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

Lecture 12

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Consideration sets

A more general model of consideration sets

- Abaluck, J. & Adams-Prassl, A. (2021). What do consumers consider before they choose? identification from asymmetric demand responses. *Quarterly Journal of Economics*, *136*(3), 1611–1663 (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 effects on choices.
- Example: 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 (not covered).

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 :

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

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.
- $s_j(\boldsymbol{p}|C)$ = 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

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

- 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 the 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:

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

Note: Assumption 1 implies that "regular" demand conditions hold **within** a consideration set.

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 are asymmetric or
  2. there is (appears to be) nominal illusion

  then

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

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

The Default Specific Model (DSC)

- Under the DSC model (''asleep'' or ''awake''), the market shares for the default and non-default goods are given by

$$\begin{aligned} s_0(\boldsymbol{p}) =& (1-\mu(p_0)) + \mu(p_0)s_0^*(\boldsymbol{p}|\mathcal{J}) \\ s_j(\boldsymbol{p}) =& \mu(p_0)s_j^*(\boldsymbol{p}|\mathcal{J}) \end{aligned} \tag{10}$$

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

- Here, μ a function of p_0 (characteristics of the default good) only. The model generalizes to richer models of μ.

The Default Specific Model (DSC)

- Taking (cross-) derivatives of s_0 and s_j w.r.t to p_j and p_0 respectively one can show that

$$\frac{\partial \ln(\mu_0)}{\partial p_0} = \frac{1}{s_j(\boldsymbol{p})}\left[\frac{\partial s_j(\boldsymbol{p})}{\partial p_0} - \frac{\partial s_0(\boldsymbol{p})}{\partial p_j}\right]$$

- Hint: Use symmetry of $\partial s_j^*/\partial p_0 = \partial s_0^*/\partial p_j$, the fact that $\partial \ln(\mu(p_0))/\partial p_0 = \partial \mu_0/\partial p_0 \times (1/\mu)$ and solve for s_j^* from second part of equation (10).
- $\partial \ln(\mu(p_0))/\partial p_0 = 0$ only if the cross-price derivatives of the **observed market shares** are symmetric.
- Intuitively, if the price of the default plan perturbs consideration by causing consumers to "wake up" (LHS), then the nondefault plan will be more sensitive to the price of the default plan than is the default plan to the price of the nondefault plan (RHS).

Theorem 2

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

- One can get the level of consideration $\mu(\tilde{p}_0)$, where $\tilde{p}_0$ is the lowest price of the default good, (up to a constant) by integrating over the support of p_0:

$$\ln(\mu(\infty)) - \ln(\mu(\tilde{p}_0)) = \int_{\tilde{p}_0}^{\infty} \frac{1}{s_j(\boldsymbol{p})} \left[\frac{\partial s_j(\boldsymbol{p})}{\partial p_0} - \frac{\partial s_o(\boldsymbol{p})}{\partial p_j} \right] dp_0 \qquad (15)$$

- 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.

ASC model

- In the ASC model (each good has independent consideration prob.), the no nominal illusion - assumption yields identification.
- Consideration sets are given by

$$\pi_C(\boldsymbol{p}) = \prod_{j \in C} \phi_j(p_j) \prod_{j' \notin C} (1 - \phi_{j'}(p_{j'})) \tag{19}$$

- where $\phi(p_j) =$ probability that good j considered.
- Observed market shares are then given by

$$s_j(\boldsymbol{p}) = \sum_{C \in P(j)} \prod_{l \in C} \phi_l(p_l) \prod_{l' \notin C} (1 - \phi_{l'}(p_{l'})) s_j^*(\boldsymbol{p}|C) \tag{20}$$

- Note: Sovinsky Goeree's model is an ASC model.

Identification of conditional market shares

- This is straight forward in the DSC model once the consideration probabilities have been identified, think back to equation (10).
- Things are more complicated in the ASC and hybrid models. Restrictions derived from nominal illusion help.
- An increase in prices that leads relative prices constant can change consideration sets by does not alter latent ("true") choice probabilities.

