Demand and supply of differentiated products

Applications

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Economics 567

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Section 1

Gaynor and Vogt (2003)

Gaynor and Vogt (2003) "Competition Among Hospitals"

- California hospitals
- Structural model of demand & pricing
- Merger simulation

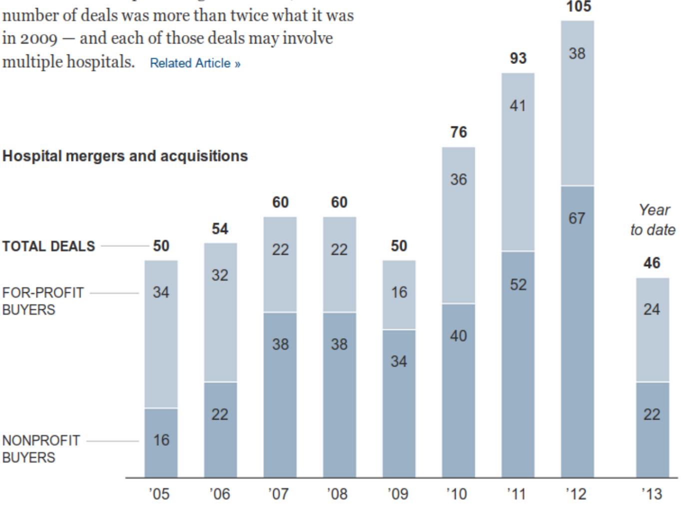
Motivation

- Many hospital mergers, 900 from 1994-2000 (among 6100 hospitals)
- Profit vs non-profit plays role in antitrust decisions
  - 1993-2002: 6 federal anti-trust cases, one initially won (but lost on appeal)
  - Non-profit hospitals have argued that they will not raise prices – court reaction mixed, generally sympathetic

Published: August 12, 2013

A Wave of Hospital Mergers

Over the last four years, there has been a surge in the number of hospital mergers. In 2012, the number of deals was more than twice what it was in 2009 — and each of those deals may involve multiple hospitals. Related Article »



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Continued relevance

- "Regulators Tamp Down on Mergers of Hospitals" NYTimes Dec 18, 2015
- "The Future of Health Care Mergers Under Trump" NYTimes Nov 20, 2016
- "How Nonprofit Hospitals Put Profits Over Patients" NYTimes The Daily Jan 25, 2023

Prior literature

- Structure-conduct-performance
  - Regress market performance (price) on market structure

$$price_{mt} = \beta concentration_{mt} + \epsilon_{mt}$$

  - Typically find $\beta > 0$
  - Results mixed when concentration interacted with non-profit
- Other contemporaneous (in 2003) structural work

Model 1

- Utility of consumer i from hospital j

$$V_{ij} = -\alpha_i^P \underbrace{p_j}_{\text{price}} \underbrace{q_i}_{\text{quantity}} + v(q_i, \underbrace{R_i}_{\text{consumer}}, \underbrace{S_j}_{\text{hospital}})$$

- Aggregate to get demand, $D_j(p)$
- Hospital profits:

$$\pi_j = p_j D_j(p) - C(D_j(p); Z_j, \zeta_j, W)$$

- For-profit pricing: $\max_{p_j} \pi_j$

$$p_j = \frac{\partial C_j}{\partial D_j} - \frac{D_j}{\partial D_j / \partial p_j}$$

Model 2

- Non-profit pricing: $\max_{p_j} U_j(\pi_j, D_j) s.t. \pi_j \geq \pi_L$

$$p_j = \frac{\partial C_j}{\partial D_j} - \frac{\partial U_j / \partial D_j}{\partial U_j / \partial \pi_j + \mu_j} - \frac{D_j}{\partial D_j / \partial p_j}$$

- Merged hospital systems maximize sum of profits or utility

Data

- California OSHPD https://www.oshpd.ca.gov/HID/Find-Hospital-Data.html
- annual discharge, annual financial, & quarterly financial data for 1995
- 913,660 discharges (*i*) and 374 hospitals

