Applications and Choice of IVs

Aviv Nevo

University of Pennsylvania and NBER

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Introduction

- In the previous lecture we discussed the estimation of DC model using market level data
- The estimation was based on the moment condition

$$E(\xi_{jt}|z_{jt}) = 0.$$

- In this lecture we will
  - discuss commonly used IVs
  - survey several applications

The role of IVs

- IVs play dual role Important!
  - generate moment conditions to identify θ_2
  - deal with the correlation of prices and error → endogeneity
    - firm knows ξ
- Simple example (Nested Logit model)

share of product in mkt, t,

$$\ln\Big(\frac{s_{jt}}{\underbrace{s_{0t}}_{\text{share outside good}}}\Big) = x_{jt}\beta + \alpha p_{jt} + \rho \ln\Big(\frac{s_{jt}}{\underbrace{s_{Gt}}_{\text{share of gp}}}\Big) + \xi_{jt}$$

even if price exogenous, "within market share" is endogenous

- Price endogeneity can be handled in other ways (e.g., panel data)

can't run ols ⇒ s_{jt} on both sides of equation

new product entry or change in characteristics ← · need instrument ⇒ something that changes relative share within the group

Commonly used IVs: 1.) competition in characteristics space

set in the past, doesn't affect ξ, no serial corr. in ξ
(before ξ is known)

- Assume that $E(\xi_{jt}|\mathbf{x}_t) = 0$, observed characteristics are mean independent of unobserved characteristics
- BLP propose using
  - own characteristics
  - sum of char of other products produced by the firm
  - sum of char of competitors products

"average"

(for price)

- Power: proximity in characteristics space to other products $\longrightarrow$ markup $\longrightarrow$ price
- Validity: x_{jt} are assumed set before ξ_{jt} is known
- Not hard to come up with stories that make these invalid
- Most commonly used
  - do not require data we do not already have
- Often called "BLP Instruments" Gandhi-Houde improve on the BLP

2.) Commonly used IVs: cost based

- Cost data are rarely 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 "Automobile Prices in Market Equilibrium" (EMA, 95) – BLP

Points to take away:

1. The effect of IV
2. Logit versus RC Logit

random coefs

Data

- 20 years of annual US national data, 1971-90 (T=20): 2217 model-years
  # 20 diff mkts
  1 mkt = 1 yr
- Quantity data by name plate (excluding fleet sales)
- Prices – list prices
- Characteristics from Automotive News Market Data Book
- Price and characteristics correspond to the base model
- Note: little/no use of segment and origin information

Demand Model

The indirect utility is

$$u_{ijt} = x_{jt}\beta_i + \alpha \ln(y_i - p_{jt}) + \xi_{jt} + \varepsilon_{ijt}$$

Note: income enters differently than before.

$$\left(\beta_i^k\right) = \beta^k + \sigma^k v_{ik} \quad v_{ik} \sim N(0,1)$$

The outside option has utility

$$u_{ijt} = \alpha \ln(y_i) + \xi_{jt} + \sigma^0 v_{i0} + \varepsilon_{ijt}$$

Estimation

- Basically estimate as we discussed before.
  - add supply-side moments to GMM obj fn. (changes last step of the algorithm)
    - help pin down demand parameters
    - adds cost side IVs
  - Instrumental variables. assume $E(\xi_{jt}|\mathbf{x}_t) = 0$, and use
    - (i) own characteristics
    - (ii) sum of char of other products produced by the firm
    - (iii) sum of characteristics products produced by other firms
  - Cost side: $E(\zeta_{jt}|\mathbf{w}_t) = 0$
  - Efficiency:
    - (i) importance sampling for the simulation of market shares
    - (ii) discussion of optimal instruments
    - (iii) parametric distribution for income (log-normal)

Table 3: effect of IV (in Logit)

TABLE III

RESULTS WITH LOGIT DEMAND AND MARGINAL COST PRICING
(2217 OBSERVATIONS)

