Lecture 1
Applied methods in Industrial Organisation

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CESifo Lectures, April 2017

Overview of three lectures

- Lecture 1: Applied methods in Industrial Organisation
  - review the development and use of random coefficients (mixed) logit model using market level data
- Lecture 2: Measurement of Consumer Welfare
  - use of random coefficients (mixed) logit model to measure consumer welfare
  - recent applications using consumer level data, including applications with “behavioural” considerations
- Lecture 3: Unobserved choice sets
  - further recent applications using consumer level data with “behavioural” considerations

A brief history of IO

- Industry case studies
  - 30s-50s
- The Structure-Conduct-Performance Paradigm
  - 50s-70s
  - more recent variants
- Game Theory
  - 70s-90s
- The New Empirical IO
  - 80s-present

The Structure Conduct Performance Paradigm

- Traditional literature
  - regress price, margins or profits on concentration
  - issues: data, econometric, interpretation
- Modern variants
  - cross market regressions (with controls or fixed effects)
  - diff-in-diff to measure the effects of mergers
  - Cost pass through regressions
    - regress (change in) price on (change in) cost
    - if cost pass through is not 100% indicates market power
    - in general, pass through depends on the curvature of demand
    - early attempts and some recent revival

The New Empirical IO

- Marginal costs (so price-cost margins) are not observed, are estimated
  - deals with the main data problem
- Study a specific industry, use time series or a cross section of geographical markets
  - deals with the simultaneity problem
- Conduct is viewed as a parameter to be estimated
  - (usually) ties more directly to theory and deals with interpretation
- General idea
  - use an economic model to invert, or reverse engineer, observed behavior in order to recover unknown quantities
    - in auctions: invert bids to recover valuations using optimal bidding rules
    - in pricing: invert optimal pricing rule to recover marginal cost

Why Do We Care About Demand (in IO)?

- Allows us to "reverse engineer" firms' optimal decisions in order to
  - obtain marginal costs
  - test models of pricing
- Compute firm strategy that depends on consumer behavior
  - price discrimination
  - advertising and promotional activity
- Simulate counterfactuals
  - likely effect of mergers
  - demand for new products
- Consumer welfare

Demand models

$$q = D(p, r, \varepsilon)$$

q: vector of quantities p: vector of prices
r: vector of exogenous variables ε: vector of random shocks

- Early work focused on how to specify $D(\cdot)$ in a way that was both flexible and consistent with economic theory
  - Linear Expenditure model (Stone, 1954)
  - Rotterdam model (Theil, 1965; Barten 1966)
  - Translog model (Christensen, Jorgenson, and Lau, 1975)
  - Almost Ideal Demand System (Deaton and Muellbauer, 1980)

Issues for IO applications

- Too many parameters
  - suppose $D(p, r, \varepsilon) = Ap + \varepsilon$
    - where A is $J \times J$ matrix of parameters
    - implies J^2 parameters to be estimated
    - with large J there are too many parameters to estimate
    - with a more flexible functional form, the problem is even greater
- Does not allow us to predict the demand for new goods
- Hard to estimate
  - need to include, and instrument for, many highly colinear prices
- Heterogeneity
  - not so easy to flexibly accommodate in above approaches

Solutions

- Aggregation across products
- Impose symmetry
- Assume weak separability and multi stage budgeting
- Models in characteristics space and discrete choice

Aggregation Across Products

- Aggregate individual products into aggregate commodities
  - can allow for flexible, even non-parametric, functional forms
  - but for many IO problems this misses the point
- Real question is not whether to aggregate but what level and whether this solves the dimensionality problem
- The answer depends on:
  - what we are interested in
  - correlation of prices of products we are aggregating over
  - substitution between the products we are aggregating over

Symmetry Across Products

- Trade and applied theory use constant elasticity of substitution (CES)
  - utility from consumption of the J products:
$$U(q_1, ..., q_J) = \left(\sum_{i=1}^{J} q_i^{\rho} \right)^{1/\rho}$$
  - ρ is a constant parameter
  - demand of representative consumer:
$$q_k = \frac{p_k^{-1/(1-\rho)}}{\sum_{i=1}^{J} p_i^{-\rho/(1-\rho)}} I \qquad i = 1, ..., J$$
  - I is income of the representative consumer
- Dimensionality reduced by imposing symmetry:
$$\frac{\partial q_i}{\partial p_j} \frac{p_j}{q_i} = \frac{\partial q_k}{\partial p_j} \frac{p_j}{q_k} \quad \text{for all } i, k, j$$
- Easy to work with, but cannot fit many patterns in micro data

