Common Ownership and Competition in the Ready-to-Eat Cereal Industry

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Today's Paper

Two Research Questions

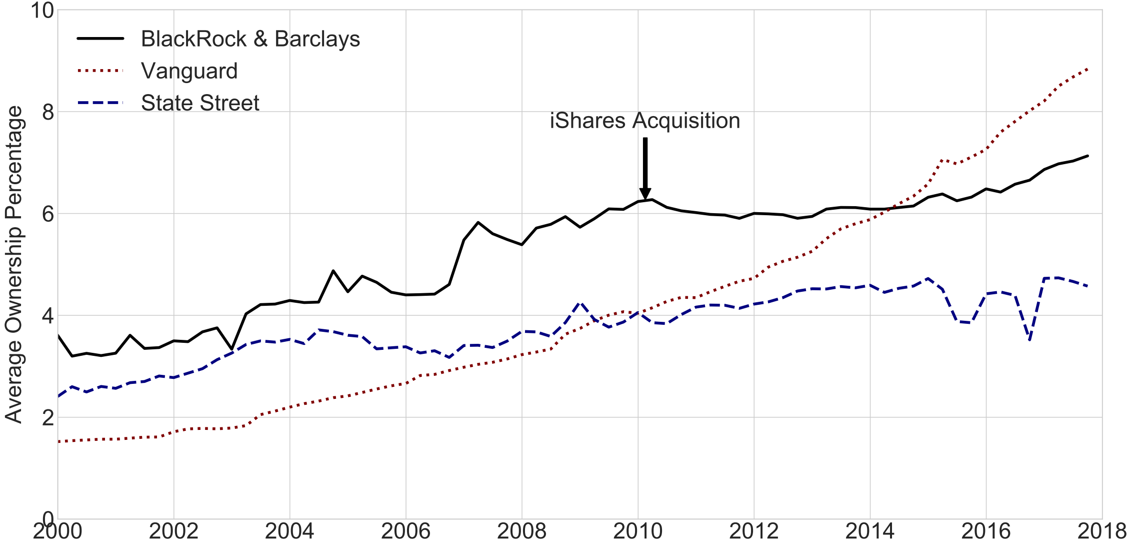
1. Applied: Do diversified investors with ownership stakes in multiple competitors *cause* firms to compete less aggressively? (aka the Common Ownership Hypothesis)
2. Methodological: How can we look at observational data on prices and quantities and use instruments to determine which model of competition generated our data? (Conduct Testing).

What is Common Ownership?

What is the Common Ownership Hypothesis?

- Economics starts from the premise that firms maximize profits.
  - Friedman (1953): natural selection of firms and billiards players.
  - Or, firms answer to investors, maximize shareholder value.
  - We generally think of these objectives as aligned (possibly subject to managers' agency frictions).
- So what do investors want?
  - Some (diversified) investors may hold stakes in you *and your competitor*. These are called "common owners."
  - Common owners are harmed when managers engage in business stealing.
- As a theory of firm behavior in joint ventures this is an old idea. The recent innovation is to extend this approach to passive or institutional investors

Rise of the Big Three (S&P 500 components, BCS AEJM 2021)



Common Ownership in the News

- The Atlantic: "Are Index Funds Evil?"
- The Economist: "Stealth Socialism"
- Bloomberg: "Index-Crazed Investors Turning S&P 500 Into One Gigantic Company"
- MoneyWeek: "Index Funds: Killing Capitalism?"
- Reuters: "When BlackRock Calls, CEOs Listen and do Deals"
    - "There is no CEO that doesn't return our call because typically we're up high on the shareholder register," Mark McCombe, global head of BlackRock's institutional client business, told Reuters reporters and editors attending the Reuters Global Wealth Management Summit on Friday.
      "We are everybody's largest shareholder."

Some Reasonable (?) Assumptions (BCS 2020 P&P)

Most models of common ownership (implicitly) make the following assumptions:

Investor Portfolios Investors are entitled to a share of profits β_{fs} and hold portfolios $V_s = \sum_f \beta_{fs} \pi_f$

Manager Agency (Rotemberg 1984) Managers maximize a (γ) weighted average of investor payoffs $Q_f = \sum_s \gamma_{fs} V_s$.

These are pretty general since s could contain the manager herself.

Derivation of Profit Weight

Easy to show:

$$Q_f\left(x_f, x_{-f}\right) = \sum_{\forall s} \gamma_{fs} \cdot V_s\left(x_f, x_{-f}\right)$$
$$\propto \pi_f + \sum_{g \neq f} \underbrace{\left(\frac{\sum_{\forall s} \gamma_{fs}\beta_{gs}}{\sum_{\forall s} \gamma_{fs}\beta_{fs}}\right)}_{\equiv \kappa_{fg}(\gamma_f, \beta)} \pi_g$$

- κ_{fg} is interpreted as a profit weight, where one dollar of profits at firm g are valued as κ_{fg} dollars in the objective function of firm f.
- Depends on two primitives: β and γ.
  - β (cash-flow rights) is often directly observable.
  - γ embeds a model of corporate governance. Literature assumes $\gamma = \beta$ ("proportional control").
- Not specific to a particular strategic game

A Simple Example (with $\gamma = \beta$)

- Firm 1 is controlled by an undiversified owner.
- Firms 2 and 3 have symmetric structures:
  - 60% undiversified, retail investors with no influence ($\gamma = 0$)
  - 20% two undiversified, institutional investors ($\gamma = 0.5$)
  - 20% commonly owned, institutional investor ($\gamma = 0.5$)

Then,

$$\mathcal{H}(\kappa) = \begin{bmatrix} 1 & 0 & 0 \\ 0 & 1 & 1/2 \\ 0 & 1/2 & 1 \end{bmatrix}$$

