Measuring Market Power in the Ready-to-Eat Cereal Industry

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Motivation

- The ready-to-eat (RTE) cereal industry is characterized by
  - high concentration
  - high price-cost margins
  - large advertising-to-sales ratios
  - numerous introduction of new products
- Previous researchers have concluded that the ready-to-eat cereal industry is a classic example of an industry with nearly collusive pricing behavior and intense nonprice competition.

History of RTE

This paper

- This paper empirically examines this conclusion.
- In particular, this paper estimates price-cost margins and separates these margins into three sources
    - product differentiation
    - multi-product firm pricing
    - price collusion
- The results suggest that given the demand for different brands of cereal, the first two effects explain most of the observed price-cost margins.
    - In particular, leading firms are able to maintain a portfolio of differentiated products and influence the perceived product quality. These two factors lead to high price-cost margins.

General Strategy

- Recall three sources of price-cost margins
  - Product differentiation
  - Portfolio effect
  - Price collusion
- General Strategy
  - Estimate brand-level demand
  - Then use the estimates jointly with pricing rules implied by different models of firm conduct to recover PCM
  - Comparing the different sets of PCM to each other and to crude measure of actual PCM, allows me to separate the different sources of these margins.

Difficulty

- The data is three-dimensional panel of quantities and prices for 25 brands of cereal up to 65 U.S. cities over a period of 20 quarters.
- Two Challenges
  - The correlation between prices and brand-city-quarter specific demand shocks (panel structure + IV)
  - Large number of substitution parameters implied by numerous products in this industry (discrete choice model structure)

Outline

- Describe the ready-to-eat cereal industry
- Outline empirical model and discuss the implication of different modeling decisions
- Describe the data, the estimation procedure, instruments, and the inclusion of brand fixed effects
- Present the results
- Conclude

History

- The first ready-to-eat breakfast cereal was probably introduced by James Caleb Jackson in 1863, in Dansville, New York.
- The real origin of the industry, however, was in Battle Creek, Michigan, where Dr. John Harvey Kellogg, the manager of vegetarian Seventh-Day Adventist (health) Sanatorium, introduced ready-to-eat cereal as a healthy breakfast alternative.
- Then later entrants include
  - Post Cereal company
  - Quaker Oats (General Mills)
  - Nabisco

Motivation

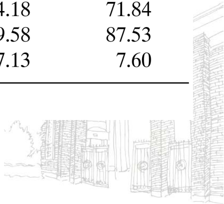
The Ready-to-Eat Cereal Industry

TABLE I

VOLUME MARKET SHARES

	88Q1	88Q4	89Q4	90Q4	91Q4	92Q4
Kellogg	41.39	39.91	38.49	37.86	37.48	33.70
General Mills	22.04	22.30	23.60	23.82	25.33	26.83
Post	11.80	10.30	9.45	10.96	11.37	11.31
Quaker Oats	9.93	9.00	8.29	7.66	7.00	7.40
Ralston	4.86	6.37	7.65	6.60	5.45	5.18
Nabisco	5.32	6.01	4.46	3.75	2.95	3.11
C3	75.23	72.51	71.54	72.64	74.18	71.84
C6	95.34	93.89	91.94	90.65	89.58	87.53
Private Label	3.33	3.75	4.63	6.29	7.13	7.60

Source: IRI Infoscan Data Base, University of Connecticut, Food Marketing Center.



The Ready-to-Eat Cereal Industry

TABLE II

AGGREGATE ESTIMATES OF PRODUCTION COSTS

	RTE Cereal (SIC 2043)		All Food Industries (SIC 20)	
Item	M$	% of value	M$	% of value
Value of Shipments	8,211	100.0	371,246	100.0
Materials	2,179	26.5	235,306	63.4
Labor	677	8.2	32,840	8.8
Energy	76	0.9	4,882	1.3
Gross Margin		64.4		26.5

Source: Annual Survey of Manufacturers 1988–1992.

Outline

- Consider different models of supply conduct
- For each model of supply, the pricing decision depends on brand-level demand, which is modeled as a function of product characteristics and consumer preferences.
- Demand parameters are estimated and used to compute the PCM implied by different models of conduct.
- Use additional information on costs to compute observed PCM and choose the conduct model that best fits these margins.