Variable	OLS Logit Demand	IV Logit Demand	OLS ln (*price*) on *w*
Constant	−10.068	−9.273	1.882
	(0.253)	(0.493)	(0.119)
*HP/Weight**	−0.121	1.965	0.520
	(0.277)	(0.909)	(0.035)
Air	−0.035	1.289	0.680
	(0.073)	(0.248)	(0.019)
MP\$	0.263	0.052	—
	(0.043)	(0.086)	
*MPG**	—	—	−0.471
			(0.049)
*Size**	2.341	2.355	0.125
	(0.125)	(0.247)	(0.063)
Trend	—	—	0.013
			(0.002)
Price	−0.089	−0.216	—
	(0.004)	(0.123)	
No. Inelastic Demands	1494	22	*n.a.*
(+/−2 s.e.'s)	(1429–1617)	(7–101)	
R^2	0.387	*n.a.*	.656

not very price sensitive

problematic

Notes: The standard errors are reported in parentheses.

Tables 5: elasticities

TABLE V

A SAMPLE FROM 1990 OF ESTIMATED DEMAND ELASTICITIES WITH RESPECT TO ATTRIBUTES AND PRICE (BASED ON TABLE IV (CRTS) ESTIMATES)

	Value of Attribute/Price Elasticity of demand with respect to:				
Model	*HP/Weight*	*Air*	*MP $*	*Size*	*Price* ($1000)
Mazda323	0.366	0.000	3.645	1.075	5.049
	0.458	0.000	1.010	1.338	6.358
Sentra	0.391	0.000	3.645	1.092	5.661
	0.440	0.000	0.905	1.194	6.528
Escort	0.401	0.000	4.022	1.116	5.663
	0.449	0.000	1.132	1.176	6.031
Cavalier	0.385	0.000	3.142	1.179	5.797
	0.423	0.000	0.524	1.360	6.433
Accord	0.457	0.000	3.016	1.255	9.292
	0.282	0.000	0.126	0.873	4.798
Taurus	0.304	0.000	2.262	1.334	9.671
	0.180	0.000	−0.139	1.304	4.220
Century	0.387	1.000	2.890	1.312	10.138
	0.326	0.701	0.077	1.123	6.755
Maxima	0.518	1.000	2.513	1.300	13.695
	0.322	0.396	−0.136	0.932	4.845
Legend	0.510	1.000	2.388	1.292	18.944
	0.167	0.237	−0.070	0.596	4.134

→ elasticities (are getting lower)

Tables 6: elasticities

change by $1000

larger for mazda

TABLE VI

A SAMPLE FROM 1990 OF ESTIMATED OWN- AND CROSS-PRICE SEMI-ELASTICITI
BASED ON TABLE IV (CRTS) ESTIMATES

	Mazda 323	Nissan Sentra	Ford Escort	Chevy Cavalier	Honda Accord	Ford Taurus	Buick Century	Nissan Maxima	Acura Legend
323	−125.933	1.518	8.954	9.680	2.185	0.852	0.485	0.056	0.009
Sentra	0.705	−115.319	8.024	8.435	2.473	0.909	0.516	0.093	0.015
Escort	0.713	1.375	−106.497	7.570	2.298	0.708	0.445	0.082	0.015
Cavalier	0.754	1.414	7.406	−110.972	2.291	1.083	0.646	0.087	0.015
Accord	0.120	0.293	1.590	1.621	−51.637	1.532	0.463	0.310	0.095
Taurus	0.063	0.144	0.653	1.020	2.041	−43.634	0.335	0.245	0.091
Century	0.099	0.228	1.146	1.700	1.722	0.937	−66.635	0.773	0.152
Maxima	0.013	0.046	0.236	0.256	1.293	0.768	0.866	−35.378	0.271
Legend	0.004	0.014	0.083	0.084	0.736	0.532	0.318	0.506	−21.820
TownCar	0.002	0.006	0.029	0.046	0.475	0.614	0.210	0.389	0.280
Seville	0.001	0.005	0.026	0.035	0.425	0.420	0.131	0.351	0.296
LS400	0.001	0.003	0.018	0.019	0.302	0.185	0.079	0.280	0.274
735*i*	0.000	0.002	0.009	0.012	0.203	0.176	0.050	0.190	0.223