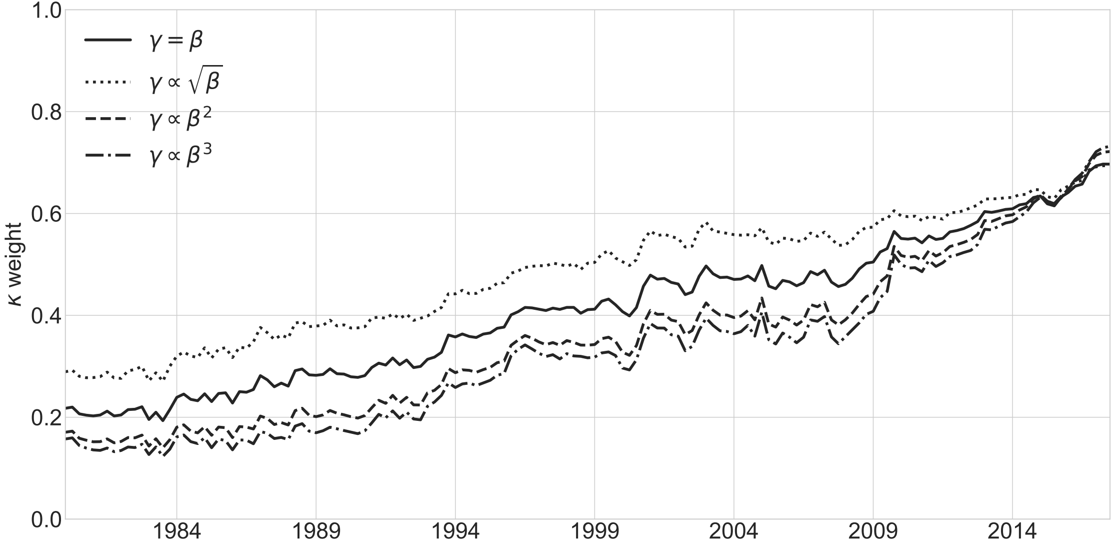
A Strange Example (still $\gamma = \beta$)

- Firm 1 has
  - N diversified, symmetric institutional investors with 1% each.
  - Undiversified retail investors ($\gamma = 0$) own remainder.
- Firms 2 has
  - Same N institutional investors with x% each.
  - Undiversified retail investors ($\gamma = 0$) own remainder.

Then,

$$\mathcal{H}(\kappa) = \begin{bmatrix} 1 & x \\ \frac{1}{x} & 1 \end{bmatrix}$$

From BCS in AEJ:Micro (2021)



Aside: MHHI and (Symmetric, Homogenenous Good) Cournot

If instead firms choose quantities

$$\max_{q_f} \left(p(Q) - mc_f\right) \cdot q_f + \sum_{g \neq f} \kappa_{fg} \cdot \left(p(Q) - mc_g\right) \cdot q_g$$

Gives share-weighted average markup:

$$\sum_f s_f \cdot \frac{p - mc_f}{p} = \frac{1}{\eta} \sum_f \sum_g \kappa_{fg} \cdot s_f \cdot s_g$$

$$MHHI = \mathbf{s}' \, \mathcal{H}(\kappa) \, \mathbf{s}$$

$$HHI = \mathbf{s} \cdot \mathbf{s}$$

$$MHHID = MHHI - HHI$$

Some regress

$$\log\left(p_{rjt}\right) = \beta \cdot MHHI\Delta_{rt} + \gamma \cdot HHI_{rt} + \theta \cdot X_{rjt} + \alpha_t + \nu_{rj} + \varepsilon_{rjt}$$

Azar, Schmalz, Tecu (JF 2018)

	Dependent Variable: Log(Average Fare)					
	Market-carrier level			Market level		
	(1)	(2)	(3)	(4)	(5)	(6)
MHHI delta	0.194***	0.219***	0.149***	0.325***	0.311***	0.202***
	(0.0459)	(0.0387)	(0.0375)	(0.0446)	(0.0397)	(0.0356)
HHI	0.221***	0.230***	0.165***	0.365***	0.357***	0.255***
	(0.0247)	(0.0246)	(0.0209)	(0.0315)	(0.0313)	(0.0244)
Number of Nonstop Carriers			-0.00979***			-0.00810**
			(0.00269)			(0.00371)
Southwest Indicator			-0.120***			-0.149***
			(0.00928)			(0.0135)
Other LCC Indicator			-0.0618***			-0.100***
			(0.00717)			(0.00989)
Share of Passengers Traveling Connect, Market Level			0.124***			0.158***
			(0.0167)			(0.0189)
Share of Passengers Traveling Connect			0.0986***			
			(0.0143)			
Log(Population)			0.306***			0.343***
			(0.106)			(0.122)
Log(Income Per Capita)			0.374***			0.304***
			(0.102)			(0.110)
Log(Distance) × Year-Quarter FE		✓	✓		✓	✓
Year-Quarter FE	✓	✓	✓	✓	✓	✓
Market-Carrier FE	✓	✓	✓			
Market FE				✓	✓	✓
Observations	1,237,584	1,237,584	1,209,517	262,350	262,350	254,999
R^2	0.820	0.825	0.836	0.852	0.861	0.876
Number of market-carrier pairs	46,513	46,513	45,248			
Number of markets				7,185	7,185	6,906

Common Ownership and Pricing: Bertrand

Let κ represent the weight a firm places on competitors. Starting with the objective function,

$$\max_{p_j : j \in \mathcal{J}_f} \sum_{j \in \mathcal{J}_f} (p_j - mc_j) \cdot s_j(\mathbf{p}) + \underbrace{\sum_{g \neq f} \kappa_{fg} \sum_{k \in \mathcal{J}_g} (p_k - mc_k) \cdot s_k(\mathbf{p})}_{\text{unique to CO}}$$