Supply

Profit and FOC

- Suppose there are F firms, each of which produces some subset, $\mathscr{F}_f$, of the $j = 1, ..., J$ different brands of RTE cereal.
- The profits of firm f are

$$\Pi_f = \sum_{j \in \mathscr{F}_f} (p_j - mc_j) M s_j(p) - C_f,$$

where $s_j(p)$ is market share of brand j, M is the market size, and C_f is the fixed cost of production.

- Assuming the existence of pure-strategy Bertrand-Nash equilibrium in prices, the F.O.C. is:

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

Supply
Markup

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

$$\Omega^*_{jr} = \begin{cases} 1, & \text{if } \exists f : \{r, j\} \subset \mathscr{F}_f \\ 0, & \text{otherwise,} \end{cases}$$

and Ω is a $J \times J$ matrix with $\Omega_{jr} = \Omega^*_{jr} * S_{jr}$. The F.O.C. becomes

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

$\Rightarrow$

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

Supply

Strategy

In order to distinguish between 3 different markup causes, estimate by defining the ownership $\mathscr{F}_f$, and ownership matrix Ω^*, and evaluate the PCM in 3 hypothetical industry conduct models:

- **the single-product firms**, in which the price of each brand is set by a profit-maximizing agent that considers only that brand's profits.
- **the current structure**, where multi-product firms set the prices of all their products jointly.
- **the joint profit-maximization of all the brands**, which corresponds to monopoly or perfect price collusion.

Demand

Indirect Utility

A market $(t = 1, ..., T)$ is defined as a city-quarter combination. The conditional indirect utility of consumer i from product j at market t is

$$u_{ijt} = x_j \beta_i^* - \alpha_i^* p_{jt} + \xi_j + \Delta\xi_{jt} + \epsilon_{ijt}, \tag{2}$$

- x_j is a K-dimensional vector of observable product characteristics
- ξ_j is the national mean valuation of the unobserved product characteristics
- $\Delta\xi_{jt}$ is a city-quarter specific deviation from this mean

$\Rightarrow$ Finally, (α_i^*, β_i^*) are $K + 1$ individual-specific coefficients.

Demand

Consumers' Heterogeneity

Let

$$\begin{pmatrix} \alpha_i^* \\ \beta_i^* \end{pmatrix} = \begin{pmatrix} \alpha \\ \beta \end{pmatrix} + \Pi D_i + \Sigma v_i, \quad v_i \sim N(0, I_{K+1}), \tag{3}$$

- D_i is a $d \times 1$ vector of demographic variables
- Π is a $(K+1) \times d$ matrix of coefficients that measure how the taste characteristics vary with demographics
- Σ is a scaling matrix.

Demand

Indirect Utility

Indirect utility for outside option

$$u_{i0t} = \xi_0 + \pi_0 D_i + \sigma_0 v_{i0} + \epsilon_{i0t}.$$

Indirect utility for inside goods

$$\begin{aligned} u_{ijt} &= \delta_{jt}(x_j, p_{jt}, \xi_j, \Delta\xi_{jt}; \theta_1) + \mu_{ijt}(x_j, p_{jt}, v_i, D_i; \theta_2) + \epsilon_{ijt}, \\ \delta_{jt} = x_j\beta - \alpha p_{jt} + \xi_j + \Delta\xi_{jt}, &\qquad \mu_{ijt} = [p_{jt}, x_j]' * (\Pi D_i + \Sigma v_i). \end{aligned} \tag{4}$$

- $\theta_1 = (\alpha, \beta)$ contains the linear parameters
- $\theta_2 = (\text{vec}(\Pi), \text{vec}(\Sigma))$ contains the nonlinear parameters.

