

Graduate IO: Price Dispersion and Search

November 6, 2016

Agenda

- ▶ price dispersion and search
 - ▶ theory: Varian (1980)
 - ▶ empirical: Sorensen (2000)
- ▶ structural estimation of search models
 - ▶ Hong and Shum (2006), Hortacsu and Syverson (2004), De Los Santos, Hortacsu, and Wildenbeest (2012)

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- ▶ however, in most retail markets, consumers do not know the prices charged by different retailers and have to learn them
 - ▶ this activity is costly, so consumers are unlikely to be fully informed
 - ▶ one of the main uses of the Internet is to provide price information cheaply

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- ▶ however, in most retail markets, consumers do not know the prices charged by different retailers and have to learn them
 - ▶ this activity is costly, so consumers are unlikely to be fully informed
 - ▶ one of the main uses of the Internet is to provide price information cheaply
- ▶ question: how does the consumer's lack of information about prices affect competition among firms?

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- ▶ demand

- ▶ consumers have unit demands and willingness to pay of r
- ▶ two types of consumers: I informed and M uninformed consumers
 - ▶ an informed consumer knows the prices charged by all N firms
 - ▶ an uninformed consumer does not know the prices and randomly selects one firm to shop

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 - ▶ informed consumers buy from the firms setting the lowest price if it does not exceed r
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- ▶ let $U = \frac{M}{n}$ be the number of uninformed consumers each firm gets
- ▶ payoffs

$$\pi_i(p_i, p_{-i}) = \begin{cases} p_i (U + I) & \text{if } p_i < p_j, j \neq i \\ p_i (U + \frac{I}{m}) & \text{if } p_i = p_j, j = 1, \dots, m - 1 \\ p_i U & \text{if } r \geq p_i > p_j, j \neq i \end{cases}$$

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- ▶ thus, the *Law of One Price* does not hold!

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 - ▶ but then firm L should raise price p^L until it is slightly below r
 - ▶ but then firm H wants to undercut p^L
- ▶ we need to look for an equilibrium in which firms cannot forecast the prices of their rivals and undercut them
 - ▶ firms are perceived as choosing prices randomly

Mixed-Strategy

- ▶ let $F(p)$ denote the probability that a rival posts a price less than p , then the expected profit to a firm when it charges p is

$$\pi(p) = [1 - F(p)]^{n-1} p(U + I) + \left\{ 1 - [1 - F(p)]^{n-1} \right\} pU$$

- ▶ the first term on the RHS is the probability that p is the lowest price, in which case firm demand is $U + I$
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 - ▶ the second term on the RHS is the probability that p is not the lowest price, in which case firm demand is only U
- ▶ in a mixed strategy equilibrium, the firm's profits at every price p has to be constant: $\pi(p) = k$
 - ▶ solving the equilibrium equation yields

$$1 - F(p) = \left[\frac{k - pU}{pI} \right]^{\frac{1}{n-1}}$$

Mixed-Strategy (Cont.)

- ▶ clearly, the upper bound on prices is r , therefore, the unknown constant k satisfies

$$F(r) = 1 \Rightarrow k = rU$$

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$$1 - F(p) = \left[\frac{(r-p)U}{pl} \right]^{\frac{1}{n-1}}$$

- ▶ the lower bound of the set of prices that firms will charge is obtained by setting $F(p) = 0$

$$\underline{p} = \frac{rU}{U+I}$$

Mixed-Strategy (Cont.)

- ▶ the lower bound \underline{p} is strictly positive
 - ▶ firms earn positive profits: escape the Bertrand trap
 - ▶ the equilibrium density of prices is U-shaped: firms will tend to either price near r or near the lower bound

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- ▶ remarks: as U falls, market becomes more competitive, prices fall and lower prices more likely

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 - ▶ online travel agents like *Travelocity* and *Expedia*

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- ▶ however, price search engines like *Pricewatch.com* provide consumers with lots of prices at very low cost
 - ▶ online travel agents like *Travelocity* and *Expedia*
- ▶ this led many researchers to predict less price dispersion and lower margins in online markets than in brick and mortar markets

Search Cost and Internet

- ▶ it is much easier to test this prediction in online markets
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 - ▶ products in online markets are not differentiated by location
- ▶ nevertheless, a long list of papers have found that price dispersion among E-retailers is similar to that of brick and mortar retailers and margins are not extremely low (e.g., Amazon reports average markups of 15%)
 - ▶ one reason may be obfuscation, online retailers try to make it difficult for consumers to determine the true price, e.g., shipping cost, taxes, etc.
 - ▶ See Ellison and Ellison: “Search, Obfuscation, and Price Elasticities on the Internet”, *Econometrica*, 2009.