Separability and Multi-Stage Budgeting

- Basic idea
  - solve the dimensionality problem by dividing the products into smaller groups and allowing for a flexible functional form within each group
- Multi-stage budgeting
  - write the consumer's problem as a sequence of separate but related decision problems
  - at each stage the allocation decision is a function of only that group total expenditure and prices of commodities in that group
- Various conditions guarantee that the solution to this multi-stage process will equal the solution to the original consumer problem
  - one important condition is weak separability of preferences

Models in Characteristics Space

- Utility comes from the characteristics of the product (Gorman (1956, 1980), Lancester (1966))
  - some products are better substitutes for each other than others
  - rather than group them (in an often ad hoc way, such as is typically the case with multi-stage budgeting models) the characteristics define their substitutability
  - reduces the dimensionality from number of products to number of characteristics
  - key challenge is how to deal with unobservable characteristics
- Usually implemented as discrete choice
  - but does not have to be (e.g. Dubois, Griffith and Nevo (2014, AER))

Models in Characteristics Space

- Indirect utility:
$$U(x_{jt}, \xi_{jt}, I_i - p_{jt}, \tau_i; \theta)$$
    - i: consumer, j: product, t: market
    - x_{jt}: vector of k observed product characteristics
    - ξ_{jt}: unobserved (by us) product characteristic
        - will play an important role; captures brand value, promotion etc.
        - implies endogeneity, e.g. if firms observe before making pricing decisions
    - I_i: income, p_{jt}: price
    - τ_i: individual characteristics
    - θ: preference parameters

Linear Random Coefficients (Mixed) Logit Model

- A common assumption is linear indirect utility

$$u_{ijt} = x_{jt}\beta_i + \alpha_i(I_i - p_{jt}) + \xi_{jt} + \varepsilon_{ijt}$$

  - utility is deterministic, ε_{ijt} captures the researcher's inability to formulate individual behaviour precisely, so that utility is stochastic from researcher's perspective
  - alternative view is that the choice process itself is probabilistic (Tversky, 1972)
- Interplay between ξ_{jt} and ε_{ijt}
  - all that ξ_{jt} is doing is changing the mean of ε_{ijt}, by j and t

Outside Option

- The outside option allows for substitution outside the market; important in many IO applications
- The indirect utility from the outside option is typically written

$$u_{i0t} = \alpha_i I_i + \varepsilon_{i0t}$$

  - or sometimes also includes time effects to capture cyclicality in market level demand

Heterogeneity

- Consumer-level taste parameters
  - consumer i's marginal utility of income

$$\alpha_i = \alpha + \sum_{r=1}^{d} \pi_{1r} D_{ir} + \sigma_1 v_{i1}$$

  - individual specific taste coefficients

$$\beta_{ik} = \beta_k + \sum_{r=1}^{d} \pi_{(k+1)r} D_{ir} + \sigma_{k+1} v_{i(k+1)}$$

  - $D_i = (D_{i1}, ..., D_{id})'$: vector of d observed demographic variables
  - $v_i = (v_{i1}, ..., v_{i(K+1)})'$: vector of unobserved consumer attributes
  - Π: matrix of taste parameters on observed demographics
  - $\sigma = (\sigma_1, ..., \sigma_{K+1})$: vector of unobserved taste parameters

Heterogeneity

- unobserved consumer attributes
  - $v_i = (v_{i1}, ..., v_{i(K+1)})'$
  - are crucial to capture realistic substitution patterns in discrete choice demand models (BLP (1995), Train (2003))
- unobserved taste parameters
  - $\sigma = (\sigma_1, ..., \sigma_{K+1})$
  - are generally modelled as random coefficients
  - typically assume joint distribution, F_v is standard normal or log normal (but are non-parametrically identified)