We obtain first order conditions

$$s_j(p) + \frac{\partial s_j}{\partial p_j}(\mathbf{p}) \cdot (p_j - mc_j) + \sum_{k \in \mathcal{J}_f} \frac{\partial s_k}{\partial p_j}(\mathbf{p}) \cdot (p_k - mc_k)$$
$$+ \underbrace{\sum_{g \neq f} \kappa_{fg} \sum_{k \in \mathcal{J}_g} \frac{\partial s_k}{\partial p_j}(\mathbf{p}) \cdot (p_k - mc_k)}_{\text{unique to CO}} = 0.$$

From κ to Markups

A bit of notation, $\mathcal{H}$ is the product-level version of κ:

$$\mathcal{H}_{jk}(\kappa) \equiv \begin{cases} 1 & \text{if } (j,k) \in \mathcal{J}_f \text{ for any } f, \\ \kappa_{fg} & \text{if } j \in \mathcal{J}_f \text{ and } k \in \mathcal{J}_g \text{ for any } (f,g), f \\ 0 & \text{otherwise.} \end{cases}$$

So that we can represent the system of first-order conditions where $\Omega_{jk}(\mathbf{p_t})) = -\frac{\partial q_k}{\partial p_j}$

$$\mathbf{s_t} = (\mathcal{H}_t(\kappa) \odot \Omega(\mathbf{p_t})) \cdot (\mathbf{p_t} - \mathbf{mc_t}).$$

And therefore

$$\mathbf{mc_t} = \mathbf{p_t} - \underbrace{(\mathcal{H}(\kappa) \odot \Omega(\mathbf{p_t}))^{-1} \mathbf{s_t}}_{\equiv \eta(\mathbf{p}, \mathbf{s}, \mathcal{H}(\kappa))}.$$

Common Questions about Common Ownership

1. Isn't this just a partial-merger? (Yes).
2. In some cases (like double marginalization) don't partial-mergers better align incentives? (Yes).
3. Can we have $\kappa > 1$? (Yes). What does that mean? (Firms value own profits less than rivals, and have incentive to tunnel$\rightarrow$ see BCS AEJ 2021).
4. What about an alternative for γ? Banzhaf Power, Voting Models, etc. (Sure, but remember Arrow says microfounding social choice is hard).

What about the mechanism?

- In some sense this is a frictionless model
  - Managers do exactly what investment managers want
  - Investment managers seek to maximize portfolio value
- Some attempts at micro foundations are questionable
  - Anton, Ederer, Gine, Schmalz: toy model has manager choose effort to reduce MC.
  - Weaker managerial incentives: higher MC and higher P
  - Some correlation that executives at commonly owned firms have peformance less correlated with profitability.

Why Cereal?

Many Reasons

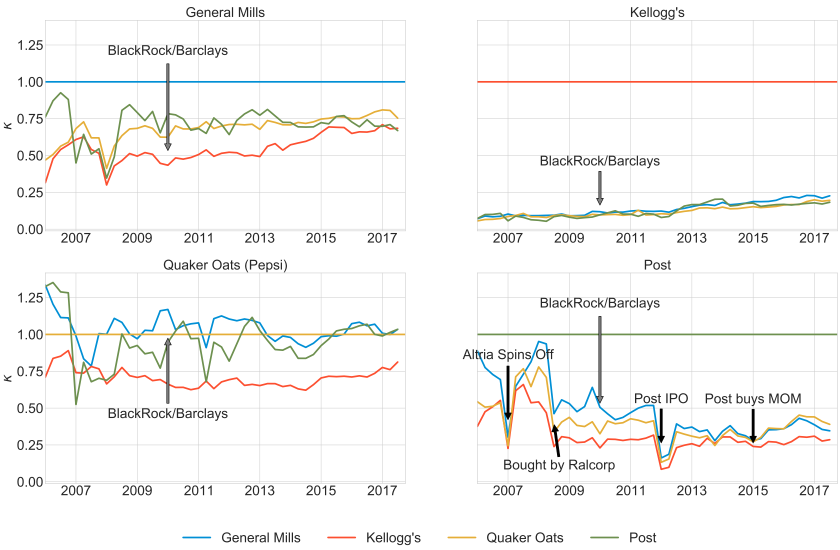
Long history in IO "model organism", but also non-Nash behavior isn't so crazy:

- Market structure: 4 big firms
- Nevo x 3
- FTC Case in the 1970's (Schmalensee 1978)
- Post/Nabisco Merger case (Rubinfeld 2000)
- Cartel/Price War in 1990s (Michel Weierergraeber 2022)

Main Dataset is NielsenIQ (from Kilts) from 2007-2017

- Consolidate to `dma-chain-week`.
- Keep largest chains who price at chain level
  - Select based on # observations from panelist data.
- Consolidate `upc` → `brand` (Honey Nut Cheerios) from multiple package sizes and box designs.
  - Divide revenue by servings
  - Maintain the fiction that households purchase servings.

Cereal Data: Variation in κ



Foreshadowing

- Kellogg's should be a maverick who ignores cooperation from rivals and cares about own profit.
  - Instead they are the highest priced (margin) firm or are uniquely inefficient.
- Quaker Oats (Pepsi) should want to tunnel profits to rivals when $\kappa > 1$ and possibly price into inelastic part of demand curve.
  - They seem to be a low margin tough competitor. (or their mc is zero).
- Post should cut prices sharply around large decreases in κ (de-listing events).
  - Actually they tend to raise prices around those times.