Demand

Market Share

The set of unobserved variables that lead to the choice of good j:

$$A_{jt}(x, p_{\cdot t}, \delta_{\cdot t}; \theta_2) = \{(D_i, v_i, \epsilon_{it}) | u_{ijt} \geq u_{ilt} \; \forall l = 0, 1, ..., J\}$$

- x are the characteristics of all brands
- $p_{\cdot t} = (p_{1t}, ..., p_{Jt})'$
- $\delta_{\cdot t} = (\delta_{1t}, ..., \delta_{Jt})'$

$$\Rightarrow s_{jt}(x, p_{\cdot t}, \delta_{\cdot t}; \theta_2) = \int_{A_{jt}} dP^*(D, v, \varepsilon) = \int_{A_{jt}} dP^*(\varepsilon)\, dP^*(v)\, dP^*(D). \quad (5)$$

Demand

How to Solve

- A simplifying assumption commonly made is that consumer heterogeneity enters the model only through the separable additive random shocks ε_{ijt}, and that $\varepsilon_{ijt} \overset{i.i.d.}{\sim}$ Type I EV. $\Rightarrow$ logit model.
- Slightly less restrictive models, in which the i.i.d. assumption is replaced with a variance structure, are available (the Generalized Extreme Value model; McFadden (1978)). However, they derive substitution patterns from a priori segmentation.
- The full model nests all of these other models and has several advantages over them.

Data

- 65 different cities (the exact number increases over time)
- 1^{st} quarter, 1988 – 4^{th} quarter, 1992
- 25 brands

TABLE IV

PRICES AND MARKET SHARES OF BRANDS IN SAMPLE

Description	Mean	Median	Std	Min	Max	Brand Variation	City Variation	Quarter Variation
Prices (¢ per serving)	19.4	18.9	4.8	7.6	40.9	88.4%	5.3%	1.6%
Advertising (M$ per quarter)	3.56	3.04	2.03	0	9.95	66.2%	—	1.8%
Share within Cereal Market (%)	2.2	1.6	1.6	0.1	11.6	82.3%	0.5%	0%

Source: IRI Infoscan Data Base, University of Connecticut, Food Marketing Center.

Comparison with BLP

Three key differences

- The instrumental variables and the identifying assumptions that support them are different.
- This paper identifies the demand side without specifying a functional form for the supply side.
- Due to data richness, this paper can control for unobserved product characteristics by using brand fixed effects.

GMM

Let $Z = [z_1, ..., z_M]$ be a set of instruments such that $E[Z'\omega(\theta^*) = 0]$.

- $\omega_{jt} = \xi_i + \Delta\xi_{jt} = \delta_{jt}(x, p_{\cdot t}, \delta_{\cdot t}; \theta_2) - (x_j\beta - \alpha p_{jt})$ is the unobserved product characteristics.
- θ^* denotes the true value of these parameters.

$$\hat{\theta} = \arg\min_{\theta} \quad \omega(\theta)' Z A^{-1} Z' \omega(\theta), \tag{6}$$

- A is a consistent estimate of $E[Z'\omega\omega' Z]$. $\Rightarrow$ two-step GMM.

Solve for the mean utility levels $\delta_{\cdot t}$

$$s_{\cdot t}(x, p_{\cdot t}, \delta_{\cdot t}; \theta_2) = S_{\cdot t} \quad \Rightarrow \quad \delta_{\cdot t} = \delta_{\cdot t}(x, p_{\cdot t}, S_{\cdot t}; \theta_2). \tag{7}$$

Instruments

- Pricing decision

$$p_{jt} = mc_{jt} + f(\xi_{jt}, \ldots) = (mc_j + f_j) + (\Delta mc_{jt} + \Delta f_{jt}) \tag{8}$$

- Much of the previous work treats this endogeneity problem by assuming the "location" of brands in the characteristics space is exogenous, or at least predetermined.
- But by construction of the data, there is no variation in each brand's observed characteristics over time and across cities.
- I use two alternative sets of IV
  - price of the brand in other cities
  - city-level marginal costs

Instruments

- The new strategy follows Hausman(1996) and exploits the panel structure of the data.
- The identifying assumption is that, controlling for brand-specific means and demographics, city-specific valuations are independent.
    - Given this assumption, the prices of the brand in other cities will be valid IVs.
    - The idea is prices of brand j in two cities will be correlated due to the common marginal cost. According to the independent assumption across markets, prices will be uncorrelated with market specific valuation.
    - This paper uses regional quarterly average prices in all twenty quarters.

