Case Studies

Chris Conlon

Summer 2023

NYU Stern and NBER

Conlon and Rao (2014/2023) on Distilled Spirits

Why does supply matter? (Conlon Rao 2014/2023)

- Looked at a wholesale price posting law challenged under the Sherman Act
  - Post your prices
  - Look at competitors prices
  - Can meet but not beat them.
  - $\rightarrow$Everyone sets monopoly price and then matches
- We can calculate η_{jt} markups using game theory
- We observe $\mathbf{p^w}$ (wholesale) and $\mathbf{p^m}$ (manufacturer) and τ_{jt} (taxes).
  - We basically know MC!

Why does supply matter? (Conlon Rao 2014/2023)

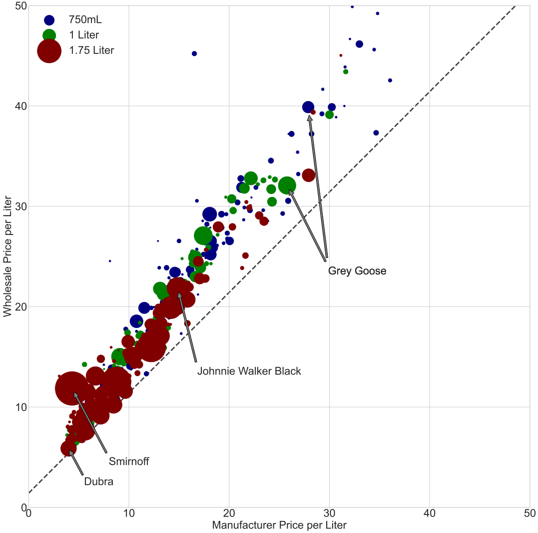
Consumer i chooses product j (brand-size-flavor) in quarter t:

$$u_{ijt} = \beta_i^0 - \alpha_i \, p_{jt} + \beta_i^{1750} \cdot \mathbb{I}[1750mL]_j + \gamma_j + \gamma_t + \varepsilon_{ijt}(\rho)$$

$$\begin{pmatrix} \ln \alpha_i \\ \beta_i \end{pmatrix} = \begin{pmatrix} \overline{\alpha} \\ \theta_1 \end{pmatrix} + \Sigma \cdot \nu_i + \sum_k \Pi_k \cdot \mathbb{I}\{LB_k \leqslant \text{Income}_i < UB_k\}$$

- Nesting Parameter ρ: Substitution within category (Vodka, Gin, etc.)
- Consumers of different income levels have different mean values for coefficients
- Conditional on income, normally distributed unobserved heterogeneity for:
  - Price α_i
  - Constant β_i^0 (Overall demand for spirits)
  - Package Size: β_i^{1750} (Large vs. small bottles)

Wholesale Margins Under Post and Hold



- Price Cost Margins (and Lerner Markups) are higher on premium products
- Markups on least expensive products (plastic bottle vodka) are very low.
- Smirnoff (1.75L) is best seller (high markup / outlier).
- A planner seeking to minimize ethanol consumption would flatten these markups!
- Matching this pattern is kind of the whole ballgame !
- Plain logit gives $\epsilon_{jj} = \alpha \cdot p_j \cdot (1 - s_j)$.

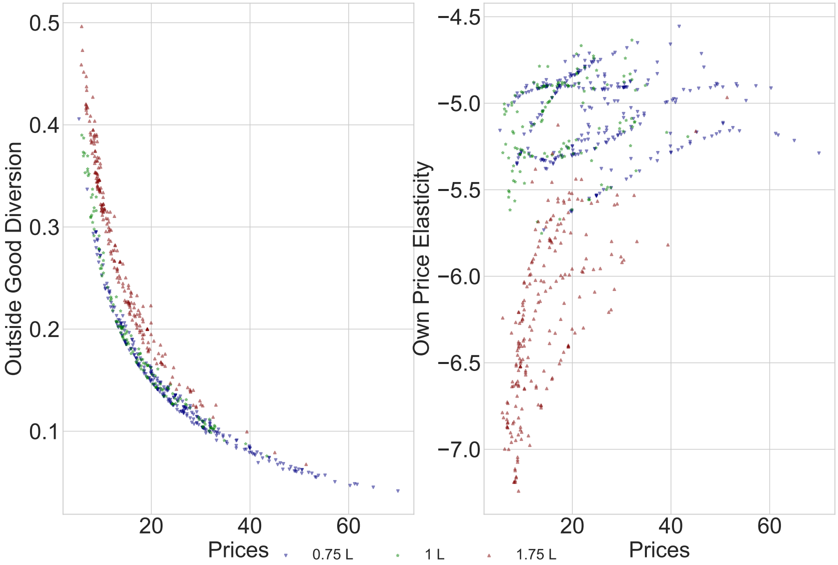
Demand Estimates (from PyBLP, Conlon Gortmaker (2020, 2023))