The “Forbidden” Slide

	(1)	(2)	(3)	(4)	(5)	(6)
	Log(Price)	Log(Price)	Log(Price)	Log(Price)	Log(Price)	Log(Price)
	b/se	b/se	b/se	b/se	b/se	b/se
hhi_servings	0.0495***	0.0857***	-0.0105	0.0181***	0.0578***	0.0559***
	(0.0068)	(0.0074)	(0.0066)	(0.0064)	(0.0057)	(0.0060)
mhhid_os_servings	-0.1216***	-0.1204***	-0.1523***	-0.1097***	-0.0833***	-0.0892***
	(0.0079)	(0.0081)	(0.0065)	(0.0064)	(0.0056)	(0.0059)
share_servings					-0.0116***	-0.0117***
					(0.0003)	(0.0003)
DMA FEs	No	Yes	No	Yes	Yes	Yes
Retailer FEs	No	No	Yes	Yes	Yes	Yes
Quadratic Time Trend	Yes	Yes	Yes	Yes	Yes	Yes
Parent FEs	Yes	Yes	Yes	Yes	Yes	Yes
Cubic HHI	No	No	No	No	No	Yes
r2_a	0.267	0.312	0.722	0.754	0.814	0.814
N	5173	5173	5173	5173	5173	5173

* p<0.10, ** p<0.05, *** p<0.01

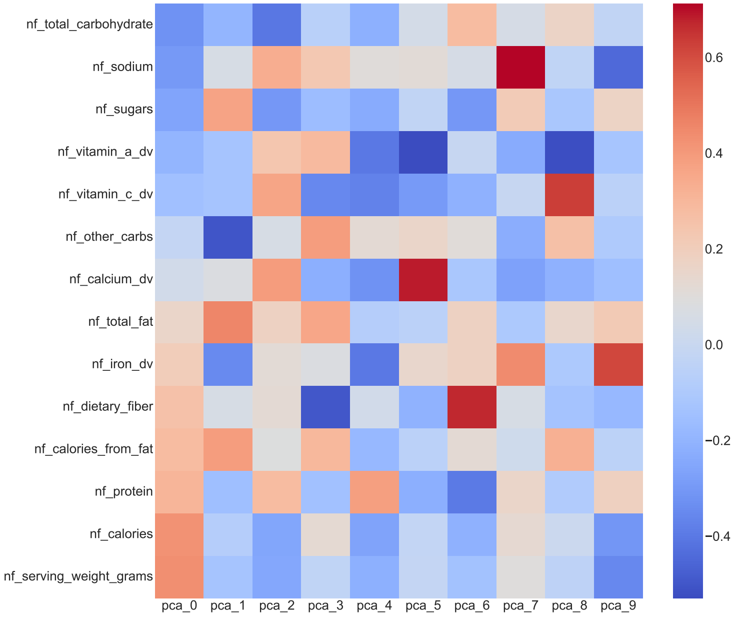
Both *HHI* and *MHHI* scaled for 1000 point increase.

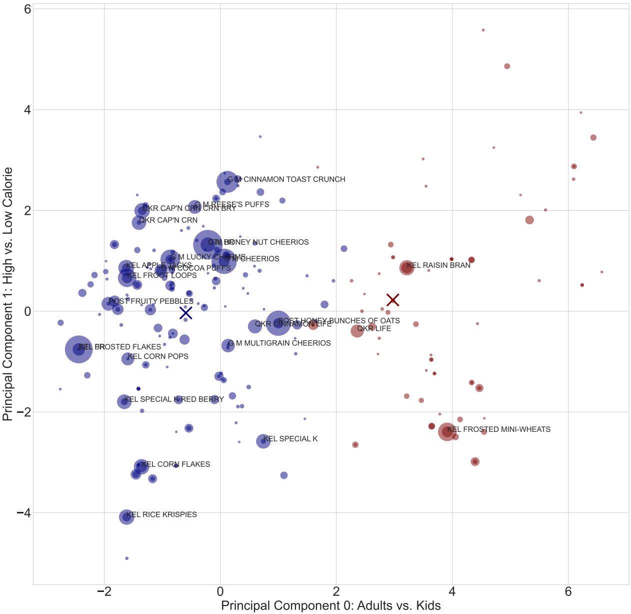
Empirical Application

Implementation: Demand Specification

$$u_{ijt} = h_d(\mathrm{x}_{jt}^{(1)}, \mathrm{v}_{jt}; \theta_1) - \alpha\, p_{jt} + \lambda \, \log(\mathrm{ad}_{jt}) + (\Sigma\, \nu_i + \Pi\, y_i) \cdot x_{jt}^{(2)} + \xi_{jt} + \varepsilon_{ijt}$$

- y_i demographics: estimated at the `dma-chain-year` level (from panelists)
- y_i is joint distribution of (*income, kids*)
  1. Fit a lognormal for income to households w/ and w/o kids.
- ν_i are random (normal) draws; price is lognormal.
- Lots of FE in $h_d(\cdot)$ (product, chain-dma, year, week of year)
- IV: Cost shifters, GH/Optimal IV $f(x_{-j})$, lagged advertising.


nf_total_carbohydrate
nf_sodium
nf_sugars
nf_vitamin_a_dv
nf_vitamin_c_dv
nf_other_carbs
nf_calcium_dv
nf_total_fat
nf_iron_dv
nf_dietary_fiber
nf_calories_from_fat
nf_protein
nf_calories
nf_serving_weight_grams
pca_0
pca_1
pca_2
pca_3
pca_4
pca_5
pca_6
pca_7
pca_8
pca_9
0.6
0.4
0.2
0.0
−0.2
−0.4



Principal Component 1: High vs. Low Calorie
Principal Component 0: Adults vs. Kids
6
4
2
0
−2
−4
−2
0
2
4
6
G M CINNAMON TOAST CRUNCH
G M REESE'S PUFFS
QKR CAP'N CRN CRN BRY
QKR CAP'N CRN
G M HONEY NUT CHEERIOS
G M LUCKY CHARMS
G M CHEERIOS
KEL APPLE JACKS
G M COCOA PUFFS
KEL FROOT LOOPS
KEL RAISIN BRAN
POST FRUITY PEBBLES
POST HONEY BUNCHES OF OATS
QKR CINNAMON LIFE
QKR LIFE
G M MULTIGRAIN CHEERIOS
KEL FROSTED FLAKES
KEL CORN POPS
KEL SPECIAL K RED BERRY
KEL FROSTED MINI-WHEATS
KEL SPECIAL K
KEL CORN FLAKES
KEL RICE KRISPIES

Demand Estimation

- We estimate demand system using `PyBLP` (Conlon Gortmaker RJE 2020)
- Highlights:
  - We estimate market size from milk and egg purchases.
  - Observable demographic preference shocks (income and children).
  - Random coefficients on: (constant, price, branded, servings per box, 3 PC's)
- Moments:
  - Own input costs and local demographic variables.
  - "Local" Gandhi-Houde differentiation instruments
  - We convert these into 21 "optimal instruments"
  - 520 micro-moments to get Π and Σ.

