Overview

- Are RTE cereal firms colluding?
  - Existing evidence says probably yes (FTC case in the 1970s; Schmalensee 1978)

- Consumers spend ~ 9B/year on cereal (wow) and firms make ~ 3B in profits

- Nevo models demand for cereals, then tests different market structures for suppliers to see which most closely matches the data

Why do we think RTE firms are colluding?

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.

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.

Approach (Supply)

- Trying to answer the question "Are RTE cereal firms colluding?"
- We know that there are different FOCs for different models of supply.
- Essentially the question is "Can we reject that firms are acting like profit-maximizing colluders?"
- Can write FOCs as

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

- The important bit is $\sum_{r \in \mathcal{F}_f}$; firms are only looking at the products that they produce, and this is what's changing when we look at different supply side models.

Approach (Supply)

- Demand estimates let us estimate price-cost margins without seeing costs.
- Look at three different models for the supply side
  1. Single-product firms
  2. Multi-product firms (existing structure)
  3. Monopoly/perfect price collusion

- Looking at these three different models of supply lets us distinguish between three different causes of markups:
  1. Product Differentiation
  2. Portfolio effect
  3. Price collusion

Approach (Demand)

- The exercise on the supply-side depends on own- and cross-price elasticities; we need to estimate these.
- Consumer Utility:

$$
\begin{aligned}
u_{ijt} &= \underbrace{\delta_{jt}(x_j, p_{jt}, \xi_{jt}; \theta_1)}_{\text{mean utility}} + \underbrace{\mu_{ijt}(x_j, p_{jt}, \nu_j, D_i; \theta_2) + \epsilon_{ijt}}_{\text{mean-zero deviation}} \\
\delta_{jt} &= x_j\beta - \alpha p_{jt} + \xi_j + \Delta\xi_{jt} \\
\mu_{ijt} &= [p_{jt}, x_j]' * (\Pi D_i + \Sigma\nu_i)
\end{aligned}
$$

Need to get shares; define A_{jt} as the unobserved variables that lead consumer to choose j. Calculate shares as

$$
\begin{aligned}
s_{jt}(x, p_{.t}, \delta_{.t}; \theta_2) &= \int_{A_{jt}} dP^*(D, \nu, \varepsilon) \\
&= \int_{A_{jt}} dP^*(\varepsilon) dP^*(\nu) dP^*(D)
\end{aligned}
$$

Logit vs. Nevo

- Don't want to use Logit, since that imposes restrictions on substitution patterns. (Ditto m-logit, etc.)
- What's different? Composite random shock $\mu_{ijt} + \varepsilon_{ijt}$ no longer independent of product characteristics, so substitution patterns can be driven by these characteristics
- Also doesn't impose arbitrary market segmentation.

Estimation—Data

1. Market shares and prices in each market
   - A market is a city-quarter
2. Brand characteristics
3. Advertising
4. The distribution of demographics

Differences with BLP

1. Different instruments and identifying assumptions

2. No need to specify functional form on the supply side to get identification.

3. Able to use brand fixed-effects to control for unobserved product characteristics
   - This is a big methodological contribution, since it does a better job fitting observed data (see $R^2 \sim 0.95$ earlier) and Nevo shows that it isn't a computational nightmare

Estimating Equations

- Estimate via GMM
- Construct an *error term* ω that satisfies $E[Z'\omega(\theta^*)] = 0$; Z are instruments

$$\hat{\theta} = \arg\min_{\theta} \omega(\theta)' Z \left(E[\widehat{Z'\omega\omega'}Z] \right)^{-1} Z'\omega(\theta)$$

- Error term $\omega \equiv \xi_j + \Delta\xi_{jt}$ (with brand dummies, $\omega \equiv \Delta\xi_{jt}$)
- Solve implicit set of equations

$$\underbrace{s_{.t}(x, p_{.t}, \delta_{.t}; \theta_2)}_{\text{share function}} = \underbrace{S_{.t}}_{\text{shares}}$$

- Invert numerically;

$$\underbrace{\omega_{jt} = \delta_{jt}(x, p_{.t}, S_{.t}; \theta_2)}_{\text{nonlinear bit}} - (x_j\beta + \alpha p_{jt})$$

Instruments (two sets)

Set 1:

- **Assumption**: city-specific valuations are independent across cities
- **Instrument**: prices of the brand in other cities
- **Violation**: National shock to only *some* types of cereal

Set 2:

- **Assumption**: direct production costs are uncorrelated with prices (too small, or captured by other variables)
- **Instrument**: direct proxies for marginal costs
- **Violation**: persistent regional shock for some brands

Results: Logit—Importance of Brand-dummies—Valid-IVs

TABLE V

RESULTS FROM LOGIT DEMAND[a]

Variable	OLS (i)	(ii)	(iii)	IV (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.

Results—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			

[a] Based on 27,862 observations. Except where noted, parameters are GMM estimates. All regressions include brand and time dummy variables. Asymptotically robust standard errors are given in parentheses.
[b] Estimates from a minimum-distance procedure.

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

[a] Cell entries i, j, where i indexes row and j column, give the percent change in market share of brand i with a one percent change in price of j. Each entry represents the median of the elasticities from the 1124 markets. The full matrix and 95% confidence intervals for the above numbers are available from http://elsa.berkeley.edu/~nevo.

Results: Firm Behavior—Nevo vs. Logit

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%)	—

[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.

Conclusions

If we are willing to accept Nash-Bertrand as a benchmark of noncollusive pricing. . . even with PCM greater than 45%, prices in the industry are not a result of collusive behavior. The results rule out an extreme version of cooperative pricing. . . the results in this paper do not rule out cooperate pricing between a subset of products . . .

As much as I would like to claim that this paper proves or disproves the FTC's case, I cannot. . . the high observed PCM are primarily due to the firms' ability to maintain a portfolio of differentiated products. . .

Quick Aside—Transparency

A comment is in place about the realism of the assumption that consumers choose no more than one brand. Many households buy more than one brand of cereal in each supermarket trip but most people consume only one brand of cereal at a time, which is the relevant fact for this modeling assumption. Nevertheless, if one is still unwilling to accept that this is a negligible phenomenon, then this model can be viewed as an approximation to the true choice model. An alternative is to explicitly model the choice of multiple products, or continuous quantities (as in Dubin and McFadden (1984) or Hendel (1999)).

Treating the characteristics as predetermined, rather than reacting to demand shocks, is as reasonable (or unreasonable) here as it was in previous work.