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:

$$\phi_{ijr} = \frac{\exp(\gamma_j + p_{ijr}\gamma_p)}{1 + \exp(\gamma_j + p_{ijr}\gamma_p)} \tag{30}$$

Estimation

- Either by maximum likelihood or by indirect inferance.
- Indirect inference:
  1. Estimate a flexible auxiliary model with observational data.
  2. Specify a structural model.
  3. Simulate the structural model.
  4. Choose (estimate) parameters of the structural model so that it leads to same auxiliary model estimates as the observational data.

Estimation results

- Column 4 Table 1 gives the ”truth”, i.e., actual consideration sets are observed.
- $\rightarrow$ Compare other columns’ results to those in Column 4.
- Columns 1-3 use only information on what product was actually chosen.
- Column 1 maintains the standard assumption that all goods are in the consideration set for all customers.
- Consideration set models
  - yield price effects whose confidence intervals include the true price value.
  - recover preference fixed effects that are in line with true values.

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)

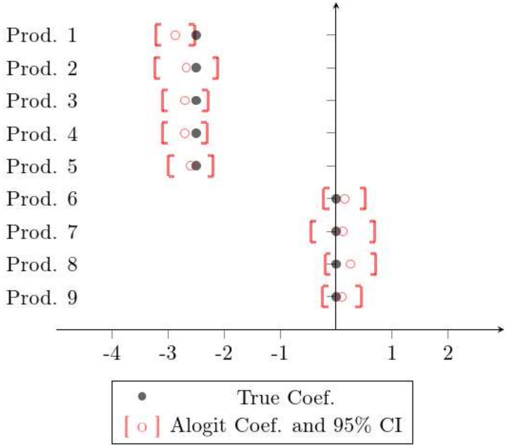
Results - Table I

Table 1: Experimental Data Estimation Results

	Conditional Logit	ASC Model MLE	ASC Model Indirect Inf.	Conditional on Consideration
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, 2021 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).

Pass-through

Pass-through

- Miravete, E., Seim, K. & Thurk, J. (2023). *Elasticity and curvature of discrete choice models* (tech. rep.). CEPR (MST)
- MST concentrate on pass-through in aggregate, unit-demand discrete choice (mixed) logit models.
- Motivation: Such models are by now the workhorse model in empirical IO, and such models are increasingly used in other fields of economics, too.
- Research questions:
  1. When do assumptions on preference heterogeneity restrict feasible curvature estimates?
  2. How can we model preference heterogeneity flexibly to simultaneously allow for the estimation of realistic estimates of demand elasticity (market power) and curvature (pass-through)?

What is pass-through?

- Pass-through answers the question: What fraction of a cost shock is passed through to price?
- From principles - course: tax incidence.

What has demand specification to do with it?

Figure 1: Breakfast Cereal: Elasticity and Curvature Estimates

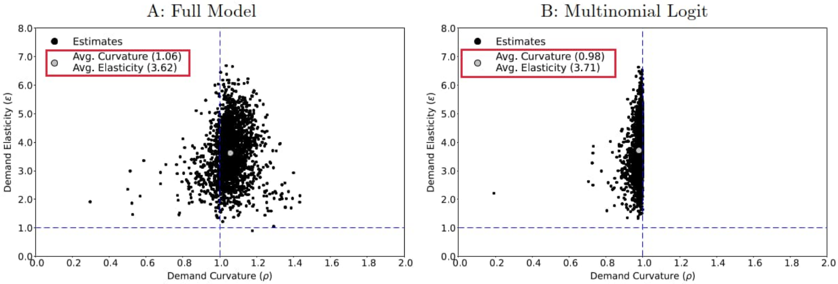


Figure Notes: Dots represent the estimated own-price elasticity and curvature for a product in the sample with the gray dot corresponding to the average elasticity and curvature.

Roadmap

- First some theory
- Linking theory to specification of demand

What is pass-through?