Linear RC (Mixed) Logit Model

- It will be convenient to rewrite

$$u_{ijt} = x_{jt}\beta_i + \alpha_i p_{jt} + \xi_{jt} + \varepsilon_{ijt}$$

- as

$$u_{ijt} \equiv \delta(x_{jt}, p_{jt}, \boldsymbol{\xi}_{jt}; \alpha, \beta) + \mu(x_{jt}, p_{jt}, D_i, \nu_i; \Pi, \sigma) + \varepsilon_{ijt}$$

  - mean utility across consumers

$$\delta_{jt} = x_{jt}\beta + \alpha p_{jt} + \xi_{jt}$$

  - variation around the mean

$$\begin{aligned} \mu_{ijt} &= -\left(\sum_{r=1}^{d} \pi_{1r} D_{ir} + \sigma_1 v_{i1}\right) p_{jt} \\ &\quad + \sum_{k=1}^{K} \left(\sum_{r=1}^{d} \pi_{(k+1)r} D_{ir} + \sigma_{k+1} v_{i(k+1)}\right) x_{jt}^{k} \end{aligned}$$

Choice Probabilities and Market Shares

- Assume consumers purchase one unit, which gives the highest utility
- The probability that type (D_i, v_i) chooses option j is

$$s_{ijt} = s_{ijt}(x_t, \delta_t, p_t, D_i, v_i; \theta) = \int 1[u_{ijt} \geq u_{ikt} \forall k | x_t, \delta_t, p_t, D_i, v_i; \theta] dF_{\varepsilon}(\varepsilon)$$

where $\theta = (\alpha, \beta, \Pi, \sigma)$

- Integrating this probability over consumer attributes (D_i, v_i) gives market shares

$$s_{jt} = s_{jt}(x_t, \delta_t, p_t; \theta) = \int s_{ijt}(x_t, \delta_t, p_t, D_i, v_i; \theta) dF_D(D) dF_v(v)$$

  - with consumer level data we integrate only over v_i

Logit with no heterogeneity

- If we assume no heterogeneity
  - $\Pi = 0$ and $\sigma = 0$, which implies $\beta_i = \beta$ and $\alpha_i = \alpha$
- and
  - ε_{ijt} are iid
  - ε_{ijt} are distributed according to a Type I extreme value distribution
- These imply

$$s_{jt} = \frac{\exp\{x_{jt}\beta - \alpha p_{jt} + \xi_{jt}\}}{1 + \sum_{k=1}^{J} \exp\{x_{kt}\beta - \alpha p_{kt} + \xi_{kt}\}}$$

Price Elasticities

$$\eta_{jkt} = \frac{\partial s_{jt}}{\partial p_{kt}} \frac{p_{kt}}{s_{jt}} = \begin{cases} -\alpha p_{jt}(1 - s_{jt}) & \text{if } j = k \\ \alpha p_{kt} s_{kt} & \text{otherwise} \end{cases}$$

- Two Problems
  - own price elasticities: market shares are typically small, so $\alpha(1 - s_{jt})$ is nearly constant and therefore the own-price elasticities are proportional to price
    - driven mostly by lack of heterogeneity
  - cross-price elasticities: cross price elasticity wrt a change in the price of product k is that same for all products such that $j \neq k$
    - driven by lack of heterogeneity and iid

Relaxing the iid assumption

- Nested Logit (still no heterogeneity):
  - $\Pi = 0$ and $\sigma = 0$
  - divide the products into mutually exclusive nests, $g = 1, ..., G$
  - let $\varepsilon_{ijt} = \lambda\varepsilon_{ig(j)t} + \varepsilon^1_{ijt}$
    - where ε^1_{ijt} is an iid extreme value shock
    - $\varepsilon_{ig(j)t}$ is a shock common to all options in segment g
    - λ is a parameter that captures the relative importance of the two
  - a particular distribution for $\varepsilon_{ig(j)t}$ gives the Nested Logit model
  - if $\lambda = 0$ we get the Logit model
- The Nested Logit model is a private case of the more general Generalized Extreme Value model which imposes correlation among the options through correlation in ε_{ijt}

