Std. Dev.	Population Mean	Population 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

$$u_{ijt} = \alpha \ln(y_{it} - p_{it}) + x_j \beta_{it} + \xi_{jt} + \epsilon_{ijt}$$
$$\beta_{it} = \beta + \Omega D_i + \Sigma \nu_{it}$$
$$\nu_{it} \sim N(0, 1)$$
$$u_{i0} = \alpha \ln(y_{it}) + \epsilon_{i0t} \text{ (utility from outside good).}$$
$$\epsilon_{ijt} \sim \text{ i.i.d. type 1 EV}$$

$D_i =$ observed consumer attributes

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

Consideration set

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

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

- Sovinsky Goeree makes ϕ a function of observables as follows:

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

Consideration set

- $\gamma_{jt} =$ common to all consumers
- $\gamma_{jt} = a_j'(\psi + \rho a_j + i_m \Psi_f) + \vartheta x_j^{age}$
- $\Psi_f =$ firm FE
- $\lambda_{ijt} =$ individual ad exposure. Not observed, thus measured through Simmons survey data.
- $\lambda_{ijt} = a_j'(\mathcal{Y} D_i^s \zeta + \kappa_i) + \tilde{D}_i' \tilde{\lambda}$, $\ln \kappa_i \sim N(0, I_m)$
- $\tilde{D} =$ a subset of D (consumer characteristics); $\mathcal{Y} =$ how advertising effectiveness (=how HH characteristics affect how much of the given media is seen by the HH) varies over consumers; $\mathcal{Y} D_i^s$ =exposure to advertising of HH i.

- $\rightarrow \phi_{ij} | no\ adv = \tilde{D}_i' \tilde{\lambda} + \vartheta x_j^{age}$
- Notice exclusion restriction: x, p do not enter.

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

- Use FOC 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
  $\tau \sim MVN(0, I)$

Ad exposure

- Market shares depend on the joint distribution of media exposure and other demographics.
- Sovinsky Goeree has
  - marginal non-media measures for all of U.S
  - quintiles of ad exposure by ad medium + demographics for a limited sample
- How to use this information? Would like to link media exposure of household i to media m to demographics D. $m =$ TV, newspapers, magazines, radio.
- Since quintiles of media exposure (by m), use ordered probit = "predict" probability of HH i being in a given quintile. These yield $\mathcal{Y}$.

Moment conditions

1 BLP

- market 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 $mr_j^{nh} = \theta_p^{nh} p_j^{nh} + x_j^{nh\prime} \theta_x^{nh}$

Complication with ad FOC

- There are many zeros = corner solutions
- One possible fix: Kuhn-Tucker conditions and inequality moments.
- Sovinsky Goeree treats s as desired advertising which is truncated at zero, yielding a Tobit (type I) model.
- Rewrite FOC $\ln mr_{jm}(a_{jm}) = w_{jm}\psi + \tau_{jm}$
- LHS is decreasing in a.
- Use generalized residuals of Tobit as a moment condition.

Moment conditions

1. demand (market shares)
2. supply (pricing decisions)
3. modified FOC for advertising
4. micro moments with aggregation (as in Petrin)
   - let θ denote all model parameters
   - let $b_{if} = 1\{\text{consumer } i \text{ buys from manufacturer } f\}$
   - 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. from media exposure

Simulation of market shares

Sovinsky Goeree simulates consumers using the following process:

1. draw demographics vector D_i from the empirical distribution
2. draw (ν_i, κ_i) from the assumed distributions
3. these yield binomial probabilities ϕ_{ijt}
4. randomize (binomials) to obtain choice set C_i.
5. plug into logit formula to get i's choice probabilities.

Preliminary empirical analysis

In a separate section, Sovinsky Goeree investigates

1. a series of probit models to establish advertising affects demand
2. nested logit (upper nest: firm, lower nest: product) models of product choice yield positive price coefficients as a sign of endogeneity problems
3. logit demand models to study the relevance of instruments.