- **Pass-through rate** $\omega = \partial p / \partial c$.
- In words: By how much does equilibrium price change when cost (e.g. through a tax) changes by one unit?
- Classic example with perfect competition: Introduction of a (marginal) producer tax t:

$$D(p) = S(p - t)$$

- where $D(p) =$ demand and $S(p - t) =$ supply at equilibrium price p and tax t.
- With the implicit function theorem (e.g. Weyl and Fabinger, 2013) $D(p) = S(p - t)$ implies that

$$D'(p)\omega = (\omega - 1)S'(S - t)$$

$$\rightarrow \omega = \frac{S'}{(S' - D')} = \frac{1}{a + \epsilon_D / \epsilon_S}$$

- Pass-through increases in the ratio of supply elasticity to demand elasticity. The inelastic side of the market bears the (larger) burden of taxation.

Why is pass-through important?

- Imagine some policy-intervention through subsidies or taxes.
- E.g. sugar tax, increasing VAT on pharmaceuticals, increasing the cost of carbon (gasoline taxes), ...
- The success of many policy interventions rest on the policy-maker having a good estimate of the pass-through rate.

Monopoly pass-through + concepts

Objective function:

$$\Pi(p) = (p - c)q(p)$$

FOC

$$\Pi_p(p) = q(p) + (p - c)q_p(p) = 1 - \frac{p - c}{p}\epsilon(p) = 0 \iff \epsilon(p) = -\frac{pq_p(p)}{q(p)} > 1 \quad (1)$$

SOC

$$\Pi_{pp}(p) = 2q_p(p) + (p - c)q_{pp}(p) < 0 \iff \rho(p) = \frac{q(p)q_{pp}(p)}{[q_p(p)]^2} < 2 \quad (2)$$

$\rho(p) =$ curvature of demand.

Monopoly pass-through + concepts

- Demand is concave when $\rho < 0$; linear when $\rho = 0$; and convex when $\rho > 0$.
- SOC rules out "too convex" demand functions.
- An attempt at intuition: You get $1 - \rho(p)$ by differentiating q/q_p wrt p.
- In words, asking how the inverse of the relative change in demand changes with a small change in p.
- Also note that $p - c = -q/q_p$.

Monopoly pass-through + concepts

Inverting (1) (=solving it for q_p) and substituting into (2) yields the **demand manifold**

$$\rho[\epsilon(p)] = -\frac{p^2 q_{pp}(p)}{\epsilon^2(p)q(p)} \tag{3}$$

- In equilibrium, demand is elastic when firms have market power.
- SOC yields a constraint on curvature of demand (at equilibrium).
- Cournot, 1838 established that for a monopolist with constant marginal cost,

$$\frac{dp}{dc} = \frac{1}{2-\rho} > 0 \tag{4}$$

- Equation (4) shows the usefulness of ρ / curvature / demand manifold.
- Weyl and Fabinger, 2013 work with a single-product oligopoly model. Then equation (4) takes the form $dp/dc = 1/[1+\theta(1-\rho)]$ where θ is the conduct parameter.

Monopoly pass-through + concepts

- Demand is **sub-convex** when $\ln q(p)$ is concave.
- Demand is **sub-concave** when $\ln q(p)$ is convex.
  - A function $f(x)$ is log-concave if $\ln f(x)$ is concave.
  - A function $f(x)$ is log-convex if $\ln f(x)$ is convex.
  - Log-concavity implies some properties, e.g., $f''f < f'^2$ (compare to equation (2)).

Monopoly pass-through + concepts

- When a monopolist faces a sub-convex (i.e., log concave) demand ($\rho < 1$), pass-through is **incomplete**, i.e., less than one.
- When a monopolist faces a log-convex demand ($\rho > 1$), pass-through is **more than complete**.
- Sub-convexity of demand = quasi-concavity of the profit fcn in own price (where profits are positive).
- Sub-convexity of demand $\rightarrow \epsilon_p(p) > 0$, i.e., price elasticity is increasing in price.