The effects of allowing heterogeneity

- Generate correlation through μ_{ijt} by allowing heterogeneity in tastes for the product attributes to drive correlation
    - for example, if "luxury" is an attribute of a car, then a consumer who likes one luxury car is more likely than the average consumer to like another luxury car
- Price elasticities

$$\eta_{jkt} = \frac{\partial s_{jt}}{\partial p_{kt}} \frac{p_{kt}}{s_{jt}} = \begin{cases} -\frac{p_{jt}}{s_{jt}} \int \alpha_i s_{ijt}(1 - s_{ijt}) dP_D(D) dP_v(v) & \text{if } j = k \\ \frac{p_{kt}}{s_{jt}} \int \alpha_i s_{ijt} s_{ikt} dP_D(D) dP_v(v) & \text{otherwise} \end{cases}$$

- own-price elasticity no longer driven by funcational form; e.g. will depend on price sensitivity of consumers who are attracted to that product
- cross-price elasticities no driven by a priori segementation, and also quite flexible

Identification

- (Π, σ) are identified from variation in demographics holding the mean utility (δ) constant
  - σ is identified from within market variation in choice probabilities
  - with market-level data we rely on cross market variation (in choice sets and demographics) to identify (Π, σ)
- (α, β) are identified from cross market variation (and appropriate exclusion restrictions)
- a key issue is ξ_{jt}
  - prices might be correlated with $\boldsymbol{\xi}_{jt}$ (the "structural" error)

Identification

- Issues vary depending on data
  - consumer level data
  - market level data
- The unobserved characteristic, ξ_{jt}
  - generates a potential for correlation with price (or other x's)
  - can exist with both consumer and market level data
- Recovering the non-linear parameters that govern heterogeneity
  - a challenge with market level data, key insight from BLP (1995) is how to do this
  - with consumer data less of a problem

Inversion

- Key insight from Berry (1994) and BLP (1995)
  - in order to use standard IV methods we need to extract ξ_{jt} from inside the non-linear share equation we wrote earlier
    - with ξ_{jt} predicted shares can equal observed shares

$$\sigma_j(\boldsymbol{\delta_t}, \boldsymbol{x}_t, \boldsymbol{p}_t; \theta_2) = \int \mathbf{1}\left[u_{ijt} \geq u_{ikt} \quad \forall k \neq j\right] dF\left(\varepsilon_{it}, D_{it}, \nu_{it}\right) = S_{jt}$$

    - under weak conditions this mapping can be inverted

$$\boldsymbol{\delta}_t = \sigma^{-1}(\boldsymbol{S}_t, \boldsymbol{x}_t, \boldsymbol{p}_t; \theta_2)$$

  - the mean utility is linear in ξ_{jt} so we can write

$$\xi_{jt} = \delta_{jt}(s_t; \Pi, \sigma) - (x_{jt}\beta - \alpha p_{jt})$$

    so we have the unobserved characteristic as a function of data and parameters

    - so we can form linear moment conditions and estimate via GMM

Identification

- Ideal experiment
  - randomly vary prices, characteristics and availability of products
  - see where consumers switch (i.e., shares of which products respond)
- In practice we will use IVs that try to mimic this ideal experiment
  - is there "enough" variation to identify substitution?
- What IVs have been used?
  - supply information (BLP)
  - many markets (Nevo)
  - add micro information (Petrin, MicroBLP)
- For further discussion and proofs see Berry and Haile (2014)

Commonly used IVs: competition in characteristics space

- Assume that $E(\xi_{jt}|\mathbf{x}_t) = 0$
  - observed characteristics are mean independent of unobserved characteristics
  - nice because we already have the data
- Often called "BLP Instruments"
  - characteristics of own products, other products produced by the firm, competitors' products
- Power
  - idea is that markups vary with degree of competition, which is appoximated by how close other products are in characteristics space
- Validity
  - x_{jt} are assumed set before ξ_{jt} is known
  - not hard to come up with stories that make these invalid

Commonly used IVs: cost based

- Cost data are often no directly observed
- BLP (1995, 1999) use characteristics that enter cost (but not demand)
- Villas-Boas (2007) uses prices of inputs interacted with product dummy variables (to generate variation by product)
- Hausman (1996) and Nevo (2001) rely on indirect measures of cost
  - use prices of the product in other markets
  - validity: after controlling for common effects, the unobserved characteristics are assumed independent across markets
  - power: prices will be correlated across markets due to common marginal cost shocks
  - easy to come up with examples where IVs are not valid (e.g., national promotions)