Implementation: Micro Moments

Also have 520 “micro-moments” grouped by `DMA-Code/Retail Chain`

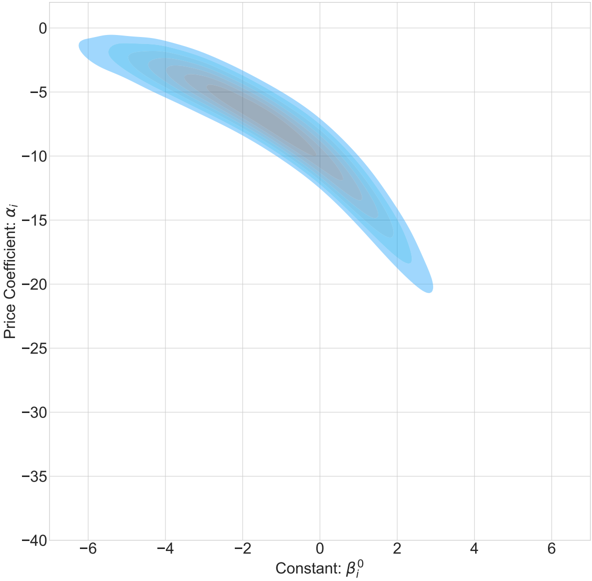
$$\mathbb{E}\left[x_{jt} \times y_{it} \mid \text{purchase}\right] - \mathbb{E}\left[x_{jt} \times y_{it} \times \frac{s_{ijt}(\theta_1, \theta_2)}{1 - s_{i0t}(\theta_1, \theta_2)}\right] = 0.$$

- Match observed interactions of characteristics (constant, price, branded, servings per box, PC) & demographics from the model and the data.
- Conditional on purchase.
- We calculate these from Nielsen Panelist data by `chain-dma-year`.
- We carefully track # of observations to get variance calculations.
- We bootstrap the covariance from the sample (but not model).

See Conlon Gortmaker (2022) for details.

Parameters

Parameter	Variable	No Π	No Σ		Full Model		
		σ^2	π_{kids}	π_{income}	π_{kids}	π_{income}	σ^2
θ_2							
	Constant	40.102	3.837	0.333	2.505	-1.771	7.402
		(1.136)	(0.106)	(0.080)	(0.124)	(0.076)	(0.496)
	Price	8.263	0.676	-0.440	0.641	-0.715	0.415
		(0.535)	(0.027)	(0.024)	(0.034)	(0.021)	(0.035)
	Cov(Const, Price)	18.203					1.750
		(0.823)					(0.128)
	PCA_0		0.061	-0.056	0.081	-0.028	
			(0.009)	(0.005)	(0.008)	(0.005)	
	PCA_1		0.084	0.011	0.077	0.007	
			(0.009)	(0.005)	(0.008)	(0.006)	
	PCA_2		-0.123	0.188	-0.090	0.074	
			(0.011)	(0.006)	(0.009)	(0.006)	
	Branded		0.043	0.158	0.807	0.582	
			(0.045)	(0.037)	(0.041)	(0.041)	
	Servings/Box		-0.048	-0.088	-0.036	-0.008	
			(0.004)	(0.004)	(0.004)	(0.003)	
θ_1							
	Price	3.143	2.445			2.472	
		(0.011)	(0.025)			(0.027)	
	Unemp x Branded	-0.043	-0.016			-0.025	
		(0.002)	(0.002)			(0.002)	
	Recall 1	-0.259	-0.299			-0.344	
		(0.083)	(0.073)			(0.075)	
	Recall 2	-0.215	-0.154			-0.159	
		(0.059)	(0.054)			(0.056)	
	Recall 3	0.035	0.05			0.058	
		(0.074)	(0.057)			(0.062)	
	log(Advertising)	0.03	0.03			0.03	
		(0.002)	(0.002)			(0.002)	
Model Predictions		50%	50%		25%	50%	75%
	Own Elasticity	-2.923	-2.676		-3.055	-2.812	-2.592
	Aggregate Elasticity	-0.351	-0.402		-0.435	-0.393	-0.348
	Outside Good Diversion	0.384	0.570		0.425	0.499	0.574
	Lerner (Own Profit Max)	0.307	0.411		0.351	0.394	0.446
	Lerner (Common Ownership)	0.351	0.446		0.372	0.428	0.501
	Lerner (Big Four)	0.444	0.512		0.408	0.497	0.621
	Lerner (Monopoly)	0.713	0.648		0.531	0.676	0.885