Sub-convexity of demand and demand elasticity

$$\epsilon_p(p) = \frac{\epsilon^2}{p}[1 + \frac{1}{\epsilon} - \rho] > 0 \iff \rho < 1 + 1/\epsilon = \rho^{CES} \quad (5)$$

- For CES demand, price elasticity constant
- CES provides a **cutoff curvature**.

Demand elasticity and curvature of discrete choice models

- General indirect utility specification for discrete choice demand:

$$u_{ij} = x_{ij}\beta_j^* + f_i(y_i, p_j) + \xi_j + \epsilon_{ij} \tag{6}$$

- We can then write the demand manifold for the above indirect demand function as:

$$\rho_j = \frac{p_j^2}{\epsilon_j^2 Q_j}[\int f_{ij}''\sigma_{ij}^2 dG(i) + \int (f_{ij}')^2 sk_{ij} dG(i)] \tag{12}$$

where

- f' and $f''$are first and second derivatives of f.
- sk_{ij} is the skewness of the choice probability P_{ij}.
- Crucially, $sk_{ij} = P_{ij}(1 - P_{ij})(1 - 2P_{ij}) = \sigma_{ij}(1 - 2P_{ij})$.
- Notice that the last item may be positive or negative.
- $G(i)$ is the measure of individual heterogeneity.

Demand elasticity and curvature of discrete choice models

Key take-away from equation (12):

- Equation (12) is the manifold of residual demand for product j.
- The value of the demand manifold crucially depends on the function f.
- With quasi-linear preferences ($f = \alpha_i^*(y_i - p_j)$), the demand manifold can be written as:

$$\rho_j = \frac{p_j^2}{\epsilon_j^2 Q_j} \int (\alpha_i^*)^2 sk_{ij} dG(i) \tag{15}$$

- Notice how the term in the integral may change sign depending on the choice probability which dictates the sign of sk_{ij}.

Demand manifolds

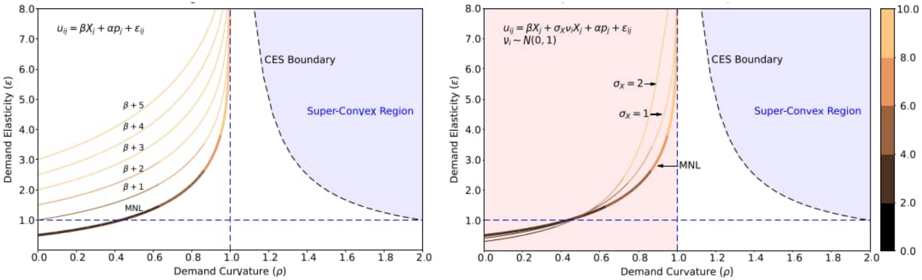
- MNL:

$$\rho_j = \frac{\alpha p_j(1 - 2P_j)}{\epsilon_j Q_j} \tag{15}$$

- Sign of $\rho^{MNL} < 0$ only in very concentrated markets where $P_j > 1/2$.
- For less concentrated markets, demand is convex, but log-concave. $\rightarrow$ pass-through necessarily **incomplete**.
- Pass-through increases as market structure gets less concentrated.
- CES: Pass-through invariant to price.

Demand elasticity - manifold

Figure 2: Multinomial and Mixed Logit Manifolds



Notes: The left panel shows six alternative MNL demand manifolds with one inside good assuming $\alpha = 0.5$, $X = 1$, and $\beta \in \{1, ..., 6\}$. The right panel shows manifolds for a ML model with a random coefficient on the product characteristic under alternative standard deviations σ_x and $\beta = 1$.