Note: Cell entries i, j, where i indexes row and j column, give the percentage change in market share of i with a $1000 change in the p

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

→ less likely that a BMW buyer not buy a car.

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

Summary

- Powerful method with potential for many applications
- Clearly show:
  - effect of IV
  - RC logit versus logit
- Common complaints:
  - instruments
  - supply side: static, not tested, driving the results
  - demand side dynamics

Goldberg "Product Differentiation and Oligopoly in International Markets: The Case of the Automobile Industry" (EMA, 95)

☆ Worth reading for presenting and discussing results in a structural model

- I will focus on the demand model and not the application
- Points to take away
  - endogeneity with household-level date
  - Nested Logit versus RC Logit

Demand Model

- Nested Logit nests determined by buy/not buy, new/used, county of origin (foreign vs domestic) and segment

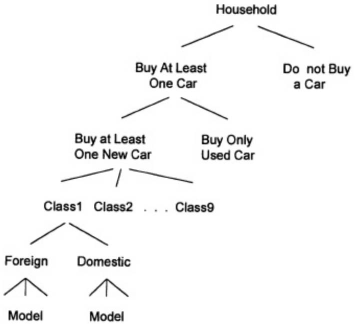

FIGURE 1.—Automobile choice model.

- This model can be viewed as using segment and county of origin as (dummy) characteristics, and assuming a particular distribution on their coefficients.

Data

- Household-level survey from the Consumer Expenditure Survey:
  - 20,571, HH between 83-87
  - 6,172 (30%) bought a car
  - 1,992 (33%) new car
  - 1,394 (70%) domestic and 598 foreign
- Prices (and characteristics) are obtained from Automotive News Market Data Book

Estimation

- The model is estimated by ML
- The likelihood is partitioned and estimated recursively:
    - At the lowest level the choice of model conditional on origin, segment and neweness, based on the estimated parameters an "inclusive value" is computed and used to estimate the choice of origin conditional on segment and neweness, etc.
- Does not deal with endogeneity. Origin and segment fixed effects are included, but these do not fully account for brand unobserved characteristics

Table II: price elasticities by class

· endog makes price coef smaller
· makes elasticities smaller.

TABLE II

PRICE ELASTICITIES OF DEMAND (AVERAGE BY CLASS)

Class	Origin	Elasticity	Elasticity (first time buyer)	Elasticity (repeat buyer)
Subcompacts	DOM	−3.2857	−3.6245	−2.9816
	FOR	−3.6797	−5.2531	−2.9488
Compacts	DOM	−3.419	−4.8722	−3.1546
	FOR	−4.0319	−5.7229	−3.3733
Intermediate	DOM	−4.1799	−5.3153	−2.8420
	FOR	−5.1524	−6.2232	−4.9274
Standard	DOM	−4.7121	−5.932	−4.3730
Luxury	DOM	−1.9121	−2.5981	−1.1137
	FOR	−2.7448	−3.1272	−1.9959
Sports	DOM	−1.0654	−2.3468	−1.3959
	FOR	−1.5254	3.0211	−1.1429
Pick-ups	DOM	−3.5259	−5.1391	−3.1647
	FOR	−2.6883	−3.9822	−2.1483
Vans	DOM	−4.3633	−5.4977	−3.9790
	FOR	−4.6548	−4.8837	−2.4376
Other	DOM	−4.0884	−4.3185	−3.5694
	FOR	−3.0271	−3.3185	−2.3345