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 - ▶ consumers have stronger incentives to search for lowest price when they have to purchase drug frequently
- ▶ hypothesis: lower markups, less dispersion for drugs that are purchased more frequently
- ▶ data: prices of 152 top-selling prescription drugs
 - ▶ 10 pharmacies in Middletown, NY
 - ▶ 11 pharmacies in Newburgh, NY

Data Overview

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- ▶ drug dosage/therapy duration used to compute expected number of purchase times per year

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PRICE RANKINGS BY PHARMACY
A. MIDDLETOWN

| PHARMACY | PRICE GROUP | | |
|-----------------|-------------|----------|-----------|
| | Lowest 3 | Middle 4 | Highest 3 |
| Eckerd | 45 | 103 | 10 |
| Eckerd | 29 | 102 | 27 |
| Immediate | 43 | 54 | 61 |
| K-Mart | 56 | 57 | 45 |
| Medicine Shoppe | 99 | 49 | 10 |
| Price Chopper | 80 | 67 | 11 |
| Rite-Aid | 3 | 11 | 144 |
| Rite-Aid | 2 | 18 | 138 |
| Rx Place | 38 | 104 | 16 |
| Wal-Mart | 79 | 67 | 12 |

Descriptive Statistics

B. NEWBURGH

| PHARMACY | PRICE GROUP | | |
|---------------|-------------|----------|-----------|
| | Lowest 3 | Middle 3 | Highest 3 |
| Ace | 26 | 112 | 30 |
| Hudson | 33 | 106 | 29 |
| Medical Arts | 73 | 65 | 30 |
| Price Chopper | 134 | 27 | 7 |
| Rite-Aid | 4 | 23 | 141 |
| Rite-Aid | 10 | 45 | 113 |
| Rite-Aid | 18 | 34 | 116 |
| Rx Place | 64 | 70 | 34 |
| Wal-Mart | 142 | 22 | 4 |

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| Rite-Aid | 18 | 34 | 116 |
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- ▶ (kind of) consistent with randomization on individual drug prices (a lot of uncertainty in rivals' prices)

Regression I

- ▶ regression equation

$$RANGE_{ij} = \beta_0 + \beta_1 PFREQ_i + \text{other controls} + \epsilon_{ij}$$

where $RANGE_{ij}$ is price range of drug i in city j , $PFREQ_i$ is purchase frequency of drug i

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PRICE DISPERSION AND PURCHASE FREQUENCY

| | DISPERSION MEASURE | | | |
|--|--------------------|------------------------------|--------------------------|--|
| | Range (1) | Standard Deviation (2) | Residual Range (3) | Residual Standard Deviation (4) |
| Purchase frequency | -.336 (.123) | -.173 (.076) | -.266 (.061) | -.102 (.016) |
| Wholesale cost | .280 (.033) | .180 (.020) | .215 (.043) | .069 (.014) |
| Branded with generic competition | -.803 (1.037) | -1.480 (.641) | -1.842 (.861) | -.362 (.248) |
| Branded without ge- neric competition | -1.505 (2.108) | -2.010 (1.303) | -1.967 (1.060) | -.772 (.339) |
| Newburgh dummy | -2.686 (.633) | -3.172 (.314) | -1.493 (.791) | -.916 (.271) |
| Constant | 20.070 (4.343) | 7.321 (2.563) | 14.570 (1.062) | 5.283 (.448) |
| R^2 | .371 | .447 | .258 | .253 |
| $\hat{\rho}$ | .338 | .585 | .149 | .648 |

Regression II

AVERAGE MARGINS AND PURCHASE FREQUENCY

| | DEPENDENT VARIABLE | | |
|--|--------------------------|-------------------------|--------------------------------------|
| | Average Margin (1) | Average Price (2) | Average Relative Margin (3) |
| Purchase frequency | -.262 (.102) | -.137 (.105) | .001 (.003) |
| Wholesale cost | ... | .994 (.032) | ... |
| Wholesale cost \times generic dummy | ... | -.208 (.059) | ... |
| Branded with generic competition | 2.101 (.720) | -.668 (1.056) | -.235 (.020) |
| Branded without generic competition | 3.415 (1.660) | -.123 (1.891) | -.255 (.046) |
| Newburgh dummy | 1.681 (.174) | 1.648 (.140) | .047 (.005) |
| Constant | 12.69 (2.435) | 11.86 (2.581) | .463 (.068) |
| R^2 | .229 | .895 | .510 |
| $\hat{\rho}$ | .915 | .936 | .898 |