Results - Table III

TABLE III

STRUCTURAL ESTIMATES OF UTILITY AND COST PARAMETERS[a]

Variable	Coefficient	Std. Error	Standard Deviation	Std. Error	Interactions With Demographics: 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 (Υ)										
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 (ζ)										
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.

Back to consideration sets

- Key question: How does the incomplete knowledge of consumers affect markups?
- How could one approach it?
- Assume her model is correct: Then could ask what would happen to pricing if all consumers were aware of the full choice set.
- Instead, Sovinsky Goeree estimates a "traditional" BLP and compares the markups thus obtained to those from her model.
- This is a different exercise, asking "what is the bias in markups arising from estimating the traditional model, assuming the true model is the one proposed in this paper?
- Notice that the sign of bias is not a priori clear in the latter exercise. Typically all parameters are affected by mis-specification.

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%	

A more general model of consideration sets

- Abaluck, J. & Adams-Prassl, A. (forthcoming). What do consumers consider before they choose? identification from asymmetric demand responses. *Quarterly Journal of Economics* (AAP)
- Most of previous literature require external (e.g. survey) data and/or exclusion restrictions (e.g. price does not affect the consideration set) for identification.
- Also a theoretical literature that shows that if all non-degenerate choice sets observed, then consideration probabilities can be recovered (Manzini and Mariotti 2014).
- AAP consider two models (+ a hybrid between them):
  1. **Default Specific Consideration** (DSC): Consumers are either
     - "asleep" and choose the default option, or
     - "awake" and choose from the full choice set.
  2. **Alternative Specific Consideration** (ASC): each good has an independent consideration probability that depends on the characteristics of the good.

Key insight

- Imperfect consideration breaks **symmetry** between cross-price choices.
- Example: Symmetry would require that in a model with a default option, raising the price of the default by a 100 or lowering the price of all other goods by 100 should be viewed as identical in a (traditional) model with symmetry.
- Assume DSC and all consumers are "asleep": The nobody reacts to the second price change, but maybe more responsive to the first if this perturbs attention.

AAB contributions

1. Proof of identification.
2. Propose estimators (indirect inference, ML).
3. A field experiment to validate the model.
4. Empirical application to Medicare Part D.

Basic framework

- Full choice set $\mathcal{J} = \{0, 1, ..., J\}$, each with price p_j.
- The set of consideration sets to which good j belongs is given by:

$$\mathbb{P}(j) = \{C : \{0, j\} \subseteq C \in \mathcal{P}(\mathcal{J})$$

- $\mathcal{P}(\mathcal{J}) =$ power set of goods, elements indexed by C.
- Observed choice probabilities are given by :

$$s_j(\boldsymbol{p}) = \sum_{C \in \mathcal{P}_j} \pi_C(\boldsymbol{p}) s_j^*(\boldsymbol{p}|C)$$

Basic framework

- $s_j(\boldsymbol{p})$ = observed probability that j bought given market prices $\boldsymbol{p}$
- $\pi_C(\boldsymbol{p})$ = probability that the set of goods C is considered.
- $\pi_C(\boldsymbol{p})$ = probability that good j chosen from consideration set C.
- Notice that both $\pi_C(\boldsymbol{p})$ and $s_j^*(\boldsymbol{p}|C)$ are proper probabilites and thus

$$\sum_{C \in \mathcal{P}_j} \pi_C(\boldsymbol{p}) = 1 \, , \, \sum_{j \in C} s_j^*(\boldsymbol{p}|C) = 1$$

- AAP take $\pi_C(\boldsymbol{p}) =$ and $s_j^*(\boldsymbol{p}|C)$ to be the objects of interest.
- Note: you can identify the parameters of utility function by assuming a convenient utility function to underlie $s_j^*(\boldsymbol{p}|C)$.