TABLE 2 **Variable Descriptions**

Name	Description	Mean	Standard Deviation
X	**Consumer Characteristics**		
q	E(quantity) from equation (9)	1.24	1.61
HMO	Membership in HMO	.50	
PPO	Membership in PPO	.31	
Unscheduled	Unscheduled admission	.53	
d	**Distance**		
$d_{i \to j}$	Distance to (chosen) hospital (miles)	11.56	27.78
$d^2_{i \to j}$	Distance^2		
Z	**Hospital Characteristics**		
p	E(price) from equation (9)	4696	1603
FP	For-profit status	.28	
NFP	Not-for-profit status	.52	
Teach	Teaching hospital	.21	
Tech Index	Technology index	15.02	6.06
System	Multihospital system member	.49	
W	**Input Prices**		
W	Wage index	.99	.15

Econometric model

- Micro-BLP

Step 1 : use individual choice data to estimate δ_j

- Specification of V_{ij}

$$V_{ij} = -\tilde{\alpha}_i^P p_j E[q_i] + \tilde{\alpha}_i^d d_{i\to j} + \tilde{\alpha}_i^{d^2} d_{i\to j}^2 + \sum_k Z_{jk}\tilde{\alpha}_{ik} + \xi_j + \epsilon_{ij}$$

where

$$q_i = \exp\left(\sum_\ell X_{i\ell}\beta_\ell + \nu_i\right) \quad \tilde{\alpha}_i^P = \exp\left(\alpha_0^P + \sum_\ell X_{i\ell}\alpha_\ell^p\right)$$

$$\tilde{\alpha}_i^d = \rho + \sum_\ell X_{i\ell}\rho_\ell^X \quad \tilde{\alpha}_i^{d^2} = \rho^2 + \sum_\ell X_{i\ell}\rho_\ell^{2X}$$

$$\tilde{\alpha}_{ik} = \alpha_0 + \sum_\ell X_{i\ell}\alpha_{\ell k} + \rho_k^Z d_{i\to j} + \rho_k^{2Z} d_{i\to j}^2$$

- Rearrange as hospital mean, δ_j, plus deviations

$$V_{ij} = \underbrace{\sum_{k=0}^K Z_{jk}\bar{\alpha}_k + \xi_j}_{=\delta_j} + (X_i - \bar{X})\alpha Z_j + \text{quadratic distance} + \epsilon_{ij}$$

- Estimate by MLE with individual choice data – gives estimates of $\hat{\delta}_j$

Econometric model 1

Step 2: estimate $\bar{\alpha}$ (include α^p) by 2SLS

$$\delta_j = Z_j \bar{\alpha} + \xi_j$$

- Instruments: wages, exogenous product characteristics, consumer characteristics
    - Functional form of instruments: from FOC,

      $$p_j = \frac{\partial C_j}{\partial D_j} - \frac{D_j}{\partial D_j / \partial p_j}$$

      use estimate of D_j and $\frac{D_j}{\partial D_j / \partial p_j}$ (with $\alpha^p = 0$ and $\xi = 0$)
    - D_j depends on coefficients first assume 0, get initial estimates, then redo to get final estimates

Econometric model 1

Step 3 : estimate marginal cost function by 2SLS

$$P + \left(\Theta \cdot \times \frac{\partial D}{\partial p}\right)^{-1} D = \omega_0 + D\omega_D + W\omega_W + Z\omega_Z + \zeta$$

- D endogenous, same instruments as step 2
- Steps 2 & 3 often combined for efficiency, but not necessary for consistency

- Results as expected
- How to do inference?
  - 913,660 patients
  - 374 hospitals
  - 413 parameters