Π	Const	Price	1750mL
Below \$25k	2.928	-0.260	0.543
	(0.233)	(0.056)	(0.075)
\$25k-\$45k	0.184	-0.170	0.536
	(0.236)	(0.054)	(0.083)
\$45k-\$70k	0.000	-0.179	0.980
	(0.000)	(0.053)	(0.093)
\$70k-\$100k	-0.452	-0.496	0.608
	(0.227)	(0.051)	(0.079)
Above \$100k	-1.777	-1.543	0.145
	(0.234)	(0.047)	(0.055)
Σ^2			
Price	0.000	0.697	0.695
	(0.107)	(0.028)	(0.048)
1750mL	0.000	0.695	1.167
	(0.086)	(0.048)	(0.236)
Nesting Parameter ρ		0.423	
		(0.026)	
Fixed Effects		Brand+Quarter	
Model Predictions	25%	50%	75%
Own Elasticity: $\frac{\partial \log q_j}{\partial \log p_j}$	-5.839	-5.162	-4.733
Aggregate Elasticity: $\frac{\partial \log Q}{\partial \log P}$	-0.333	-0.329	-0.322
Own Pass-Through: $\frac{\partial p_j}{\partial c_j}$	1.256	1.284	1.320
Observed Wholesale Markup (PH)	0.188	0.233	0.276
Predicted Wholesale Markup (PH)	0.205	0.231	0.259

- Demographic Interactions w/ 5 income bins (matched to micro-moments)
- Correlated Normal Tastes: (Constant, Large Size, Price)
- Supply moments exploit observed upstream prices and tax change (ie: match observed markups).

  $$\mathbb{E}[\omega_{jt}] = 0, \text{ with } \omega_{jt} = \left(p_{jt}^{w} - p_{jt}^{m} - \tau_{jt}\right) - \eta_{jt}\left(\theta_2\right).$$
- Match estimate of aggregate elasticity from tax change $\varepsilon = -0.4$.
- Pass-through consistent with estimates from our AEJ:Policy paper.