Assumption 1

- AAB assume the **Daly-Zachary** (see Train's book) conditions:

1 Properties: $s_j^*(\boldsymbol{p}|C) \geq 0$, $\sum_{j \in C} s_j^*(\boldsymbol{p}|C) = 1$, and

$$\frac{\partial^J s_j^*(\boldsymbol{p}|C)}{\partial p_0 ... \partial p_{j-1} \partial p_{j+1} \partial p_J} \geq 0$$

(& exist & are cont.)

2 Symmetry: cross-price derivatives are symmetric:

$$\frac{\partial s_j^*(\boldsymbol{p}|C)}{\partial p_{j'}} = \frac{\partial s_{j'}^*(\boldsymbol{p}|C)}{\partial p_j}$$

3 Absence of nominal illusion:

$$s_j^*(\boldsymbol{p} + \boldsymbol{\delta}|C) = s_j^*(\boldsymbol{p}|C)$$

Assumption 2 & Theorem 1

- Assumption 2: Population market shares, own- and cross-price derivatives observed at $\boldsymbol{p}$.
- Theorem 1: if either
  1. cross-price derivatives asymmetric or
  2. there is (appears to be) nominal illusion

  then

  $$\pi_{\mathcal{J}}(\boldsymbol{p}) < 1$$

  where $\pi_{\mathcal{J}}(\boldsymbol{p}) < 1$ is the probability that a consumer considers all goods.

The Default Specific Model (DSC)

- Under the DSC model, the market shares for the default and non-default goods are given by

$$s_0(\boldsymbol{p}) = (1 - \mu(p_0)) + \mu(p_0) s_0^*(\boldsymbol{p}|\mathcal{J})$$

$$s_j(\boldsymbol{p}) = \mu(p_0) s_j^*(\boldsymbol{p}|\mathcal{J})$$

where $\mu(p_0) =$ probability of considering all goods given the price of the default good.

- The model generalizes to richer models of μ.

The Default Specific Model (DSC)

- Taking derivatives of the market shares w.r.t to p_0 and p_j one can show that
$$\frac{\partial \ln(\mu_0)}{\partial p_0} = \frac{1}{s_j(\boldsymbol{p})} \left[\frac{\partial s_j(\boldsymbol{p})}{\partial p_0} - \frac{\partial s_o(\boldsymbol{p})}{\partial p_j} \right]$$

- This is zero only if the cross-price derivatives are symmetric.

Theorem 2

Theorem 2 shows that $\frac{\partial \ln(\mu_0)}{\partial p_0}$ is constructively identified.

- One can get the level of consideration (up to a constant) by integrating over the support of p_0:

$$\ln(\mu(\infty)) - \ln(\mu(\tilde{p}_0)) = \int_{\tilde{p}_0}^{\infty} \frac{1}{s_j(\boldsymbol{p})} \left[\frac{\partial s_j(\boldsymbol{p})}{\partial p_0} - \frac{\partial s_o(\boldsymbol{p})}{\partial p_j} \right] dp_0$$

- If one is willing to assume that at very high price of the default good, all inside goods are considered, then $\ln(\mu(\infty)) = 0$.
- This is what DSC does, and hence $\mu(\tilde{p}_0)$ is identified.

Theorems 3 & 4

- Theorems 3 & 4 show that the consideration probabilities are
  1. identified in general (Th 3)
  2. identified with logit consideration (as in Sovinsky Goeree) as long as one observes two prices for the default good.
- Note: AAP identification hinges on observing the price of the default good.
- This is a natural assumption in some settings, not so in others.

Identification of market shares

- This is straight forward in the DSC model once the consideration probabilities have been identified.
- In the ASC model, the no nominal illusion - assumption yields identification.