TABLE 3 **Multinomial Logit Results**

Variable	Estimate	Standard Error
$p\ q$	−.0261	.0005
p HMO	−.157	.002
p PPO	−.121	.003
p Unscheduled	.006	.002
FP q	.082	.004
FP HMO	.721	.016
FP PPO	.787	.018
FP Unscheduled	−.195	.013
NFP q	.046	.003
NFP HMO	.617	.013
NFP PPO	.695	.015
NFP Unscheduled	−.216	.011
Teach q	.040	.002
Teach HMO	.285	.008
Teach PPO	.078	.009
Teach Unscheduled	.052	.006
Tech Index q	.009	.0002
Tech Index HMO	.048	.001
Tech Index PPO	.034	.001
Tech Index Unscheduled	−.028	.001
$d_{i\to j}$	−23.92	.05
$d^2_{i\to j}$	3.15	.01
$d_{i\to j}\ q$	.717	.003
$d^2_{i\to j}\ q$	−.119	.001
$d_{i\to j}$ HMO	−6.517	.018
$d^2_{i\to j}$ HMO	1.023	.003
$d_{i\to j}$ PPO	−2.860	.017
$d^2_{i\to j}$ PPO	.412	.003
$d_{i\to j}$ Unscheduled	−1.909	.014
$d^2_{i\to j}$ Unscheduled	.314	.003
$d_{i\to j}\ p$	.596	.005
$d^2_{i\to j}\ p$	−.069	.002
$d_{i\to j}$ FP	.621	.035
$d^2_{i\to j}$ FP	−.080	.008
$d_{i\to j}$ NFP	.280	.029
$d^2_{i\to j}$ NFP	−.022	.007
$d_{i\to j}$ Teach	4.06	.019
$d^2_{i\to j}$ Teach	−.583	.005
$d_{i\to j}$ Tech Index	.048	.002
$d^2_{i\to j}$ Tech Index	−.004	.001

First stage

- This paper was written at same time the weak identification literature was developing

TABLE A1 **First-Stage Regression for 2SLS Estimates of Demand Equation Dependent Variable = Price in $1000s**

Variable	Estimate
Constant	2.38 (.64)
$D_j/(\partial D_j/\partial p_j)^{IV}$	.12 (.04)
W	2.20 (.63)
D^{IV}	-4.89×10^{-5} (7.87×10^{-5})
FP	.20 (.26)
NFP	−.29 (.23)
Teach	.74 (.26)
Tech Index	-1.22×10^{-3} (1.78×10^{-2})
R^2	.086
F	4.91
N	374

Demand

- Average elasticity -4.85 (2.03)

TABLE 4 Demand Equation

Variable	OLS	2SLS
Constant	−1.92 (.53)	1.40 (1.84)
p	−.52 (.08)	−1.22 (.38)
FP	3.16 (.36)	3.15 (.40)
NFP	1.54 (.34)	1.27 (.40)
Teach	.22 (.32)	.67 (.43)
Tech Index	.25 (.02)	.25 (.03)
R^2	.42	
N	374	374

Standard errors in parentheses.

- For-profit prices \$248 (187) higher
  - Behavioral marginal cost \$592 (329) higher
  - Markup 1183 (587) for profit, 948 (345) non-profit
- First-stage F-stat p-value < 0.01
- What is being assumed about dependence of ξ_j when calculating standard errors?

TABLE 5 **Pricing Equation**

Variable	OLS	2SLS
Constant	.008 (.64)	.43 (.70)
W	3.24 (.65)	2.82 (.70)
D	−.15 (.11)	.16 (.20)
$D\times$ FP	−.10 (.14)	−.30 (.25)
$D\times$ NFP	.07 (.11)	−.17 (.19)
FP	.91 (.31)	1.07 (.43)
NFP	−.12 (.29)	.10 (.37)
Teach	.87 (.23)	.90 (.24)
Tech Index	.03 (.02)	.002 (.25)
System	−.52 (.18)	−.48 (.19)
R^2	.17	
N	374	374

Standard errors in parentheses.