Demand manifolds

Random coefficient on price

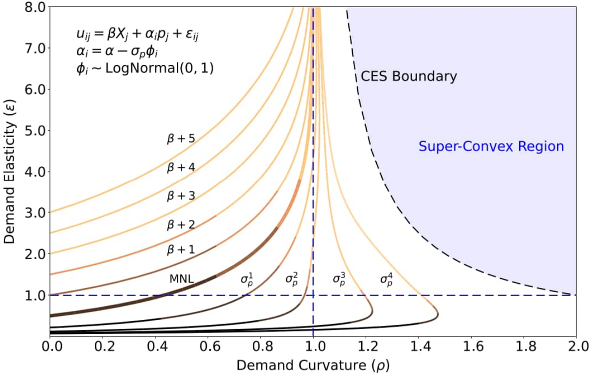
- Now $\alpha_i^* = \alpha + \sigma_p \phi_i$.
- ϕ_i is the random term and σ_p its coefficient.

$$\rho_j = \frac{p_j^2}{\epsilon_j^2 Q_j} \int (\alpha + \sigma_p \phi)^2 sk_{ij} d\Phi(i) \tag{18}$$

- Notice how the term in the integral may change sign depending on the choice probability which dictates the sign of sk_{ij}.

Demand elasticity - manifold

Figure 3: Multinomial and Mixed Logit Manifolds



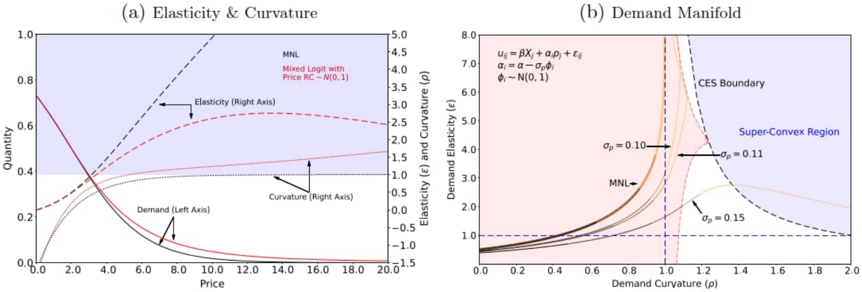
Notes: Starting with the demand manifold of the *MNL* model, $\beta+1, \beta+2, \ldots$ indicate the demand manifolds of *MNL* models for higher valuations of the inside good. The other manifolds refer to the *ML* model with price random coefficients where $\sigma_p^1 < \sigma_p^2 < \sigma_p^3 < \sigma_p^4$. The random component of the slope of demand is more important for large values of σ_p.

Demand elasticity - manifold

- MNL with random coefficient on price (and sufficient variation in the price coefficient through σ_p accomodates **over 100%** pass-through.
- In Figure 3, ϕ has log-normal distribution.

Demand elasticity - manifold with normal distribution for price coefficient

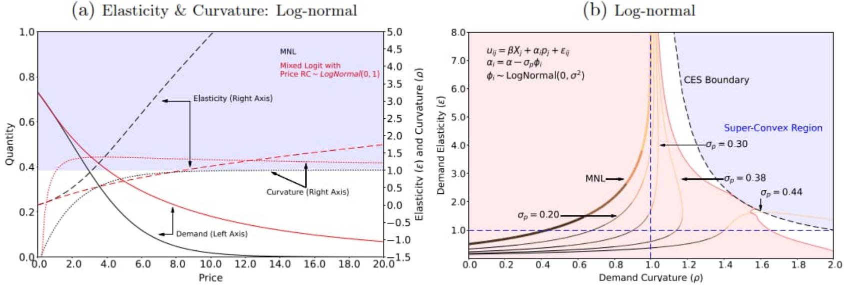
Figure 4: Demand Manifolds: Standard Normal Price Mixing Distribution



Notes: Panel (a) contrasts quantity, elasticity, and curvature under *MNL* in black and *ML* in red. Panel (b) represents demand manifolds in the (ε, ρ) plane. Light-shaded regions represent all feasible (ε, ρ) pairs conditional on the price-mixing distribution.