”

Table III: price semi-elasticities

TABLE III

CROSS PRICE SEMI-ELASTICITIES FOR SELECTED MODELS

	Chevette	Civic	Tercel	Escort	Accord
Chevette	−3.2	49.1E − 07	16.4E − 07	0.9E − 07	9.0E − 07
Civic	7.6E − 07	−3.4	35.5E − 07	0.8E − 07	14.9E − 07
Tercel	7.7E − 07	109.8E − 07	−3.4	0.8E − 07	11.6E − 07
Escort	6.3E − 07	34.6E − 07	11.3E − 07	−3.4	12.5E − 07
Accord	6.1E − 07	66.2E − 07	16.2E − 07	1.3E − 07	−3.4
Mazda 626	6.4E − 07	50.1E − 07	15.3E − 07	1.7E − 07	72.2E − 07
Century	5.5E − 07	28.0E − 07	9.6E − 07	0.8E − 07	7.1E − 07
Skylark	5.5E − 07	28.6E − 07	9.9E − 07	0.8E − 07	7.1E − 07
Audi 5000	5.7E − 07	48.6E − 07	16.6E − 07	0.8E − 07	10.1E − 07
Diplomat	4.9E − 07	25.5E − 07	8.7E − 07	0.8E − 07	6.6E − 07
Cad. Fleetwood	0.3E − 07	2.1E − 07	0.7E − 07	0.1E − 07	0.5E − 07
Park Avenue	0.3E − 07	2.1E − 07	0.7E − 07	0.1E − 07	0.5E − 07
Jaguar	0.3E − 07	3.2E − 07	1.0E − 07	0.0E − 07	0.6E − 07
Fiero	0.4E − 07	3.0E − 07	1.0E − 07	0.1E − 07	0.7E − 07
Ferrari	0.4E − 07	4.0E − 07	1.3E − 07	0.1E − 07	0.8E − 07

Table IV: implied markups

Model	Cost	Price	Markup	(Price − Cost)
Civic	4884	5680	0.14	796
Escort	3068	4565	0.33	1497
Lynx	3069	4325	0.29	1256
Accord	5286	5854	0.10	567
Audi 5000	7353	14165	0.48	6812
Oldsmobile 98	5372	11295	0.52	5923
Jaguar	10768	19091	0.44	8323
Mercedes 300	13188	22662	0.42	9474
Porsche 944	5714	13136	0.56	7422
Ferrari	7679	19698	0.61	12018

higher

Nevo, "Measuring Market Power in the Ready-to-eat Cereal Industry" (EMA, 2001)

Points to take away:

1. industry where characteristics are less obvious.
2. effects of various IV's
3. testing the model of competition
4. comparison to alternative demand models (later)

The RTE cereal industry

- 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)
- This has been used to claim that this is a perfect example of collusive pricing

Questions

- Is pricing in the industry collusive?
- What portion of the markups in the industry due to:
  - Product differentiation?
  - Multi-product firms?
  - Potential price collusion?

Hold margins > 0

"Ok" cereal vs cheerios

- cheerios have a slight metallic aftertaste

Strategy

- Estimate brand level demand
- Compute PCM predicted by different industry structures models of conduct:
  - Single-product firms
  - Current ownership (multi-product firms)
  - Fully collusive pricing (joint ownership)
- Compare predicted PCM to observed PCM

Supply

The profits of firm f

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

brand

Similar to Bresnahan

the first order conditions are

$$\underbrace{s_j(p)}_{\text{doesn't matter}} + \sum_{r \in F_f} (p_r - mc_r) \frac{\partial q_r(p)}{\partial p_j} = 0$$

q_j

Define $S_{jr} = -\partial s_r / \partial p_j \quad j, r = 1, ..., J$, and

$$\Omega_{jr} = \begin{cases} S_{jr} & \text{if } \exists \{r, j\} \subset F_f \\ 0 & \text{otherwise} \end{cases}$$

$$s(p) + \Omega(p - mc) = 0 \text{ and } (p - mc) = \Omega^{-1} s(p)$$

Therefore by: (1) assuming a model of conduct; and (2) using estimates of the demand substitution; we are able to compute price-cost margins under different "ownership" structures