Cross-price elasticities

FIGURE 1

SPATIAL DIFFERENTIATION

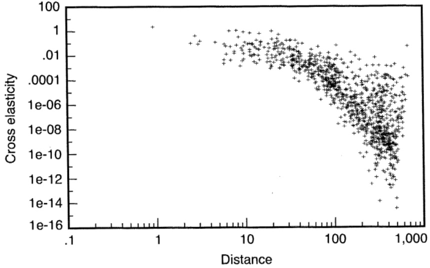
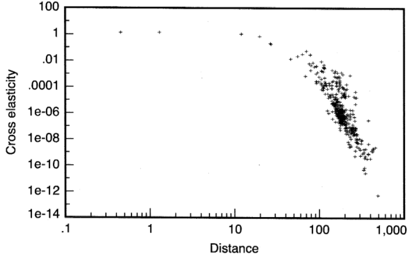


FIGURE 2

SUBSTITUTION WITH FRENCH HOSPITAL



Merger simulation

- Tenet & Ornda merged in 1997
- FTC required Tenet divest French Hospital (bought by Vista)
- Simulate assuming:
  - No divestiture of French
  - With divestiture of French
  - No divestiture, but assuming non-profit

Merger simulation

TABLE 6 San Luis Obispo County Hospitals

Hospital	Owner	p	D	Beds	Distance (Miles)
French Hospital	Ornda	4,434	2,179	147	.28
General	County	4,577	255	46	.72
Sierra Vista	Tenet	4,134	3,722	186	.99
Arroyo Grande	Vista	3,477	546	65	12.03
Twin Cities	Tenet	4,216	1,683	84	19.21
Marian Medical Center	Catholic	3,289	2,240	225	26.24
Valley Community	Ornda	4,439	2,313	53	26.79

Standard errors in parentheses.

TABLE 7 Price Elasticities, San Luis Obispo County

Hosptial	French	General	Sierra Vista	Arroyo Grande	Twin Cities	Marian Medical Center	Valley Communit
French Hospital	−4.17	.17	2.35	.22	.53	.16	.20
General	1.38	−5.37	2.27	.24	.46	.16	.21
Sierra Vista	1.47	.17	−2.84	.18	.61	.13	.16
Arroyo Grande	1.11	.14	1.50	−3.69	.05	.57	.72
Twin Cities	.72	.08	1.32	.01	−2.30	.01	.01
Marian Medical Center	.22	.02	.27	.15	.00	−2.63	2.08
Valley Community	.19	.02	.24	.13	.00	1.49	−3.45

Merger simulation

TABLE 8 Merger Simulation, San Luis Obispo County

			Post-Merger p		
			Divestiture		
Hospital	Owner	p	No	Yes	NFP
French Hospital	Ornda	4,434	6,784	4,467	6,697
General	County	4,577	4,784	4,607	4,753
Sierra Vista	Tenet	4,134	5,469	4,202	5,437
Arroyo Grande	Vista	3,477	3,654	3,712	3,654
Twin Cities	Tenet	4,216	5,587	4,261	5,587
Marian Medical Center	Catholic	3,289	3,331	3,319	3,331
Valley Community	Ornda	4,439	4,552	4,512	4,552

Merger simulation

TABLE 9 Merger Simulation By Location

			Post-Merger p		
			Divestiture		
Area	Owner	p	No	Yes	NFP
San Luis Obispo	Tenet/Ornda	4,238	5,636	4,293	5,615
	All	4,199	5,260	4,271	5,247
Los Angeles	Tenet/Ornda	4,671	4,706	4,706	4,706
	All	4,274	4,277	4,276	4,277
San Diego	Tenet/Ornda	3,596	3,609	3,609	3,609
	All	3,932	3,933	3,933	3,933
Remainder	Tenet/Ornda	4,699	4,716	4,714	4,716
	All	4,650	4,650	4,651	4,650

Related papers

- Gowrisankaran, Nevo, and Town (2015): BLP model of hospital demand, but hospital prices set through negotiations with MCOs
- Bundorf, Levin, and Mahoney (2012), Starc (2014): BLP model of insurance demand
- Goto and Iizuka (2016): BLP model of flu vaccine demand