- ▶ margins are negatively correlated with drug frequency: 37% lower for drugs that are purchased monthly versus drugs purchased only once

Remarks

- ▶ alternative explanations
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- ▶ alternative explanations
 - ▶ pharmacy heterogeneity: fixed effects account for 33% of the dispersion in prices
 - ▶ cost heterogeneity: differences in drug acquisition costs across pharmacies are too small
- ▶ main conclusion: price dispersion is substantial, it is positively correlated with drug purchase frequency

Consumer Search Models

- ▶ Varian (1980) isn't technically a model of consumer search
- ▶ various subsequent authors proposed models in which consumers' "informedness" is endogenous
 - ▶ consumers have search costs
 - ▶ the search for lower prices if expected benefit of search is greater than search cost
- ▶ two main modeling approaches
 - ▶ fixed sample size search
 - ▶ sequential search

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- ▶ if cost of each price quote is c , then getting n price quotes gives an expected total purchase cost equal to

$$cn + \int_0^{\infty} np [1 - F(p)]^{n-1} dF(p)$$

- ▶ this is a convex function of n , so there exists a unique integer that minimizes total purchase cost (or two adjacent integers that tie)

Sequential Search: Stahl (1989)

- ▶ consumers know price distribution $F(p)$
 - ▶ fraction μ of zero-search-cost “shoppers”
 - ▶ fraction $1 - \mu$ have common search cost $c > 0$ per price quote

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- ▶ if best price found so far is z and $z < WTP$, expected benefit from an additional search is

$$\int_{\underline{p}}^z (z - p) dF(p)$$

- ▶ search again if expected benefit is greater than cost c

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- ▶ optimal search rule is a reservation price rule: if you find a price smaller than r^* , then buy; otherwise searching

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- ▶ what if instead they learn about the distribution through search?
- ▶ Rothschild (1974)
 - ▶ many properties of optimal search behavior look similar
 - ▶ but no longer possible to characterize equilibrium price distribution

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- ▶ but what about estimating search models directly?
- ▶ can we use price distribution to estimate search costs?
 - ▶ Hong and Shum (2006), Hortacsu and Syverson (2004), etc.

Hong and Shum (2000): Nonsequential Search Case

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- ▶ consumers who obtain k price quotes must have search costs between Δ_k and Δ_{k+1}

Hong and Shum (2000): Nonsequential Search Case

- ▶ how many consumers are obtaining k price quotes? use supply-side mixed-strategy equilibrium condition: expected profits must equal at all prices

$$(\bar{p} - c) \hat{q}_1 = (p_i - c) \left[\sum_{k=1}^K \hat{q}_k k \left(1 - \hat{F}_p(p_i)\right)^{k-1} \right]$$

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- ▶ use estimates \hat{q}_k to solve for $F_c(\Delta_1), \dots, F_c(\Delta_{K-1})$

Hortacsu and Syverson (2004)

- ▶ question: what explains the diffuse prices of seemingly similar mutual funds? specifically, what level of search costs would rationalize the observed price dispersion?

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- ▶ question: what explains the diffuse prices of seemingly similar mutual funds? specifically, what level of search costs would rationalize the observed price dispersion?
- ▶ strategy: use price and quantity data from S&P 500 funds, estimate a search model that allows for vertical differentiation in addition to search frictions

Model: Brief Overview

- ▶ consumers know empirical CDF of offered utilities:
 $u_1 < u_2 < \dots < u_N$, but cannot identify any product's position
- ▶ optimal search implies cutoff points of the search cost distribution

$$c_j = \sum_{k=j}^N \rho_k (u_k - u_j)$$

where ρ_k is the sampling probability of k

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- ▶ market shares can be mapped to these cutoffs

$$\begin{aligned}q_1 &= \rho_1 [1 - G(c_1)] \\q_2 &= \rho_2 [1 - G(c_1)] + \frac{\rho_2}{1 - \rho_1} [G(c_1) - G(c_2)] \\&\vdots\end{aligned}$$

- ▶ search cost distribution: recovered from market shares and optimal search condition