Elasticities and Diversion Ratios



Diversion Ratios

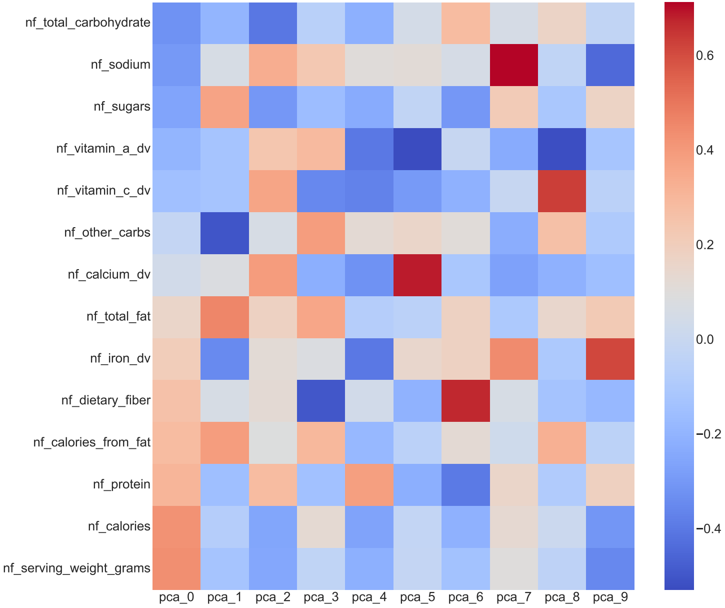
	Median Price	% Substitution		Median Price	% Substitution
Capt Morgan Spiced 1.75 L ($15.85)			Cuervo Gold 1.75 L ($18.33)		
Bacardi Superior Lt Dry Rum 1.75 L	12.52	13.07	Don Julio Silver 1.75 L	22.81	5.00
Bacardi Dark Rum 1.75 L	12.52	2.71	Cuervo Gold 1.0 L	21.32	3.82
Bacardi Superior Lt Dry Rum 1.0 L	15.03	2.44	Sauza Giro Tequila Gold 1.0 L	8.83	3.07
Smirnoff 1.75 L	11.85	2.36	Smirnoff 1.75 L	11.85	2.44
Lady Bligh Spiced V Island Rum 1.75 L	9.43	2.18	Absolut Vodka 1.75 L	15.94	2.06
Woodford 0.75 L ($34.55)			Beefeater Gin 1.75 L ($17.09)		
Jack Daniel Black Label 1.0 L	27.08	7.66	Tanqueray 1.75 L	17.09	12.80
Jack Daniel Black Label 1.75 L	21.85	4.91	Gordons 1.75 L	11.19	4.14
Jack Daniel Black Label 0.75 L	29.21	4.83	Seagrams Gin 1.75 L	10.23	2.85
Makers Mark 1.0 L	32.79	4.52	Bombay 1.75 L	21.95	2.27
Makers Mark 0.75 L	31.88	2.80	Smirnoff 1.75 L	11.85	2.27
Dubra Vdk Dom 80P 1.75 L ($5.88)			Belvedere Vodka 0.75 L ($30.55)		
Popov Vodka 1.75 L	7.66	7.56	Grey Goose 1.0 L	32.08	5.09
Smirnoff 1.75 L	11.85	3.15	Absolut Vodka 1.75 L	15.94	3.82
Sobieski Poland 1.75 L	9.09	3.14	Absolut Vodka 1.0 L	24.91	2.74
Grays Peak Vdk Dom 1.75 L	9.16	2.87	Smirnoff 1.75 L	11.85	2.43
Wolfschmidt 1.75 L	6.92	2.48	Grey Goose 0.75 L	39.88	2.22

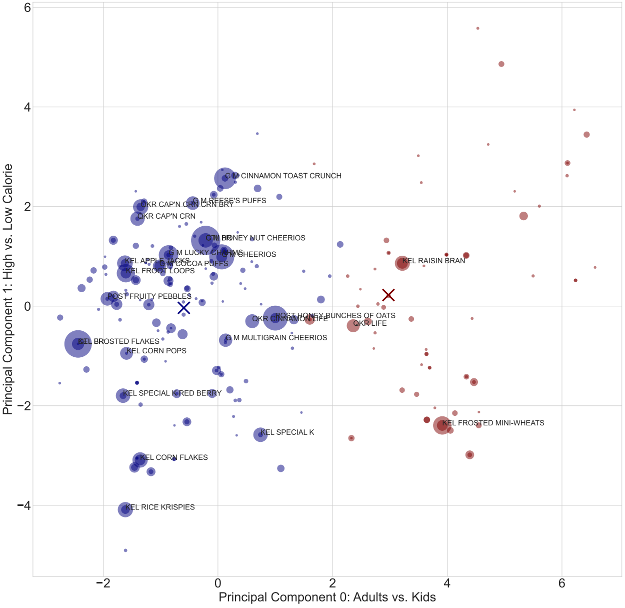
Backus, Conlon, Sinkinson (2021): RTE Cereal

Implementation: Demand Specification

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

- 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



6
4
2
0
−2
−4
−2
0
2
4
6
Principal Component 1: High vs. Low Calorie
Principal Component 0: Adults vs. Kids
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
POST FRUITY PEBBLES
KEL RAISIN BRAN
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`

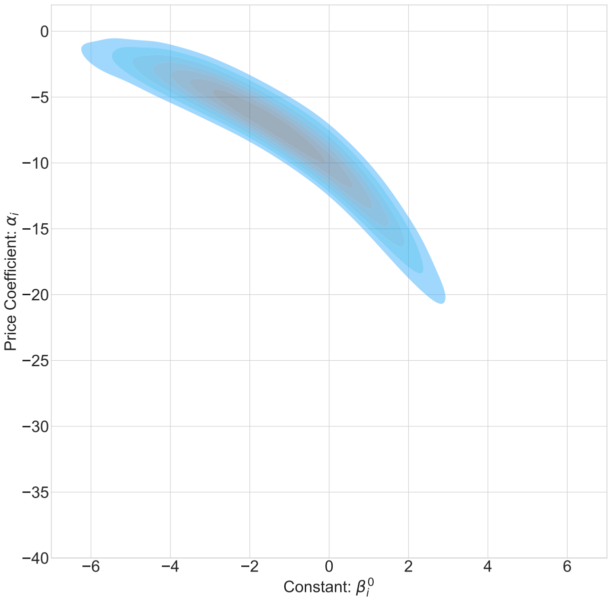
$$\mathbb{E}\left[x_{jt} \times y_{it} \mid \text{purchase}\ \right] - \mathbb{E}\left[x_{jt} \times y_{it} \times \frac{s_{ijt}(\theta_1, \theta_2)}{1 - s_{i0t}(\theta_1, \theta_2)}\right] = 0.$$

- 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 (Micro 2023) for details.