Demand elasticity - manifold with log-normal distribution for price coefficient

Figure 5: Demand Manifolds: Log-normal Mixing Distribution



Notes: Panel (a) contrasts quantity, elasticity, and curvature under *MNL* in black and *ML* in red. Panel (b) represents demand manifolds in the (ε, ρ) plane. Light-shaded regions represent all feasible (ε, ρ) pairs conditional on the price-mixing distribution

Demand elasticity - manifold

- With normal distribution, price elasticity starts to eventually decrease in price (LHS Fig 4).
- With log-normal distribution, price elasticity monotonically increasing in price (LHS Fig 5).
- With log-normal distribution, the feasible area with $\rho > 1$ much larger than with normal distribution (RHS, Fig 4 & Fig 5).
- Summary: Allowing for heterogeneity in price responses yields substantial flexibility in demand curvature and hence in what level of pass-through rates the model allows for.
- (Not covered here, see Section 5 in MST): Especially when the products are expensive (=large part of consumer budget), modeling income effects nonlinearly helps tremendously.

Empirical application: Breakfast cereals

- The authors model the effect of income in various ways and analyze how this modeling choice affects elasticity and curvature estimates.
- Data: IRI 2007 - 2011 for 7 large markets and 2 small markets for which also micro data; purchase and price data at weekly level.
- Prices, quantities, product characteristics, cost data, demographic data.
- MST aggregate products to brand-flavor combos.
- Prices measured as prices per one-ounce serving.
- Chains use (within-chain) uniform pricing.
- Store choice not modelled.

Income effects on price coefficient

$$y_{il}^{(\lambda)} = \begin{bmatrix} \frac{y_{il}^{\lambda}-1}{\lambda} \; if \; \lambda > 0 \\ \ln(y_{il}) \; if \; \lambda = 0 \end{bmatrix} \tag{30}$$

$$\alpha_i^* = -exp(\alpha + \pi^p y_i^{(\lambda)} + \pi^k D_i^{kids}) \tag{31}$$

- Random coefficient on sugar content (also having kids and income affect taste for sugar).
- IV: differentiation IVs for random coefficient on sugar; # products for random coefficient on outside good; and cost data (use Random Forest) for price.
- Also some micro-moments.
- 3 specifications: λ estimated; $\lambda = 0 =$ log-income; and $\lambda = 1 =$ income.

Estimation results

Table 2: IRI Ready-To-Eat Estimation Results

Parameter	Flexible	Income	Log-Income
Box-Cox Transform (λ)	3.1511	1.0000	0.0000
	(1.5118)	-	-
Price (α)	2.1368	2.4980	2.2425
	(0.0617)	(0.0131)	(0.0171)
Random Coefficients (Σ):			
Constant	1.6540	1.7483	2.8162
	(2.357)	(2.0901)	(1.2726)
Sugar	1.6256	1.5683	2.7426
	(1.1222)	(1.119)	(1.0542)
Demographic Interactions (Π):			
Income-Constant	-1.7258	-1.3255	-1.2753
	(0.3391)	(0.2445)	(0.1962)
Income-Price	1.1549	0.4041	0.3202
	(0.1744)	(0.0265)	(0.0235)
Income-Sugar	-0.1013	0.1703	0.5913
	(0.0705)	(0.0472)	(0.0416)
Kids-Constant	0.7176	0.7551	0.8736
	(0.3212)	(0.3251)	(0.2125)
Kids-Price	-0.0375	-0.0259	-0.0023
	(0.0325)	(0.0192)	(0.0306)
Kids-Sugar	0.3332	0.2718	0.5638
	(0.095)	(0.0907)	(0.0954)
Implications:			
- Elasticity	2.21	2.93	2.23
- Curvature	1.06	1.01	1.00

Notes: Estimates (standard errors in parentheses) based on IRI scanner data from 2007 to 2011 for Boston (5.2% of total revenue), Philadelphia (4.5%), Chicago (4.2%), San