De Los Santos, Hortacsu, and Wildenbeest (2012)

- ▶ question: which model of search, sequential or non-sequential, is better supported by data on actual consumers' searches

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- ▶ question: which model of search, sequential or non-sequential, is better supported by data on actual consumers' searches
- ▶ strategy: use Comscore data on book purchases (and searches) to test key predictions of the sequential model: no recall (should always buy from the last store visited), and price dependence (decision to search again should depend on price of last store searched)

Comscore Data

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- ▶ not a random sample of internet users (because users must agree to be tracked)
- ▶ this paper: focus on searches and purchases of books
 - ▶ approx 15,500 purchase transactions from 2002 to 2004
 - ▶ approx 325,000 site visits to 15 online bookstores

Testing Predictions of Sequential Search

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- ▶ no recall: under sequential search, buyers should purchase from last store visited (unless their search exhausts all stores: would buy from the lowest price in this case, by assumption)
- ▶ price dependence: under sequential search, the probability of another search depends on the value of the last price quote (only keep searching if last quoted price is high)

Summary Stats: Stores

| Bookstore | Transactions | | Visits | |
|------------------------|--------------|--------|---------|--------|
| | Number | % | Number | % |
| Amazon | 10,197 | 65.5% | 249,593 | 76.3% |
| Barnes and Noble | 3,042 | 19.6% | 25,758 | 7.9% |
| <i>Book Clubs</i> | | | | |
| christianbook.com | 615 | 3.9% | 3,968 | 1.2% |
| doubledaybookclub.com | 468 | 3.0% | 4,001 | 1.2% |
| eharlequin.com | 61 | 0.4% | 3,647 | 1.1% |
| literaryguild.com | 322 | 2.1% | 3,500 | 1.1% |
| mysteryguild.com | 187 | 1.2% | 2,095 | 0.6% |
| <i>Other Bookstore</i> | | | | |
| 1bookstreet.com | 10 | 0.1% | 120 | 0.0% |
| allbooks4less.com | 5 | 0.0% | 199 | 0.1% |
| alldirect.com | 27 | 0.2% | 490 | 0.1% |
| ecampus.com | 114 | 0.7% | 1,206 | 0.4% |
| powells.com | 68 | 0.4% | 1,326 | 0.4% |
| varsitybooks.com | 16 | 0.1% | 218 | 0.1% |
| walmart.com | 183 | 1.2% | 28,663 | 8.8% |
| booksamillion.com | 246 | 1.6% | 2,290 | 0.7% |
| Total | 15,561 | 100.0% | 327,074 | 100.0% |

Summary Stats: Searches

| | 2002 | | 2004 | |
|--|--------|-----------|---------|-----------|
| | Mean | Std. Dev. | Mean | Std. Dev. |
| <i>Duration of each website visit (in minutes)</i> | | | | |
| Visits not within 7 days of transaction | 8.89 | 13.03 | 7.69 | 12.36 |
| Visits within 7 days, excluding transactions | 12.72 | 15.83 | 11.02 | 15.00 |
| Visits within 7 days, including transactions | 19.04 | 18.26 | 15.74 | 17.37 |
| Transactions only | 28.06 | 17.69 | 26.08 | 17.71 |
| Total duration, excluding transaction visits | 32.47 | 49.80 | 38.41 | 78.33 |
| Total duration, including transaction visits | 43.88 | 43.27 | 47.43 | 66.11 |
| Number of stores searched | 1.27 | 0.54 | 1.30 | 0.56 |
| Number of books per transaction | 2.38 | 2.10 | 2.20 | 1.95 |
| Transaction expenditures (books only) | 36.67 | 40.64 | 32.21 | 35.68 |
| Number of books purchased | 17,956 | | 17,631 | |
| Number of transaction sessions | 7,559 | | 8,002 | |
| Number of visits within 7 days | 18,350 | | 25,556 | |
| Number of visits not within 7 days | 94,011 | | 189,157 | |

