Search, Obfuscation, and Price Elasticities on the Internet

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This Version: January 28, 2017

Contents

Motivation

- Background:
  - Search technology would have a dramatic effect by making it easy for consumers to compare prices at online and offline merchants.
  - Advances in search technology are accompanied by investment by firm in obfuscation.

Overview

- Revelent Theory
  - Obfuscation can raise search costs, leading to less consumer learning and higher profits.
  - Sales of "add-ons" at high unadvertised prices can raise equilibrium profits in a competitive price discrimination model
- Data: Pricewatch
  - Not too complicated
  - Unusually rich data
  - Extreme aspects of the environment

Overview

- Informal evidence of obfuscation
  - Extended-version loss-leader strategy: offer a low-quality product at a low price to attract consumers and then try to convince them to pay more for a superior product
    - Upgrade rather than buy both
    - Loss leader may be sold for a slight profit rather than at a loss

Overview

- Formal Empirical Analysis
  - Demand and substitution patterns within four categories of computer memory modules
  - Matching Data:
    - Yearlong hourly price series: repeatedly conducting price searches on Pricewatch.
    - Sales data: a single private firm that operates several computer parts websites and derives most of its sales from Pricewatch referrals

Overview

- Results:
  1. Price search technologies can dramatically reduce search frictions. The firm faces a demand elasticity of **-20** or more for its lowest quality memory modules.
  2. Charging a low price for a low-quality product increases our retailer's sales of medium- and high-quality products.

Overview

3. Evidence of the relevance of both mechanisms:
    - In the search-theoretic model, obfuscation raises profits by making consumers less informed (search costs)
    - In Ellison's (2005) add-on pricing model, obfuscation raises profits by creating an adverse-selection effect that deters price-cutting (price discrimination)
4. Retailers' obfuscation strategies have been successful in raising markups beyond the level that would otherwise be sustainable, supported by additional cost data
    - Price-cost margin($\frac{p-MC}{p}$): 3%-6%
    - Markup($\frac{p-MC}{MC}$): 12%

Literature Review

- Empirical studies on price search engines
  - Brynjolfsson and Smith (2001): using a data set containing the click sequences of tens of thousands of people who conducted price searches for books on Dealtime to estimate several discrete-choice models of demand.
  - Baye, Gatti, Kattuman, and Morgan (2006): an extensive data set on the Kelkoo price comparison site, finding that there is a big discontinuity in clicks at the top, in line with clearinghouse models.

Literature Review

- Online price dispersion
  - Price elasticities obtained from quantity data in an online retail sector: Chevalier and Goolsbee (2003).
  - Internet search and price levels: Brown and Goolsbee (2002); Scott Morton, Zettelmeyer, and Silva-Risso (2001, 2003).

Contribution

- Quantity rather than rank
- Spawned a broader literature on obfuscation

Incomplete Consumer Search

- Stahl (1989,1996): a model with search cost - mixed strategy randomizing over prices with some interval; fully informed consumer purchase with lowest price and others stop searching before finding the lowest
- Basic intuition from search models: obfuscation might lead to higher profits by making consumer learning less complete

Add-Ons and Adverse Selection: Setup

- Two firm i=1,2
- Two versions of goods j=L,H
- Constant marginal costs c_L and c_H;
  upgrade cost $c_U = c_H - c_L$
- Post prices p_{iL} and nonposted prices p_{iH};
  upgrade price $p_{iU} \equiv p_{iH} - p_{iL}$
- Time cost per website s
- Buy at most one unit

Add-Ons and Adverse Selection: Setup

- Incremental price of the "upgrade" ε: for $\varepsilon < s$, no consumer will switch to the other firm
- $x(p_{iU}, p_{iL}, p_{-iL})$: the fraction of consumers choosing to upgrade
- $p*_{iU}(p_{iL}, p_{-iL}) = p^m_{iU}(p_{iL}, p_{-iL}) \equiv$ $Arg\max_p (p - c_U) x(p, p_{iL}, p_{-iL})$
- $x*(p_{1L}, p_{2L})$ for $x(p*_{iU}(p_{iL}, p_{-iL}))$
- $D_1(p_1, p_2)$: number of consumers who visit firm 1 (In any pure strategy equilibrium, all consumers who visit firm i will buy from firm i)

Add-Ons and Adverse Selection: Model

- Firm 1's profit:

$$\begin{aligned}\pi_1(p_{1L}, p*_{2L}) &= (\text{unit profit from low quality} \\ &\quad + \text{fraction of upgrade} * \text{unit profit from upgrade}) \\ &\quad * \text{number of consumers buying} \\ &= [(p_{1L} - c_L) + x^*(p_{1L}, p^*_{2L}) * (p^m_{1U}(p_{1L}, p^*_{2L}) - c_U)] \\ &\quad * D_1(p_{1L}, p*_{2L})\end{aligned}$$

Add-Ons and Adverse Selection: Model

- First-order condition:

$$\frac{\delta \pi_1}{\delta p_{1L}} = \frac{\delta D_1}{\delta p_{1L}}(p_{1L} - c_L + x^*(p_{1L}, p_{2L}^*)(p_{1U}^m(p_{1L}, p_{2L}^*) - c_U))$$
$$+ D_1(p_{1L}, p_{2L}^*)[1 + \frac{\delta x^*}{\delta p_{1L}}(p_{1U}^*(p_{1L}, p_{2L}^*) - c_U)$$
$$+ x^*(p_{1L}, p_{2L}^*)\frac{\delta p_{1U}^m}{\delta p_{1L}}]$$