Elasticity - curvature results

Figure 11: IRI Breakfast Cereal: Elasticity and Curvature Estimates

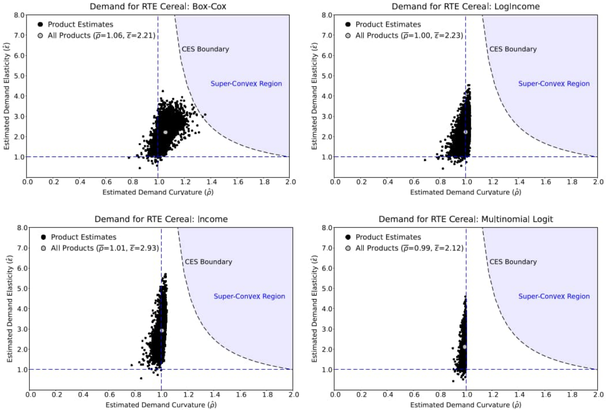


Figure Notes: Dots represent the point elasticity and curvature estimates for each observation in the sample with the silver dot corresponding the the average elasticity and curvature estimates.

Elasticity - curvature results

- $\hat{\lambda} = 3.2$ implies that low-income consumers have similar price sensitivity, but high-income consumers are heterogenous.
- Both log-income (top-right in Fig 11) and income (bottom-left) models imply that low-income consumers are more heterogenous in their price sensitivity.
- The preferred model exhibits less elastic demand and greater curvature $\rightarrow$ more market power and cost pass-through.

Elasticity - curvature results

Table 3: Elasticity, Curvature, and Flexible Demand

	Flexible	Income	Log-Income	MNL
Elasticity				
- Mean	2.21	2.93	2.23	2.12
- Median	2.21	2.91	2.21	2.10
- Stand. Dev.	0.47	0.67	0.53	0.52
- 90%	2.82	3.79	2.91	2.80
- 10%	1.60	2.06	1.56	1.46
Curvature				
- Mean	1.06	1.01	1.00	0.99
- Median	1.05	1.01	1.01	0.99
- Stand. Dev.	0.05	0.02	0.03	0.01
- 90%	1.11	1.02	1.02	1.00
- 10%	1.01	0.98	0.97	0.98

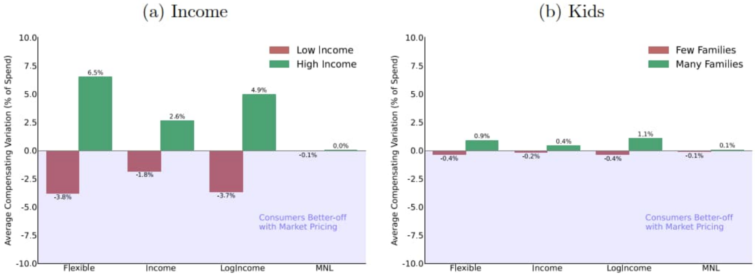
How do the models match data?

Table 4: Matching Consumption Patterns

Moment	Data	Flexible ($\hat{\lambda}=3.2$)	Income ($\lambda=1$)	Log-Income ($\lambda=0$)	MNL
$\mathbb{E}[\text{Price}\|\text{Income}Q_2]/\mathbb{E}[\text{Price}\|\text{Income}Q_1]$	1.0011	1.0019	1.0109	1.0152	1.0000
$\mathbb{E}[\text{Price}\|\text{Income}Q_3]/\mathbb{E}[\text{Price}\|\text{Income}Q_1]$	1.0087	1.0090	1.0235	1.0289	1.0000
$\mathbb{E}[\text{Price}\|\text{Income}Q_4]/\mathbb{E}[\text{Price}\|\text{Income}Q_1]$	1.0492	1.0496	1.0460	1.0421	1.0000
Corr(Price,Kids)	-0.0149	-0.0149	-0.0131	-0.0110	0.0000
$E[\text{Income}\|\text{Buy}]$	0.9852	0.9852	0.9867	0.9857	1.0000
$E[\text{Kids}\|\text{Buy}]$	1.2470	1.2470	1.2432	1.2450	1.0000

Effects of going from uniform to store-level prices

Figure 13: Distributional Implications of Uniform Pricing



Notes: Figure present average CV/spend across markets of similar demographic characteristic where each characteristic is divided into quartiles. "Low Income" ("High Income") reflects markets which are in the bottom (top) 25% of average income in the sample. "Few Families" ("Many Families") reflects markets which are in the bottom (top) 25% of percent of households with a child.