Validation experiment

- 149 Yale students, 10 goods sold at the Yale Bookstore for prices 19.98 - 24.98$.
- Each subject endowed with 25$ and made 50 choices from random subsets with randomized prizes.
- Choice sets appeared as images.
- After the 50 choices, one of the choices selected and subjects received the item + 25$ - price of the item.
- $\rightarrow$ 7 450 choices.
- AAP treat each choice set as the consideration set. They set the probability that good j was in participant i's consideration set in round r as:

$$\phi_{ijr} = \frac{\exp(\gamma_j + p_{ijr}\gamma_p)}{1 + \exp(\gamma_j + p_{ijr}\gamma_p)}$$

Results - Table I

Table 1: Experimental Data Estimation Results

	Conditional Logit	ASC Model		Conditional on Consideration
		MLE	Indirect Inf.	
Utility:				
Price (dollars)	-0.054***	-0.196***	-0.1284**	-0.173***
	(0.003)	(0.028)	(0.048)	(0.004)
Product 1	-1.411***	1.465***	0.5806	0.368***
	(0.054)	(0.539)	(0.361)	(0.069)
Product 2	-1.955***	-0.065	-0.483*	-0.497***
	(0.069)	(0.478)	(0.283)	(0.080)
Product 3	-1.627***	0.625	0.452	0.093
	(0.059)	(0.476)	(0.295)	(0.073)
Product 4	-1.640***	0.629	-0.007	0.088
	(0.060)	(0.466)	(0.302)	(0.073)
Product 5	-1.447***	0.707	0.165	0.306***
	(0.056)	(0.478)	(0.269)	(0.070)
Product 6	-0.435***	-0.737***	-0.475***	-0.581***
	(0.039)	(0.121)	(0.135)	(0.045)
Product 7	-0.855***	-1.280***	-0.875***	-1.075***
	(0.045)	(0.141)	(0.155)	(0.051)
Product 8	-0.662***	-1.185***	-0.811***	-0.909***
	(0.041)	(0.137)	(0.138)	(0.048)
Product 9	-0.316***	-0.561***	-0.430***	-0.405***
	(0.038)	(0.118)	(0.161)	(0.044)

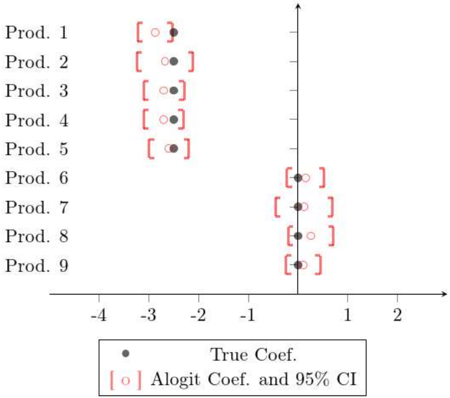
Results - Table I

Table 1: Experimental Data Estimation Results

	Conditional Logit	ASC Model		Conditional on Consideration
		MLE	Indirect Inf.	
Attention:				
Price (dollars)		0.137***	0.141***	0.15
		(0.017)	(0.025)	
Product 1		-2.872***	-2.910***	-2.5
		(0.177)	(0.236)	
Product 2		-2.674***	-2.311***	-2.5
		(0.288)	(0.257)	
Product 3		-2.695***	-2.674***	-2.5
		(0.209)	(0.238)	
Product 4		-2.704***	-2.687***	-2.5
		(0.205)	(0.267)	
Product 5		-2.592***	-2.581***	-2.5
		(0.204)	(0.245)	
Product 6		0.152	0.390	0
		(0.192)	(0.249)	
Product 7		0.123	0.137	0
		(0.292)	(0.281)	
Product 8		0.258	-0.200	0
		(0.230)	(0.259)	
Product 9		0.103	-0.129	0
		(0.176)	(0.253)	

Results - Figure II

Figure 2: Product Fixed Effects in Attention: Truth vs. ASC Model



Two general approaches

- Crawford, Griffith and Iaria, 2020 distinguish between two approaches:
  1. "Integrating over" all possible choice sets.
  2. "Differencing out" choice sets.
- Both Sovinsky Goeree, 2008 and Abaluck and Adams-Prassl, forthcoming belong to the first class.
- The second class builds (for the most part) on
  1. shocks being i.i.d extreme value Type I
  2. this leading to the fact that (under some assumptions), one need not observe all the choices to estimate the parameters for the remaining consistently (thanks to IIA).