Add-Ons and Adverse Selection: Model

Let

$$\varepsilon = \frac{\delta D_1}{\delta P_{1L}} \frac{p^*_{1L} + x^*(p_{1L}, p^*_{2L}) p^m_{1U}}{D_1(p^*_{1L}, p^*_{2L})}$$

Add-Ons and Adverse Selection: Model

Therefore,

$$\frac{p_{1L}^* - c_L + x^*(p_{1U}^m - c_U)}{p_{1L}^* + x^*(p_{1L}, p_{2L}^*)p_{1U}^m}$$
$$= -\frac{1}{\varepsilon}(1 + \frac{\delta x^*}{\delta p_{1L}}(p_{1U}^*(p_{1L}, p_{2L}^*) - c_U) + x^*(p_{1L}, p_{2L}^*)\frac{\delta p_{1U}^m}{\delta p_{1L}})$$

Add-Ons and Adverse Selection: Model

- First-order condition:

$$\text{Firm's revenue-weighted average markup} = \text{Inverse of a demand elasticity and a multiplier}$$

Suppose p_{1U} is independent of p_{1L},

$$\frac{\delta p_{1U}^m}{\delta p_{1L}} = 0$$
$$\frac{\delta x*}{\delta p_{1L}} = 0$$

Add-Ons and Adverse Selection: Model

Therefore,

$$\frac{p_{1L}^* - c_L + x^*(p_{1U}^m - c_U)}{p_{1L}^* + x^*(p_{1L}, p_{2L}^*)p_{1U}^m} = -\frac{1}{\varepsilon}$$

Add-Ons and Adverse Selection: Implication

- Constant-upgrade-fraction assumption is not compelling(Ellison, 2005)
  - Price cuts disproportionately attract cheap models who have a lower willingness to pay for upgrades: $\frac{\delta p_{1U}^m}{\delta p_{1L}} > 0, \frac{\delta x^*}{\delta p_{1L}} > 0$
- Such demand systems has an adverse-selection problem when add-ons are sold.
  - Sales of add-ons will raise equilibrium profit margins above the inverse-elasticity benchmark
  - Taking a low-cost, high-value feature out of the low-quality good and making it available in the high-quality good may be a profit-enhancing strategy.

Variables

- LowestPrice: lowest price listed on Pricewatch
- Range 1-12: the difference between the twelfth lowest listed price and the lowest listed price
- PLow, PMid and PHi: prices for tree qualities of memory modules at the two websites
- QLow, QMid, and QHi: average daily quanitities of each quality of module sold by each website
- PLowRank: the rank of the website's first entry in Pricewatch's sorted list of prices within the category

Methodology for Demand Estimation

- Product category: c
- Quality: q
- Website: w
- Day: t

Methodology for Demand Estimation

$$Q_{wcqt} = e^{X_{wct}\beta_{cq}} u_{wcqt}$$

with

$$\begin{aligned} X_{wct}\beta_{cq} = {} & \beta_{cq0} + \beta_{cq1} log(PLow_{wct}) + \beta_{cq2} log(PMid_{wct}) \\ & + \beta_{cq3} log(PHi_{wct}) + \beta_{cq4} log(LowestPrice_{ct}) \\ & + \beta_{cq5} log(1 + PLowRank_{wct}) + \beta_{cq6} Weekend_t \\ & + \beta_{cq7} SiteB_w + \sum_{s=1}^{12} \beta_{cq(7+s)} TimeTrend_{st} \end{aligned}$$

Demand for 128MB PC100 Memory Modules(Table II)

- Demand for low-quality modules at a website is extremely price-sensitive - the effect of Pricewatch rank on demand
    - Coefficient on log(1+PLowRank): moving from first to seventh reduces 83% ??
    - Highly significant

Demand for 128MB PC100 Memory Modules(Table II)

- Low-quality memory is an effective loss leader
  - Coefficients on log(1+PLowRank) in the second and third columns are negative and highly significant - higher position, higher sales
  - Effect is strong: medium - 66%; high - 51% ??
  - Pricewatch ranks change frequently, whereas medium- and high-quality prices are left unchanged for substantial periods of time, so that most of the variation in the attractiveness of our firm's medium- and high-quality prices will occur around the occasional price changes.

Demand for 128MB PC100 Memory Modules(Table II)

- Site B dummy are negative and significant - website design is important

Price Elasticities for Memory Modules(Table III)

- An own-price elasticity of ?24.9 for low-quality 128MB PC100 modules.
- low-quality products have highly elastic demand and that there are loss-leader benefits from selling low-quality goods at a low price are consistent across categories

The Mechanics of Obfuscation: Incomplete Consumer Search

- Motivation:
  - An alternate explanation for the finding could be that PLowRank is correlated with the rank of a site's higher quality offerings
- Method:
  - Logit models
  - Dependent variable: Site A
  - Independent variable: log(1+PLowRank),log(PMid),log(PHi),time trends

The Mechanics of Obfuscation: Incomplete Consumer Search

- Results(Table IV):
  - Consumers are influenced by the prices of the product they are buying
  - Consumers are also more likely to purchase from the site with a lower low-quality price

The Mechanics of Obfuscation: Add-Ins and Adverse Selection

- If the elasticity on the low-quality memory is larger (in absolute value) than that for medium- or high-quality memory, there is evidence of adverse selection (Note on constant-fraction assumption of Section 2)
- Firm's quality mix using sample means: 63% low-quality in first place; 35% in tenth place ??

Instrumental Variables Estimates

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