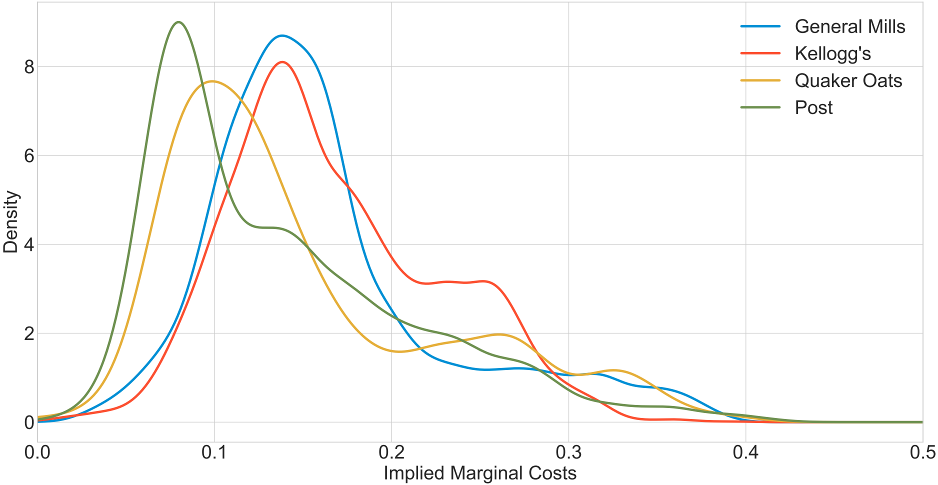
Diversion Ratios

$$D_{jk} = \frac{\partial q_j}{\partial p_k} / \left| \frac{\partial q_j}{\partial p_j} \right| = \frac{e_{jk}}{e_{jj}} \cdot \frac{q_j}{q_k}$$

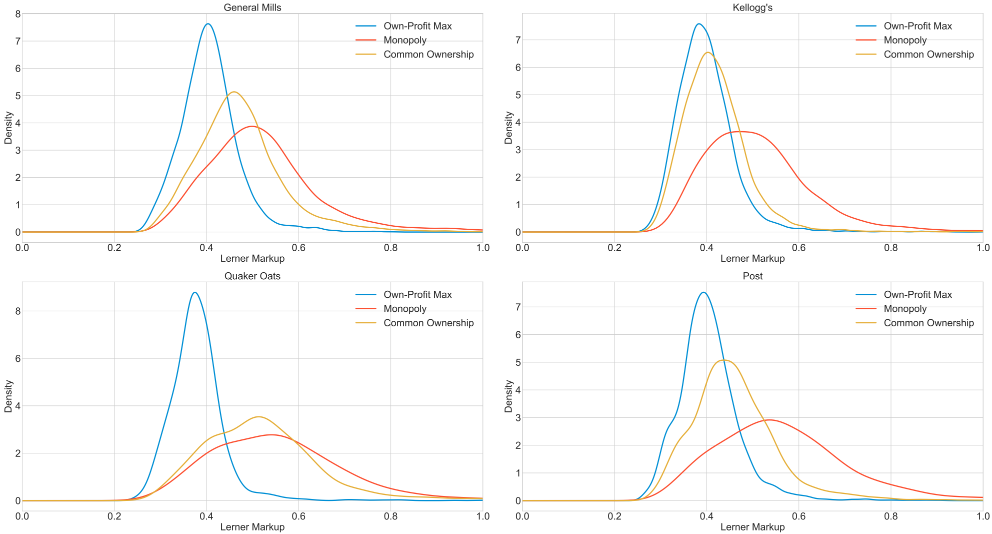
- Easier to interpret than cross elasticity
- Higher diversion implies closer competition
- See Conlon Mortimer (RJE 2021) for all kinds of tricks.

	Cheerios	Special K	Corn Flakes	Reese's Puffs	Capt Crunch	Froot Loops	Shares
HN Cheerios	5.07	4.27	3.75	5.33	3.58	3.48	2.69
Frosted Flakes	2.46	2.54	4.54	4.00	5.35	7.24	2.65
Cheerios	-	5.91	3.13	3.19	1.36	1.77	2.10
Honey Bunches	2.47	2.51	2.21	2.08	1.94	1.99	1.47
Cinn Toast Crunch	3.43	2.10	1.69	3.00	1.78	1.84	1.43
Froot Loops	1.26	1.19	1.64	1.69	1.82	-	1.18
Lucky Charms	2.18	1.64	1.57	2.99	1.59	1.58	1.14
Frosted Mini-Wheats	0.36	0.50	0.74	0.68	0.87	1.27	1.01
Corn Flakes	2.01	2.18	-	1.31	1.24	1.52	0.98
Rice Krispies	1.50	1.72	1.56	0.89	0.68	1.25	0.96
Apple Jacks	0.91	0.80	1.24	1.27	1.42	2.45	0.85
Raisin Bran (KEL)	0.46	0.47	0.63	0.78	0.82	1.24	0.79
Special K Red Berry	0.96	1.45	0.95	0.78	0.68	0.90	0.75
Special K	2.06	-	1.18	0.71	0.44	0.58	0.74
MG Cheerios	1.11	0.99	0.75	0.89	0.54	0.66	0.71
Reese's Puffs	1.36	0.86	0.87	-	1.08	1.01	0.69
Life	1.15	1.12	1.05	1.02	1.72	0.89	0.68
Cocoa Puffs	1.18	0.92	0.95	1.47	1.05	0.97	0.67
Capt Crunch	0.63	0.58	0.88	1.21	-	1.19	0.62
Capt Crunch Berry	0.68	0.61	0.83	1.15	3.29	1.00	0.58
Corn Pops	0.43	0.43	0.71	0.66	0.75	1.45	0.56
Cinn Life	0.76	0.75	0.83	0.84	1.59	0.78	0.54
Fruity Pebbles	0.61	0.59	0.71	0.71	0.75	0.77	0.44
Own Elas	-2.46	-2.66	-2.64	-2.70	-2.68	-2.71	-

Single Product: Implied Marginal Costs



Predicted Markups (Q4 2016)



Counterfactual Price Increases

	GM-KEL	GM-QKR	GM-POST	KEL-QKR	KEL-POST	QKR-POST	Monopoly	κ^{CO}
GIS	6.94	1.53	3.30	-0.03	-0.09	-0.05	12.22	4.81
K	6.69	-0.03	-0.06	1.46	3.43	-0.03	12.07	6.87
PEP	-0.21	8.86	-0.22	8.72	-0.22	4.48	22.41	10.67
POST	-0.10	-0.08	7.43	-0.09	7.98	1.75	17.49	8.49
Overall	4.49	1.10	2.25	1.08	2.40	0.57	12.50	6.01

NB: Computed using marginal costs as predicted by own-profit maximization.