Potential Instrument Violation

Several plausible situations in which

- Case 1: suppose there is a national (or regional) demand shock. For example, the discovery that fiber reduces the risk of cancer. This discovery will increase the unobserved valuation of all fiber-intensive brands in all cities. (large companies)
- Case 2: suppose one believes that local advertising and promotions are coordinated across city borders, but are limited to regions, and that these activities influence demand. (large area)

Brand-Specific Dummy Variables

Why include brand-specific dummy variables as product characteristics

- improve the fit of the model
- captures the characteristics that do not vary by market. Therefore, the correlation between prices and the unobserved quality is fully accounted for and does not require IV.

Potential objections are defeated

- Introducing brand fixed effects increases the number of parameters only with J.
- Brand-specific intercepts enter as part of the linear parameters and do not increase the computational burden.

Brand-Specific Dummy Variables

In order to retrieve the taste coefficients β, when brand fixed-effects are included, I regress the estimated brand effects on the characteristics. Let

$$d = X\beta + \xi.$$

If we assume that $E[\xi|X] = 0$, the estimates of β and ξ are

$$\hat{\beta} = (X' V_d^{-1} X)^{-1} X' V_d^{-1} \hat{d}, \qquad \hat{\xi} = \hat{d} - X\hat{\beta},$$

where $\hat{d}$ is the vector of coefficients estimated from the procedure described previously, and V_d is the covariance matrix of these estimates.

Logit Results

Regress $\ln(X_{jt}) - \ln(X_{0t})$ on prices, ad., brand and time dummy, to show

- importance of instrumenting for price
- effects of different sets of instrumental variables

TABLE V

RESULTS FROM LOGIT DEMAND[a]

	OLS			IV						
Variable	(i)	(ii)	(iii)	(iv)	(v)	(vi)	(vii)	(viii)	(ix)	(x)
Price	−4.96	−7.26	−7.97	−8.17	−17.57	−17.12	−22.56	−23.77	−23.37	−23.07
	(0.10)	(0.16)	(0.15)	(0.11)	(0.50)	(0.49)	(0.51)	(0.53)	(0.47)	(1.17)
Advertising	0.158	0.026	0.026	0.157	0.020	0.020	0.018	0.017	0.018	0.013
	(0.002)	(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	15.06
				(26.30)	(30.14)	(16.92)	(30.14)	(16.92)	(42.56)	(42.56)
1st Stage R^2	—	—	—	0.889	0.908	0.908	0.910	0.909	0.913	0.952
1st Stage F-test	—	—	—	5119	124	288	129	291	144	180
Instruments[c]	—	—	—	brand dummies	prices	cost	prices	cost	prices, cost	prices, cost

[a] Dependant variable is $\ln(S_{jt}) - \ln(S_{0t})$. Based on 27,862 observations. All regressions include time dummy variables, and with the exception of columns (i) and (iv), all regressions also include brand dummy variables. The regressions in columns (i) and (iv) include product characteristics (calories from fat, sugar, fiber, mushy and segment dummy variables); see text for reported coefficients. The regression in column (x) includes city dummy variables. Asymptotically robust s.e. are reported in parentheses.
[b] Adjusted R^2 for the OLS regressions, and a test of over identification for the IV regressions (Hausman (1983)) with the 0.95 critical values in parentheses.
[c] Prices denote the average regional price of the brand; cost denotes cost proxies; both are described in the text.

Table 8 PCM

Results from the Full Model

$$u_{ijt} = \delta_{jt}(x_j, p_{jt}, \xi_j, \Delta\xi_{jt}; \theta_1) + \mu_{ijt}(x_j, p_{jt}, v_i, D_i; \theta_2) + \epsilon_{ijt},$$
$$\delta_{jt} = x_j\beta - \alpha p_{jt} + \xi_j + \Delta\xi_{jt}, \qquad \mu_{ijt} = [p_{jt}, x_j]' * (\Pi D_i + \Sigma v_i).$$

- Predicted market shares are based on the empirical distribution of demographics, independent normal distributions for v, and Type I extreme value for ε.
- The IV's include both average regional prices in all quarters and the cost proxies.

Results from the Full Model

The ratios of the variance explained by the demographics to the total variation in the distribution of the estimated coefficients: over 90%.