Commonly used IVs: dynamic panel

- Ideas from the dynamic panel data literature (Arellano and Bond, 1991, Blundell and Bond, 1998) have been used to motivate the use of lagged characteristics as instruments
- Proposed in a footnote in BLP
- For example, Sweeting (2011) assumes
  - $\xi_{jt} = \rho \xi_{jt-1} + \eta_{jt}$
  - where $E(\eta_{jt} | \mathbf{x}_{t-1}) = 0$
  - Then
    $$E(\xi_{jt} - \rho \xi_{jt-1} | \mathbf{x}_{t-1}) = 0$$
    is a valid moment condition

Berry, Levinsohn, Pakes (1995) – BLP

"Automobile Prices in Market Equilibrium" (Econometrica, 1995)

- Market level data on car sales (by model) with characteristics and demographic variation across markets
- Key points to take away from this paper:
  1. Using instruments has a big effect (see Table 3 in BLP)
  2. Random Coefficients (RC) Logit gives much more realistic substitution patterns than standard Logit

BLP Table 7: substitution to the outside option

TABLE VII

SUBSTITUTION TO THE OUTSIDE GOOD

Model	Given a price increase, the percentage who substitute to the outside good (as a percentage of all who substitute away.) Logit	BLP
Mazda 323	90.870	27.123
Nissan Sentra	90.843	26.133
Ford Escort	90.592	27.996
Chevy Cavalier	90.585	26.389
Honda Accord	90.458	21.839
Ford Taurus	90.566	25.214
Buick Century	90.777	25.402
Nissan Maxima	90.790	21.738
Acura Legend	90.838	20.786
Lincoln Town Car	90.739	20.309
Cadillac Seville	90.860	16.734
Lexus LS400	90.851	10.090
BMW 735*i*	90.883	10.101

in logit model 90% of substitute away to the outside good ($s_0/(1-s_j)$)

with BLP model lower proportion and more varied

BLP Table 8: markups

TABLE VIII

A SAMPLE FROM 1990 OF ESTIMATED PRICE-MARGINAL COST MARKUPS AND VARIABLE PROFITS: BASED ON TABLE 6 (CRTS) ESTIMATES

	Price	Markup Over MC $(p - MC)$	Variable Profits (in $'000's) $q*(p - MC)$
Mazda 323	$5,049	$ 801	$18,407
Nissan Sentra	$5,661	$ 880	$43,554
Ford Escort	$5,663	$1,077	$311,068
Chevy Cavalier	$5,797	$1,302	$384,263
Honda Accord	$9,292	$1,992	$830,842
Ford Taurus	$9,671	$2,577	$807,212
Buick Century	$10,138	$2,420	$271,446
Nissan Maxima	$13,695	$2,881	$288,291
Acura Legend	$18,944	$4,671	$250,695
Lincoln Town Car	$21,412	$5,596	$832,082
Cadillac Seville	$24,353	$7,500	$249,195
Lexus LS400	$27,544	$9,030	$371,123
BMW 735*i*	$37,490	$10,975	$114,802

BLP Summary

- Powerful method with potential for many applications
- Clearly show:
  - effect of IV
  - Random Coefficient (RC) logit versus logit
  - BLP (2004) show that unobserved heterogeneity matters much more than observed in capturing realistic substitution patterns
- Common complaints:
  - instruments
  - supply side: static, not tested, driving the results
  - demand side dynamics

Nevo (2001)

"Measuring Market Power in the Ready-to-eat Cereal Industry" Econometrica

Points to take away:

1. industry where characteristics are less obvious
2. effects of various instrumental variables
3. testing the model of competition

The Ready-to-eat cereal market

- Characterized by:
  - high concentration (C3≈75%, C6≈90%)
  - high price-cost margins (≈45%)
  - large advertising to sales ratios (≈13%)
  - numerous introductions of brands (67 new brands by top 6 in 80's)
- Claim that this is a good example of collusive pricing
  - is pricing in the industry collusive?
  - what portion of the markups in the industry due to:
    - product differentiation?
    - multi-product firms?
    - potential price collusion?