Greater than pairwise mergers, 48% of way to monopoly.

Private label provides a LOT of discipline.

Strategic substitutes: Negative correlation of (β_{i0}, α_i)

Main Results: These are $N(0,1)$

	Others' Cost	Demographics	BLP Inst.	Dmd. Opt. Inst.
Own Profit Max vs.	Panel 1: $A(\mathbf{z}_t) = \mathbf{z}_t$, linear $h_s(\cdot)$			
Single Product	1.6489	1.1116	0.9977	1.6432
Common Ownership	-3.8928	-1.1957	0.5044	-1.0329
Double Marginalization	1.4435	0.9892	-0.0427	5.5684
Common Ownership + Double Marginalization	-0.1919	0.6815	0.1404	5.4688
Perfect Competition	1.1730	0.4171	0.7364	3.9589
Monopolist	-1.4097	-1.0680	-0.4523	-1.0908
Own Profit Max vs.	Panel 2: $A(\mathbf{z}_t) = \mathbb{E}[\Delta\eta^{12}\vert\mathbf{z_t}]$, linear $h_s(\cdot)$ and $g(\cdot)$			
Single Product	1.4264	0.5795	0.6662	0.7516
Common Ownership	-2.3044	-0.5105	-0.0384	-1.4297
Double Marginalization	0.8644	0.4421	-0.5311	2.9800
Common Ownership + Double Marginalization	-0.9382	-0.2389	-0.3684	0.2460
Perfect Competition	0.7164	0.6135	-0.1080	1.8776
Monopolist	-0.8577	-0.4002	-0.3868	-1.1097
Own Profit Max vs.	Panel 3: $A(\mathbf{z}_t) = \mathbb{E}[\Delta\eta^{12}\vert\mathbf{z_t}]$, random forest $h_s(\cdot)$ and $g(\cdot)$			
Single Product	5.0725	5.3347	5.2702	5.5758
Common Ownership	-3.9823	-3.6775	-4.0786	-4.3977
Double Marginalization	-6.3295	-9.9033	-6.5311	-7.6302
Common Ownership + Double Marginalization	-6.6568	-6.8735	-6.6624	-7.5578
Perfect Competition	-5.5005	-7.7749	-6.4083	-7.7653
Monopolist	-3.7240	-4.4602	-3.6134	-3.8959

An Internalization Parameter

Let κ represent the weight a firm places on competitors and τ the internalization of those weights.

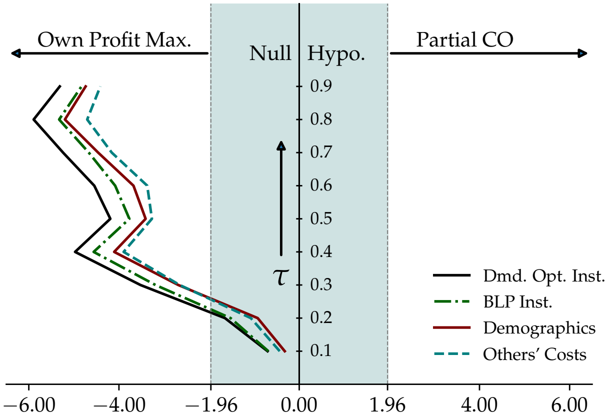
$$arg \max_{p_j : j \in \mathcal{J}_f} \sum_{j \in \mathcal{J}_f} (p_j - mc_j) \cdot s_j(\mathbf{p}) + \sum_{g \neq f} \tau \kappa_{fg} \sum_{j \in \mathcal{J}_g} (p_k - mc_k) \cdot s_k(\mathbf{p})$$

Now,

- $\tau = 0$ implies own-profit maximization
- $\tau = 1$ implies common ownership pricing
- τ in between is..? Agency?

We test $\tau \in (0.1, \ldots, 0.9)$ against own-profit maximization.

Internalization Parameter Results



Stepping Back

- In order to evaluate the common ownership hypothesis, we developed a conduct testing procedure building on the identification results of Berry and Haile (2014)
- Have another specification of common ownership? We can test any pair of models such that
  1. Are fully specified, i.e. predict markups.
  2. Yield distinct markups ($\Delta\eta \neq 0$).
  3. We have instruments that are relevant to $\Delta\eta$, excluded from the supply function $h_s(\cdot)$, and mean independent of ω^0.
- Note that this is not specific to common ownership
  - Cartels: collusive versus oligopoly pricing?
  - Vertical contracts: DM or manufacturer pricing?
  - Labor: monopsony versus perfectly competitive labor markets?
  - Behavioral: suboptimal versus rational pricing rules?