Parameters

Parameter	Variable	No Π	No Σ		Full Model		
θ_2		σ^2	π_{kids}	π_{income}	π_{kids}	π_{income}	σ^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



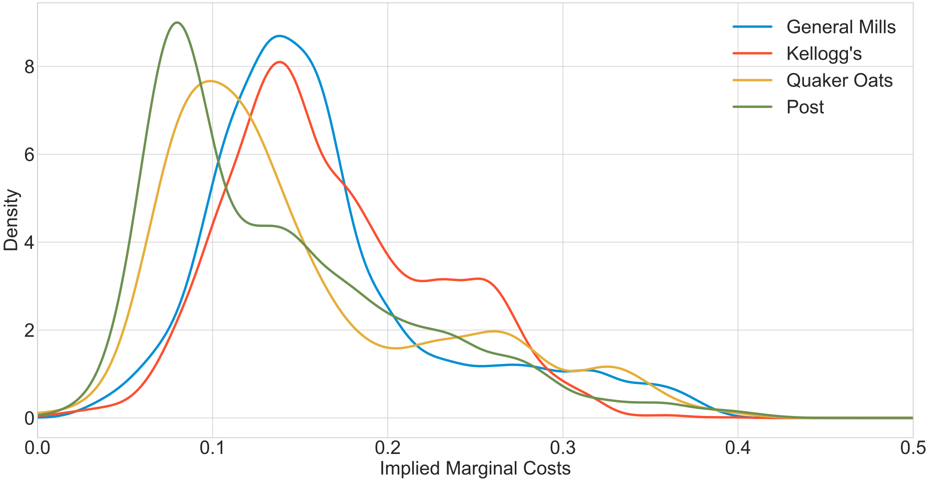
Diversion Ratios

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

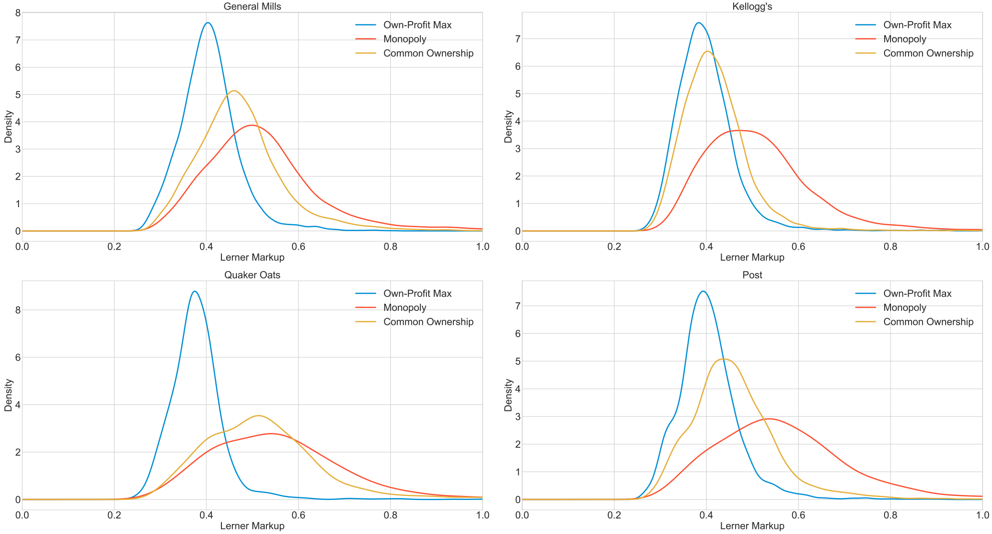
- Easier to interpret than cross elasticity
- Higher diversion implies closer competition
- See Conlon Mortimer (RJE 2021) for all kinds of tricks.

	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)

References i