Strategy

- Estimate brand level demand
- Compute price-cost margin predicted by different industry structures, models of conduct:
  - single-product firms
  - current ownership (multi-product firms)
  - fully collusive pricing (joint ownership)
- Compare predicted price-cost margin to observed price-cost margin

Supply

- The profits of firm f

$$\Pi_f = \sum_{j \in F_f} (p_j - mc_j) s_j(p) - C_f$$

  - the first order conditions are

$$s_j(p) + \sum_{r \in F_f} (p_r - mc_r) \frac{\partial s_r(p)}{\partial p_j} = 0$$

    - define

$$\begin{aligned} \Omega &= \Omega_{jr} * S_{jr} \\ S_{jr} &= -\partial s_r / \partial p_j \\ \Omega_{jr} &= \begin{cases} 1 & \text{if } \{r, j\} \text{ owned by f} \\ 0 & \text{otherwise} \end{cases} \end{aligned}$$

  - so that

$$s(p) + \Omega(p - mc) = 0$$

$$(p - mc) = \Omega^{-1} s(p)$$

Supply

- using

$$(p - mc) = \Omega^{-1} s(p)$$

- we can recover the unobserved marginal costs (mc)
- then we can do counterfactuals such as what if the market had a different structure by
  - assuming a model of conduct
  - change the "ownership" structure Ω_{jr} in

$$\begin{aligned} \Omega &= \Omega_{jr} * S_{jr} \\ S_{jr} &= -\partial s_r / \partial p_j \\ \Omega_{jr} &= \begin{cases} 1 & \text{if } \{r, j\} \text{ owned by f} \\ 0 & \text{otherwise} \end{cases} \end{aligned}$$

Data

- IRI Infoscan scanner data
  - market shares and prices of 25 brands (top 25 in last quarter), in 67 cities (number increases over time) over 20 quarters (1988-1992)
  - 1124 markets, 27,862 observations
- LNA advertising data
- Characteristics from cereal boxes
- Demographics varies across markets (not over time)
- Cost instruments vary across market and time

Identification

- Explores various instruments:
  - characteristics of competition; problematic for this sample, with brand FE
  - prices in other cities
  - proxies for city level costs: density, earning in retail sector, and transportation costs
- Brand fixed effects
  - control for unobserved quality (instead of instrumenting for it)

Results from the Full Model

TABLE VI

RESULTS FROM THE FULL MODEL[a]

Variable	Means (β's)	Standard Deviations (σ's)	Interactions with Demographic Variables: Income	Income Sq	Age	Child
Price	−27.198	2.453	315.894	−18.200	—	7.634
	(5.248)	(2.978)	(110.385)	(5.914)		(2.238)
Advertising	0.020	—	—	—	—	—
	(0.005)					
Constant	−3.592[b]	0.330	5.482	—	0.204	—
	(0.138)	(0.609)	(1.504)		(0.341)	
Cal from Fat	1.146[b]	1.624	—	—	—	—
	(0.128)	(2.809)				
Sugar	5.742[b]	1.661	−24.931	—	5.105	—
	(0.581)	(5.866)	(9.167)		(3.418)	
Mushy	−0.565[b]	0.244	1.265	—	0.809	—
	(0.052)	(0.623)	(0.737)		(0.385)	
Fiber	1.627[b]	0.195	—	—	—	−0.110
	(0.263)	(3.541)				(0.0513)
All-family	0.781[b]	0.1330	—	—	—	
	(0.075)	(1.365)				
Kids	1.021[b]	2.031	—	—	—	
	(0.168)	(0.448)				
Adults	1.972[b]	0.247	—	—	—	
	(0.186)	(1.636)				
GMM Objective (degrees of freedom)			5.05 (8)			
MD χ^2			3472.3			
% of Price Coefficients > 0			0.7			