Demand

- Utility, as before

$$u_{ijt} = x_{jt}\beta_i + \alpha_i p_{jt} + \overbrace{\xi_{jt}}^{\text{unobs char}} + \varepsilon_{ijt}$$

- Allow for brand dummy variables (to capture the part of ξ_{jt} that does not vary by market)
    - captures characteristics that do not vary over markets

· i.e. captures some x's that are invariant over time

· requires another stage for β_i

Data

- IRI Infoscan scanner data
  - market shares – defined by converting volume to servings
  - prices – pre-coupon real transaction per serving price
  - 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 from March CPS
- Cost instruments from Monthly CPS
- Market size – one serving per consumer per day

• Market share: total # servings sold / Mkt size

Estimation

- Follows the method we discussed before
- Uses only demand side moments (b/c had 1124 markets)
- Explores various IVs:
  - 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)
  - identify taste coefficients by minimum distance

Logit Demand

TABLE V

RESULTS FROM LOGIT DEMAND[a]

Variable	OLS (i)	(ii)	(iii)	IV (iv)	(v)	(vi)	(vii)	(viii)	(ix)
Price	−4.96	−7.26	−7.97	−8.17	−17.57	−17.12	−22.56	−23.77	−23.37
	(0.10)	(0.16)	(0.15)	(0.11)	(0.50)	(0.49)	(0.51)	(0.53)	(0.47)
Advertising	0.158	0.026	0.026	0.157	0.020	0.020	0.018	0.017	0.018
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Log of Median Income	—	—	0.89	—	—	—	1.06	1.13	1.12
			(0.02)				(0.02)	(0.02)	(0.02)
Log of Median Age	—	—	−0.423	—	—	—	−0.063	0.003	−0.007
			(0.052)				(0.059)	(0.062)	(0.061)
Median HH Size	—	—	−0.126	—	—	—	−0.053	−0.036	−0.038
			(0.027)				(0.029)	(0.031)	(0.031)
Fit/Test of Over Identification[b]	0.54	0.72	0.74	436.9	168.5	181.2	83.96	82.95	85.87
				(26.30)	(30.14)	(16.92)	(30.14)	(16.92)	(42.56)
1st Stage R^2	—	—	—	0.889	0.908	0.908	0.910	0.909	0.913
1st Stage F-test	—	—	—	5119	124	288	129	291	144
Instruments[c]	—	—	—	brand dummies	prices	cost	prices	cost	prices, cost

Hausman use.

· Prices of same brand in another mkt,

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			

Elasticities

MEDIAN OWN AND CROSS-PRICE ELASTICITIES[a]

#	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% (31.8%–35.6%)	35.8% (24.4%–46.4%)
Current Ownership of 25 Brands	35.8% (33.9%–38.0%)	42.2% (29.1%–55.8%)
Joint Ownership of 25 Brands	41.9% (39.7%–44.4%)	72.6% (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%)	—

Comments/Issues

- Is choice discrete?
- Ignores the retailer – uses retailer prices to study manufacturer competition
  - retail margins go into marginal cost
  - marginal costs do not vary with quantity, therefore this restricts the retailers pricing behavior
    - which direction will this bias the finding? Most likely towards finding collusion where there is none (the retailer behavior might take into account effects across products)
  - Sofia Villas Boas (2007) extends the model
- Much of the price variation at the store-level is coming from "sales". How does this impact the estimation?
  - data is quite aggregated:quarter-brand-city
  - "sales" generate incentives for consumer to stockpile
  - Follow up work by Hendel and Nevo looked at this