Section 2

Gowrisankaran, Nevo, and Town (2015)

Gowrisankaran, Nevo, and Town (2015) “Mergers When Prices Are Negotiated: Evidence from the Hospital Industry”

Slides:
http://www.u.arizona.edu/~gowrisan/pdf_papers/hospital_merger_negotiated_prices_slides.pdf

Section 3

Goolsbee and Petrin (2004)

Goolsbee and Petrin (2004)

- In U.S. in 1996 cable television deregulated
  - Hope was that multiple cable operators would enter each area and compete
  - Did not happen, but direct broadcast satellite (DBS) companies did enter
- Questions:
  - How much did competition from DBS lower cable prices?
  - How much did consumers gain from DBS?

Model

- Consumers n, products j, markets m
- Utility:

$$U_{nj} = \alpha_0 p_{mj} + \underbrace{\sum_{g=2}^{5} \alpha_g p_{mj} d_{gn}}_{\text{income effects}} + \beta^x x_{mj} + z_n \beta_j^z + (\xi_{mj} + \epsilon_{nj})$$

$$= \underbrace{\delta_{mj}}_{=\alpha_0 p_{mj} \beta^x x_{mj} + \xi_{mj}} + \sum_{g=2}^{5} \alpha_g p_{mj} d_{gn} + z_n \beta_j^z + \epsilon_{nj}$$

- $\epsilon_n \sim$ multivariate normal with unrestricted covariance across j (avoids IIA problem)

Estimation

- Similar to micro-BLP
- Use micro data to estimate δ_{mj}, β^z
- Use estimated δ, instruments for price to estimate α_0, β^x
    - Uses local tax on cable revenues as instrument for price
- Effect of entry, need to know price as function of model primitives
    - Could fully specify costs and form of competition
    - Instead estimate reduced form pricing equation,

$$p_{mj} = f(\text{observables})$$

- Use pricing equation to predict prices without DBS, calculate compensating variation as measure of consumer welfare

Results: demographics and demand

TABLE V

MARGINAL EFFECTS ON PURCHASE PROBABILITIES (ESTIMATED PERCENTAGE CHANGES)

For changing to: Change in probability (in %)	MU Dweller SU Dweller	Renter Nonrenter	Household Income Increases 10%
Antenna only	−1.81	−.72	−4.32
Expanded basic	−4.33	−1.67	.42
Premium	−8.95	−3.43	2.61
Satellite	95.83	25.57	.61
For changing to: Change in probability (in %)	**Not Male Single Male Single**	**Not Female Single Female Single**	**High School Educ. College Educ.**
Antenna only	6.84	−.99	22.79
Expanded basic	−11.85	15.72	1.45
Premium	8.11	−5.56	−17.52
Satellite	19.34	−46.10	−12.08

Notes: The table reports the average percentage change in purchase probabilities arising from changing all people with the characteristic in the top row to having the characteristic listed in the bottom row. Because they are percentage changes, they do not sum to one. MU/SU Dwelling is Multi-Unit/Single Unit Dwelling, and Educ. is an index of average household education.

Results: demand elasticities

TABLE VIII

ESTIMATED DEMAND ELASTICITIES
(MARSHALLIAN AND HICKSIAN)

	SUR	3SLS	3SLS
Method		Marshallian	Hicksian
Price of expanded basic			
Antenna only share	.020	1.301	1.323
Expanded basic share	.014	−1.538	−1.516
Premium share	−.040	1.263	1.284
Satellite share	−.014	.929	.951
Price of premium			
Antenna only share	−.000	.917	.932
Expanded basic share	−.030	.924	.938
Premium share	.074	−3.175	−3.161
Satellite share	−.035	1.173	1.187
Price of satellite			
Antenna only share	.001	.123	.129
Expanded basic share	−.005	.286	.292
Premium share	−.015	.492	.498
Satellite share	.050	−2.448	−2.442

Note: Specification is estimated using the 254 markets for which the tax on franchise revenues is reported in Warren Publishing. SUR is seemingly unrelated regressions (not instrumented). 3SLS is three stage least squares using the tax to instrument price.