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			

Taste Heterogeneity for Brand Characteristics

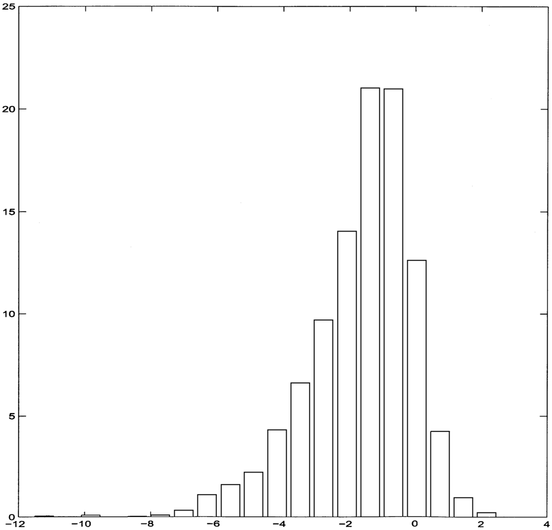


FIGURE 1.—Frequency distribution of taste for sogginess (based on Table VI).

Distribution of the Individual Price Sensitivity

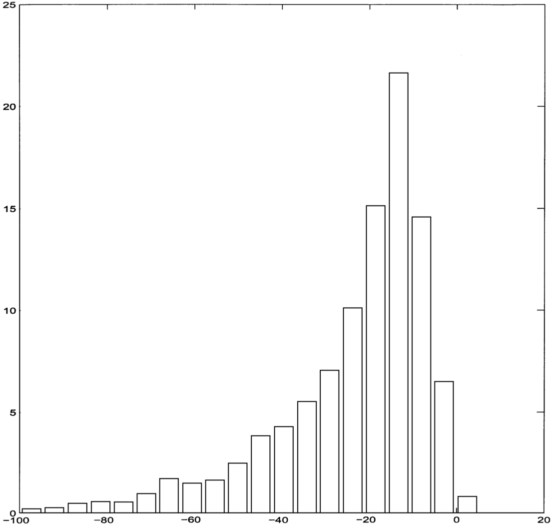


FIGURE 2.—Frequency distribution of price coefficient (based on Table VI).

Median Own and Cross-Price Elasticities

TABLE VII

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

Price-Cost Margins

Predicted PCM

- compute PCM for three hypothetical industry structures
- Recall: $p - mc = \Omega^{-1} s(p)$.

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%)	

[a] Margins are defined as $(p - mc)/p$. Presented are medians of the distribution of 27,862 (brand-city-quarter) observations. 95% confidence intervals for these medians are reported in parentheses based on the asymptotic distribution of the estimated demand coefficients. For the Logit model the computation is analytical, while for the full model the computation is based on 1,500 draws from this distribution.

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Price-Cost Margins

Observed PCM

TABLE III

DETAILED ESTIMATES OF PRODUCTION COSTS

Item	$/lb	% of Mfr Price	% of Retail Price
Manufacturer Price	2.40	100.0	80.0
Manufacturing Cost:	1.02	42.5	34.0
Grain	0.16	6.7	5.3
Other Ingredients	0.20	8.3	6.7
Packaging	0.28	11.7	9.3
Labor	0.15	6.3	5.0
Manufacturing Costs (net of capital costs)[a]	0.23	9.6	7.6
Gross Margin		57.5	46.0
Marketing Expenses:	0.90	37.5	30.0
Advertising	0.31	13.0	10.3
Consumer Promo (mfr coupons)	0.35	14.5	11.7
Trade Promo (retail in-store)	0.24	10.0	8.0
Operating Profits	0.48	20.0	16.0

[a] Capital costs were computed from ASM data.
Source: Cotterill (1996) reporting from estimates in CS First Boston Reports "Kellogg Company," New York, October 25, 1994.

Conclusions

- This paper uses a random coefficients discrete choice (mixed logit) model to estimate a brand-level demand system for RTE cereal.
- Parameter Identification exploits the panel structure of the data, and is based on an independence assumption of demand shocks across cities for each brand.
- If we are willing to accept Nash-Bertrand as a benchmark of noncollusivepricing, we are left to conclude, unlike previous work, that even with PCM greater than 45%, prices in the industry are not a result of collusive behavior.

The End