unlike BLP the unobserved heterogeneity is not so important

Elasticities

MEDIAN OWN AND CROSS-PRICE ELASTICITIES*

#	Brand	Corn Flakes	Frosted Flakes	Rice Krispies	Froot Loops	Cheerios	Total	Lucky Charms	P Raisin Bran	CapN Crunch	Shredded Wheat
1	K Corn Flakes	−3.379	0.212	0.197	0.014	0.202	0.097	0.012	0.013	0.038	0.028
2	K Raisin Bran	0.036	0.046	0.079	0.043	0.145	0.043	0.037	0.057	0.050	0.040
3	K Frosted Flakes	0.151	−3.137	0.105	0.069	0.129	0.079	0.061	0.013	0.138	0.023
4	K Rice Krispies	0.195	0.144	−3.231	0.031	0.241	0.087	0.026	0.031	0.055	0.046
5	K Frosted Mini Wheats	0.014	0.024	0.052	0.043	0.105	0.028	0.038	0.054	0.045	0.033
6	K Froot Loops	0.019	0.131	0.042	−2.340	0.072	0.025	0.107	0.027	0.149	0.020
7	K Special K	0.114	0.124	0.105	0.021	0.153	0.151	0.019	0.021	0.035	0.035
8	K Crispix	0.077	0.086	0.114	0.034	0.181	0.085	0.030	0.037	0.048	0.043
9	K Corn Pops	0.013	0.109	0.034	0.113	0.058	0.025	0.098	0.024	0.127	0.016
10	GM Cheerios	0.127	0.111	0.152	0.034	−3.663	0.085	0.030	0.037	0.056	0.050
11	GM Honey Nut Cheerios	0.033	0.192	0.058	0.123	0.094	0.034	0.107	0.026	0.162	0.024
12	GM Wheaties	0.242	0.169	0.175	0.025	0.240	0.113	0.021	0.026	0.050	0.043
13	GM Total	0.096	0.108	0.087	0.018	0.131	−2.889	0.017	0.017	0.029	0.029
14	GM Lucky Charms	0.019	0.131	0.041	0.124	0.073	0.026	−2.536	0.027	0.147	0.020
15	GM Trix	0.012	0.103	0.031	0.109	0.056	0.026	0.096	0.024	0.123	0.016
16	GM Raisin Nut	0.013	0.025	0.042	0.035	0.089	0.040	0.031	0.046	0.036	0.027
17	GM Cinnamon Toast Crunch	0.026	0.164	0.049	0.119	0.089	0.035	0.102	0.026	0.151	0.022
18	GM Kix	0.050	0.279	0.070	0.101	0.106	0.056	0.088	0.030	0.149	0.025
19	P Raisin Bran	0.027	0.037	0.068	0.044	0.127	0.035	0.038	−2.496	0.049	0.036
20	P Grape Nuts	0.037	0.049	0.088	0.042	0.165	0.050	0.037	0.051	0.052	0.047
21	P Honey Bunches of Oats	0.100	0.098	0.104	0.022	0.172	0.109	0.020	0.024	0.038	0.033
22	Q 100% Natural	0.013	0.021	0.046	0.042	0.103	0.029	0.036	0.052	0.046	0.029
23	Q Life	0.077	0.328	0.091	0.114	0.137	0.046	0.096	0.023	0.182	0.029
24	Q CapN Crunch	0.043	0.218	0.064	0.124	0.101	0.034	0.106	0.026	−2.277	0.024
25	N Shredded Wheat	0.076	0.082	0.124	0.037	0.210	0.076	0.034	0.044	0.054	−4.252
26	Outside good	0.141	0.078	0.084	0.022	0.104	0.041	0.018	0.021	0.033	0.021

Margins

TABLE VIII

MEDIAN MARGINS[a]

	Logit (Table V column ix)	Full Model (Table VI)
Single Product Firms	33.6%	35.8%
	(31.8%–35.6%)	(24.4%–46.4%)
Current Ownership of 25 Brands	35.8%	42.2%
	(33.9%–38.0%)	(29.1%–55.8%)
Joint Ownership of 25 Brands	41.9%	72.6%
	(39.7%–44.4%)	(62.2%–97.2%)
Current Ownership of All Brands	37.2%	—
	(35.2%–39.4%)	
Monopoly/Perfect Price Collusion	54.0%	—
	(51.1%–57.3%)	

can reject the null that actual margins (31%-46%)

are equal to those predicted by the model of joint profit maximization

Summary and comments

- These methods have proved very useful and been the basis of an enormous body of empirical work, has been extended in many directions
  - further testing of supply behaviour
  - dynamics in demand and in supply
  - incorporating aspects of quantity choice into discrete choice framework
  - retailer and manufacturer vertical relations and pricing behaviour
  - etc. etc. etc.
- In the next two lectures I will consider a few papers that extend this literature to look at
  - distributional consequences of reforms
  - impacts of advertising and constrained choice sets (touching on some issues of interest in the recent "behavioural" literature)