Results: welfare

- No DBS would increase cable prices by \$4.17 per month
- Monthly consumer gains from DBS:
  - \$10.57 in consumer surplus for DBS subscribers
  - \$4.17 per month for cable subscribers from lower prices
  - \$1 per month for cable subscribers from increased quality

Section 4

Fan (2013)

Fan (2013)

- Question: effect of mergers on product characteristics
  - Merged firm will generally produce different product(s) than two separate firms
  - Need to endogenize choice of product characteristics
- Setting: U.S. daily newspapers

Model 1

- BLP style demand with endogenous price and other product characteristics, x_{jt} = quality index, local news ratio (share of local news staff), news variety (HHI of staff shares across sections)
- Demand for advertising:

$$\log a_{jt} = \eta + \underbrace{\lambda_0 \log H_{jt}}_{\text{market size}} + \underbrace{\lambda_1 \log q_{jt}}_{\text{circulation}} + \underbrace{\lambda_2 \log r_j t}_{\text{advertising price}} + \iota_{jt}$$

Note: no cross price elasticities, i.e. no competition

- Variable profits:

$$\pi_j^{II} = (p_j q_j - ac_j^{(q)} q_j) + (r_j a_j - mc_j^{(a)} a_j) + (\mu_1 q_j + \mu_2/2 q_j^2)$$

where

Model 2

- $ac_j^{(q)}$ is average cost of producing quantity q and has some parametric form
- $mc_j^{(q)}$ is marginal cost of advertising sales and has some parametric form

- Definition of market:
  - Newspapers compete in many overlapping local markets, so local paper in Portland, Maine potentially competes with local paper in Portland, Oregon
  - Define market for newspaper j as the counties where 85% of circulation for newspaper j is contained
- Equilibrium: solving backward
  3. Given Q_{jt}, advertising rate chosen to equalize marginal cost and marginal revenue of advertising
     - No competition in advertising rates
  2. Given characteristics, prices chosen in simultaneous Nash equilibrium
  1. Characteristics chosen simultaneous Nash equilibrium

Data 1

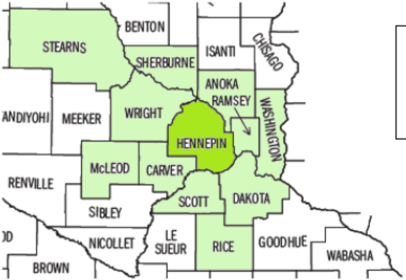
- 1997-2005, market level data on newspaper quantity, price, and characteristics, and advertising quantity and price
- County demographics (education, age, income, urbanization)
- 5843 newspaper-year observations of newspaper characteristics and prices
- 11203 newspaper-county-year observations of quantity
- 422 newspaper-year also with advertising information

Estimation 1

- Moment conditions
  - Consumer demand: $\mathrm{E}[\xi_{jt}|w_{jt}] = 0$
  - Advertiser demand: $\mathrm{E}[\iota_{jt}|w_{jt}] = 0$
  - Advertising first order condition: $\mathrm{E}[\zeta_{jt}|w_{jt}] = 0$
  - Price first order condition: $\mathrm{E}[\omega_{jt}|w_{jt}] = 0$
  - Characteristics first order condition: $\mathrm{E}[\nu_{jt}|w_{jt}] = 0$
- Instruments from overlapping markets
  - Suppose newspaper A is only in county 1, but newspaper B is in counties 1 and 2
  - Demographics in county 2 affect prices and characteristics of newspaper B, which in turns affects newspaper A's price and characteristics
  - Use demographics in county 2 to instrument for newspaper A's price