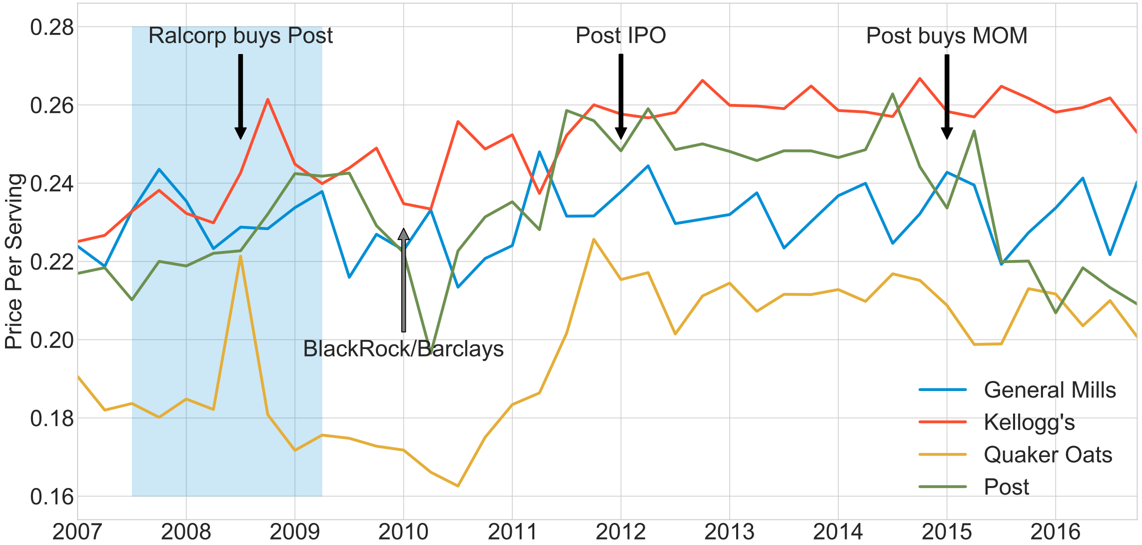
Wrapping Up

Takeaways:

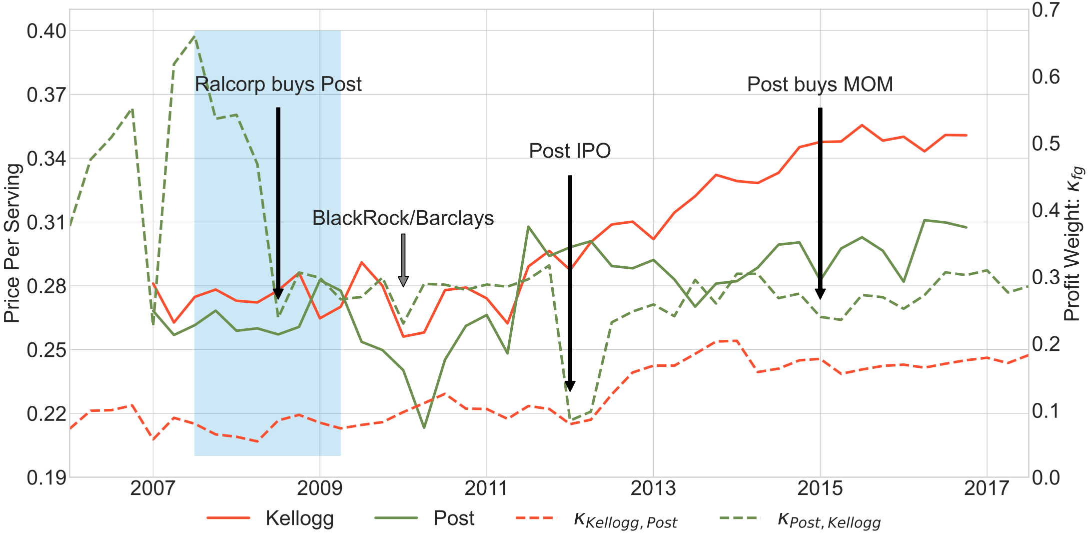
- Equilibrium markups are a nonlinear function of everything in the model. Using the model to get that nonlinearity right makes for a more powerful conduct test.
- In RTE cereal, we see strong evidence in favor of own-profit maximization rather than common ownership pricing.
- Discussion
    - We reject evidence of CO short-run price comepetition in RTE Cereal.
    - Can't reject other mechanisms (CEO's living the quiet life)
    - Can't explain stock market pricing anomalies
    - In some sense CO is what we would see absent agency problems, so where are they?

Thanks!

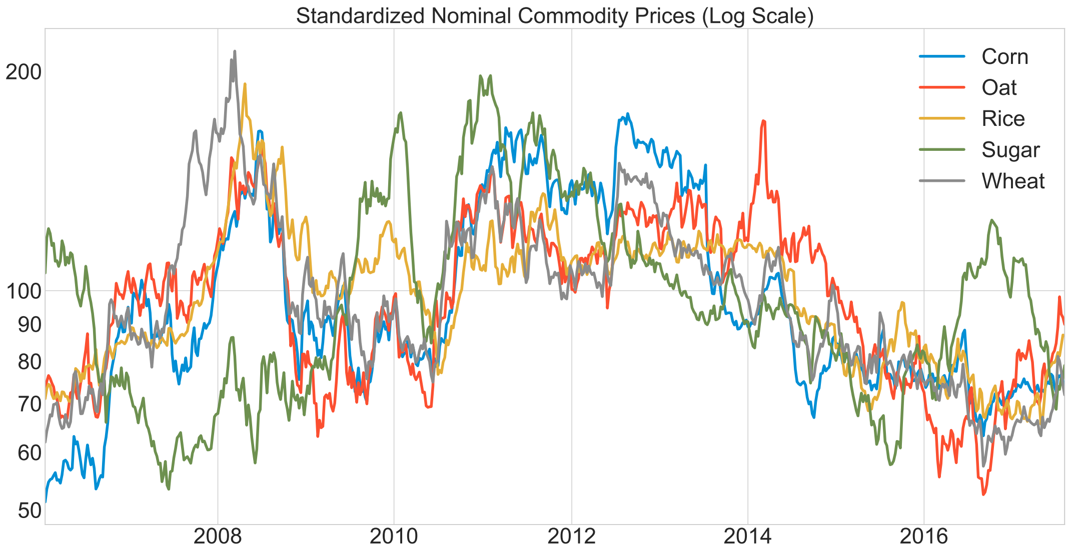
Cereal Data: Prices



Model Free Evidence?: Raisin Bran



Cereal Data: Input Prices



Cereal Data: Concentration