Evidence of Recall

| Search window | No. of stores visited | | If 2 or more stores, bought from: | Exhausted search? | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | |
|---------------|-----------------------|-----|-----------------------------------|-------------------|-----|----------|-----|-----|--------------------------------|------------|-----|-----------|-----|----------|-----|-----|--------------------------------|------------|-----|-----------|-----|----------|-----|-----|--------------------------------|------------|-----|-----------|-----|----------|-----|-----|--------------------------------|------------|-----|-----------|-----|----------|-----|-----|--------------------------------|------------|-----|-----------|-----|----------|-----|-----|--------------------------------|------------|-----|-----------|-----|----------|-----|-----|--------------------------------|
| 7 Days | One | 76% | Last store sampled Recalled | 65% 35% | 55% | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | |
| | 2 or more | 24% | | | | 6 Days | One | 77% | Last store sampled Recalled | 64% 36% | 55% | 2 or more | 23% | 5 Days | One | 79% | Last store sampled Recalled | 63% 37% | 55% | 2 or more | 21% | 4 Days | One | 80% | Last store sampled Recalled | 61% 39% | 55% | 2 or more | 20% | 3 Days | One | 82% | Last store sampled Recalled | 61% 39% | 56% | 2 or more | 18% | 2 Days | One | 84% | Last store sampled Recalled | 61% 39% | 56% | 2 or more | 16% | 1 Day | One | 86% | Last store sampled Recalled | 61% 39% | 56% | 2 or more | 14% | Same day | One | 90% | Last store sampled Recalled |
| 6 Days | One | 77% | Last store sampled Recalled | 64% 36% | 55% | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | |
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| | 2 or more | 10% | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | |

Evidence of Price Dependence

- ▶ dependent variable: indicator for searching more than 1 store

| Variable | (A) | (B) | (C) | (D) | (E) |
|----------------------------------|----------------|----------------|----------------|----------------|----------------|
| <i>Panel A. All transactions</i> | | | | | |
| <i>Coefficients</i> | | | | | |
| Intercept | -1.817 (0.093) | -1.796 (0.123) | -0.818 (0.154) | 0.295 (0.133) | — |
| First price lower or equal | -0.071 (0.119) | 0.090 (0.152) | 0.040 (0.157) | -0.223 (0.165) | -0.073 (0.371) |
| Loyal | — | — | -1.446 (0.151) | — | — |
| <i>Average marginal effects</i> | | | | | |
| First price lower or equal | -0.008 (0.014) | 0.011 (0.019) | 0.005 (0.019) | -0.055 (0.041) | -0.015 (0.078) |
| Loyal | — | — | -0.171 (0.017) | — | — |
| Number of observations | 2,593 | 1,504 | 1,504 | 649 | 235 |

- ▶ weak relation between decision to continue searching and observed prices

Outline of Demand Estimation with Search

- ▶ basic idea: probability i purchases from j is $P_{iS}P_{ij|S}$
 - ▶ $P_{ij|S}$ is the probability of choosing j if set of searched stores was S
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 - ▶ P_{iS} is probability i chooses to search the set of stores S
- ▶ expected payoff if search set is S

$$m_{iS} = E \left[\max_{j \in S} \{ \mu_j + X_j \beta_j + \alpha_i p_j + \epsilon_{ij} \} \right] - kc_i$$

Computing $P_i S$

- ▶ if consumers know ϵ and prices have T1EV distribution, then

$$E \left[\max_{j \in S} \{u_{ij}\} \right] = \alpha_i \sigma \log \left(\sum_{j \in S} \exp \left[\frac{\mu_j + X_i \beta_j + \epsilon_{ij} + \alpha_i \gamma_j}{\alpha_i \sigma} \right] \right)$$

where γ_j and σ are location and scale parameters of stores' price distributions

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- ▶ to smooth the choice probabilities, add a logit shock ς_{iS} to each m_{iS} , so

$$P_{iS} = \frac{\exp(m_{iS}/\sigma_\varsigma)}{\sum_{S'} \exp(m_{iS'}/\sigma_\varsigma)}$$

Estimation Details

- ▶ $P_{ij|S}$ cannot be calculated analytically
- ▶ calculate γ_j 's and σ_p from observed price distributions in a first step, then treat as known by consumers
- ▶ normalization: variance of ϵ 's set to 1, so variance of choice-set error σ_ζ is estimated relative to variance of store-specific errors

Main Results

- ▶ average search costs around \$1.35
- ▶ own-price elasticities around -1 for Amazon, around -2 for B&N
- ▶ if demand is estimated assuming full information, then estimated elasticities are much smaller
 - ▶ consumers' unresponsiveness to price differences attributed to small α instead of to search frictions

Reading for Next Class

- ▶ Akerberg, D., “Empirically Distinguishing Informative and Prestige Effects of Advertising”, *RAND Journal of Economics*, 2001.