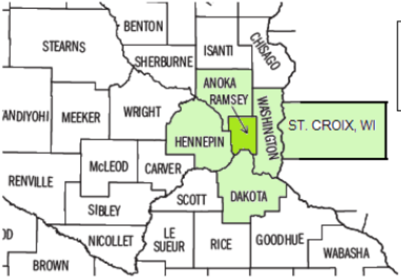
Results 1

- Parameter estimates
- Simulation of merger of *Minneapolis Star Tribune* and *St. Paul Pioneer*
  - In reality: owner of *Pioneer* bought *Star*, DOJ filed antitrust complaint 3 months later, owner of *Pioneer* sold *Star* 2 months later
- Simulate with and without characteristic adjustment, compare results



Market of the *Star Tribune*

Hennepin (Home County), Anoka, Carver, Dakota, McLeod, Ramsey, Rice, Scott, Sherburne, Stearns, Washington, Wright



Market of the *Pioneer Press*

Ramsey (Home County), Anoka, Dakota, Hennepin, St. Croix, Washington

Table 5: Effects of Ownership Consolidation of the *Star* and the *Pioneer*

(a) Without Characteristic Adjustment

	price ($/year)			ad rate ($/column inch)			circulation		
	before	after	change	before	after	change	before	after	change
Star Tribune	172.79	175.98	3.19	230.88	227.00	-3.87	317337	310148	-7189
Pioneer Press	171.51	179.52	8.01	153.08	147.07	-6.00	159864	148519	-11345
Faribault Daily	111.31	111.32	0	12.37	12.39	0.02	6384	6434	50
St. Cloud Times	150.07	149.95	-0.12	44.15	44.19	0.03	24578	24667	89
Stillwater Gazette	78.33	75.03	-3.30	11.13	11.25	0.12	3341	3644	303

(b) With Characteristic Adjustment

	content quality index			local news (%)			variety		
	before	after	change	before	after	change	before	after	change
Star Tribune	788.49	771.78	-16.72	22	21.15	-0.85	83.38	81.79	-1.58
Pioneer Press	474.29	422.59	-51.7	27.48	23.88	-3.60	82.07	74.61	-7.46
Faribault Daily	7.00	7.17	0.17	14.29	14.47	0.18	50.00	50.35	0.35
St. Cloud Times	65.28	66.26	0.98	35.42	35.6	0.18	74.50	75.01	0.51
Stillwater Gazette	0.7	0.31	-0.40	0	0.05	0.05	0	0	0
	price ($/year)			ad rate ($/column inch)			circulation		
Star Tribune	172.79	175.39	2.59	230.88	227.09	-3.79	317337	310223	-7114
Pioneer Press	171.51	178.83	7.32	153.08	144.4	-8.68	159864	140635	-19229
Faribault Daily	111.31	111.26	-0.05	12.37	12.42	0.05	6384	6518	134
St. Cloud Times	150.07	149.64	-0.43	44.15	44.29	0.13	24578	24939	361
Stillwater Gazette	78.33	87.41	9.08	11.13	10.83	-0.30	3341	2597	-744

Table 6: Welfare Effects of Ownership Consolidation of the *Star* and the *Pioneer*

	change in RS (million \$)	% change in RS (%)	change in AS (%)	change in PS (million \$)	% change in PS (%)
without characteristic adjustment	-2.22	-4.67	-4.66	4.23	36.41
with characteristic adjustment	-3.28	-6.87	-7.10	4.32	37.25

Section 5

Gandhi, Lu, and Shi (2014)

"Demand Estimation with Scanner Data: Revisiting the Loss-Leader Hypothesis" gandhi2014 1

- Motivation:
    - Frequent price discounts (sales) in scanner data
    - Chevalier, Kashyap, and Rossi (2003): loss-leader model implies prices can fall when demand increases because of promotional effect; evidence that prices fall during seasonal peak demand (e.g. tuna during Lent)
    - Nevo and Hatzitaskos (2006): prices could also fall during high demand because elasticity of demand could increase (if buying more quantity, makes more sense to search for lower price)
- Methodology: estimate BLP demand model, see if demand elasticity is different during seasonal peak
- Data: Dominick's scanner data (grocery store)

"Demand Estimation with Scanner Data: Revisiting the Loss-Leader Hypothesis" gandhi2014 2

- Difficulty: many product categories have hundreds of products, so many products have 0 observed share in some markets
- Solution: optimally shift observed shares away from 0

Data

- Dominick's scanner data (grocery store)
- Estimate separately for each product category
- Market = store × week (all stores in Chicago, 1989-1997, gives $\approx 400,000$ markets)
- Many products in each category (Table 4) – 283 cheese, 537 soft drinks, 820 shampoos, 118 canned tuna, etc
- Sales concentrated among top 20% of products in each category (Table 4) – approximately 80%
- High percent (20-80) of products with 0 sales (Table 4) – 35% for canned tuna
- Distribution of sales approximately follows Zipf's law – kth most popular product has sales proportional to $1/k^s$ for some $s > 1$

Model and zero share problem 1

- BLP setup (but empirical results are without random coefficients)
- Zero share problem, $0 = \sigma(\delta)$ implies $\delta = -\infty$
  - Cannot just drop goods with 0 share because that creates selection (0 share implies low ξ)
- Laplace: when observe zero share, add 1 sale to each product

$$s_{jt}^{L} S = \frac{n_t s_{jt} + 1}{n_t + J_t + 1}$$

  Optimal Bayes estimator under uniform prior
- Could use Laplace transformation here, but what is optimal for estimating shares might not be optimal for estimating demand

Model and zero share problem 2

- Choose transformation $\pi^*(s_t, n_t)$ that minimizes asymptotic (slowly growing n_t) MSE

$$\pi^*(s_t, n_t) = \sigma\left(\mathrm{E}\left[\sigma^{-1}(\pi_t) | s_t, n_t\right]\right)$$

- $F_{\pi_t | s_t, n_t}$ unknown, show that if assume Zipf's law, can estimate it
- Use estimated $F_{\pi_t | s_t, n_t}$ to estimate optimal transformation
- Estimate rest of model using BLP with transformed shares

Zero share correction reduces bias

Table: Table 6: Average Bias for a Repeated Simulation

Fraction of Zeros	16.48%	36.90%	49.19%	63.70%
Using Empirical Share	.3833	.6589	.7965	.9424
Using Laplace Rule	.2546	.5394	.6978	.8476
Inverse Demand EB	-.0798	-.0924	-.0066	.0362

Note: $T = 500$, $n = 10,000$, Number of Repetitions $= 1,000$.

Table 7: Demand Estimation Results

		Price Coefficient	Nesting Parameter	Average Own Price Elasticity	Fraction of Inelastic Products
Logit	Emp. Shares	-.51	-	-.77	82.82 %
		(<.01)			
	Opt. Shares	-2.01	-	-3.01	.33 %
		(.01)			
Nested Logit	Emp. Shares	-.52	.51	-1.50	29.26 %
		(<.01)	(<.01)		
	Opt. Shares	-.98	.82	-7.56	<.01 %
		(<.01)	(<.01)		

Note: The instrumental variables for price include wholesale price, its first and second lags (for the same product/store). IV for the within group (nest) share is the number of products in the group.

Table 8: Demand in Lent vs. Non-Lent

		Price Coefficient		Nesting Parameter		Average Own Price Elasticity	
		Lent	Non-Lent	Lent	Non-Lent	Lent	Non-Lent
Logit	Emp. Share	-.60	-.50		-	-.89	-.75
		(.02)	(.01)				
	Opt. Share	-1.96	-2.01		-	-2.90	-3.01
		(.03)	(.01)				
Nested Logit	Emp. Share	-.57	-.52	.43	.53	-1.39	-1.54
		(.01)	(<.01)	(.01)	(<.01)		
	Opt. Share	-1.02	-.98	.76	.83	-5.81	-7.79
		(.01)	(<.01)	(<.01)	(<.01)		

Note: The instrumental variables for price include wholesale price, its first and second lags (for the same product/store). IV for the within group (nest) share is the number of products in the group.

Section 6

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