Search, Obfuscation, and Price Elasticities on the Internet[1]

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Abstract

We examine the competition between a group of Internet retailers that operate in an environment where a price search engine plays a dominant role. We show that for some products in this environment, the easy price search makes demand tremendously price-sensitive. Retailers, though, engage in obfuscation—practices that frustrate consumer search or make it less damaging to firms—resulting in much less price sensitivity on some other products. We discuss several models of obfuscation and examine its effects on demand and markups empirically.

Keywords: search, obfuscation, Internet, retail, search engines, loss leaders, add-on pricing, demand elasticities, frictionless commerce.

1 Introduction

When Internet commerce first emerged, one heard a lot about the promise of "frictionless commerce." Search technologies would have a dramatic effect by making it easy for consumers to compare prices at online and offline merchants. This paper examines an enviroment where Internet price search plays a dominant role: small firms selling computer parts through Pricewatch.com. A primary observation is that the effect of the Internet on search frictions is not so clear-cut: advances in search technology are accompanied by investments by firms in obfuscation.

We begin with a brief discussion of some relevant theory. One way to think about obfuscation is in relation to standard search-theoretic models in which consumers do not learn all prices in equilibrium. Obfuscation can be thought of as an action that raises search costs, which can lead to less consumer learning and higher profits. Another way to think about obfuscation is in relation to Ellison (2005), which describes how sales of "add-ons" at high unadvertised prices can raise equilibrium profits in a competitive price discrimination model. Designing products to require add-ons can thereby be a profit-enhancing obfuscation strategy even when consumers correctly infer all prices.

Pricewatch is an Internet price search engine popular with savvy computer-parts shoppers. Dozens of small, low-overhead retailers attract consumers just by keeping Pricewatch informed of their low prices. Although atypical as a retail segment, Pricewatch-retail has many of the features one looks for as a setting for an empirical industrial organization study: it is not too complicated; there is unusually rich data; and the extreme aspects of the environment should make the mechanisms of the theory easier to examine.

We present an informal evidence section describing various practices that can be thought of as forms of obfuscation. Some of these are as simple as making product descriptions complicated and creating multiple versions of products. We particularly call attention to the practice of offering a low quality product at a low price to attract consumers and then trying to convince them to pay more for a superior product. We refer to this as a "loss-leader strategy" even though it sometimes differs from the classic loss-leader strategy in two respects: it involves getting consumers to upgrade to a superior product rather than getting them to buy both the loss-leader and a second physical good; and the "loss-leader" may be sold for a slight profit rather than at a loss.

The majority of the paper is devoted to formal empirical analyses. We analyze demand and substitution patterns within four categories of computer memory modules. Data come from two sources. We obtained year-long hourly price series by repeatedly conducting price searches on Pricewatch. We matched this to sales data obtained from a single private firm that operates several computer parts websites and derives most of its sales from Pricewatch referrals.

Our first empirical result is a striking confirmation that price search technologies can dramatically reduce search frictions. We estimate that the firm faces a demand elasticity of -20 or more for its lowest quality memory modules!

Our second main empirical result is a contribution to the empirics of loss leaders. We show that charging a low price for a low quality product increases our retailer's sales of medium- and high-quality products. Intuitively, this happens because one cannot ask a search engine to find "decent-quality memory module sold with reasonable shipping, return, warranty and other terms." Hence, many consumers use Pricewatch to do what it is good at—finding websites that offer the lowest prices for *any* memory module—and then search within a few of these websites to find products that better fit their preferences.

Other empirical results examine how obfuscation affects profitability. We examine predictions of the two obfuscation mechanisms mentioned above. In the search theoretic model, obfuscation raises profits by making consumers less informed. In Ellison's (2005) add on pricing model, obfuscation raises profits by creating an adverse-selection effect that deters price-cutting. We find evidence of the relevance of both mechanisms.

Finally, we examine an additional data source, cost data, for direct evidence that retailers' obfuscation strategies have been successful in raising markups beyond the level that would otherwise be sustainable. Given the extreme price sensitivity of the demand for low-quality products, a naive application of single-good markup rules would suggest that equilibrium price-cost margins might be just 3% to 6%. We find that the average markup on the memory modules sold by the firm that provided us with data is about 12%.

A few previous papers have examined price search engines empirically. Brynjolfsson and Smith (2001) use a dataset 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) examine an extensive dataset on the Kelkoo price comparison site and note that there is a big discontinuity in clicks at the top in line with clearinghouse models. One advantage of our dataset relative to others we are aware of is that we observe actual quantities sold and not just clickthroughs. A large number of studies have documented online price dispersion.[1] The one study we know of that reports price elasticities obtained from quantity data in an online retail sector is

[1] See Baye, Morgan, and Scholten (2007) for a survey.

Chevalier and Goolsbee (2003). Some other studies that provide evidence related to Internet search and price levels are Brown and Goolsbee (2002) and Scott Morton, Zettelmeyer and Silva-Risso (2001, 2003). This paper has also spawned a broader literature on obfuscation.[2]

2 Theory of search and obfuscation

Our most basic observation is that it is not *a priori* obvious that the Internet will lead us toward "frictionless commerce." Price search engines and other Internet tools will help consumers to find and process information, but retailers may simultaneously harness the power of the Internet to make information processing problems more formidable and/or to make consumer informedness less damaging to their their profits. In this section we quickly sketch two ways in which one might think about obfuscation.[3]

2.1 Incomplete consumer search

A number of authors have developed models in which consumer search costs affect market efficiency and firm profits. Stahl (1989, 1996), for example, considers a model in which some consumers incur a search cost every time they incur a price quote, whereas other consumers do not. The model has a mixed strategy equilibrium: retailers randomize over prices in some interval; fully informed consumers purchase from the lowest-priced firm; other consumers often stop searching before finding the lowest-priced firm. Firm profits are increasing in the fraction of consumers with positive search costs and in the level of the search costs.

One could regard obfuscation as an action that raises search costs and/or the fraction of consumers who incur search costs. Such actions would increase average markups and the fraction of consumers buying from relatively high-priced firms. Developing such a formal model for our application is well beyond the scope of this paper: one would want all consumers' searches to be directed by the Pricewatch list, whereas Stahl's consumers search in a random manner; one would want to extend the model to include multiple products per firm; amd one would also want to make search costs firm-specific so that obfuscation could be an action taken by individual firms and not by firms as a whole.[4] Nonetheless, the basic intuition from search models that obfuscation might lead to higher profits by making

[2]See Ellison (2005), Gabaix and Laibson (2006), Spiegler (2006), and Hossain and Morgan (2006).

[3]See Ellison and Ellison (2004) for a longer discussion of search engines and search and obfuscation, and Baye and Morgan (2001, 2003) for two formal models of search engines and their effects on prices and firm profits.

[4]Another difficulty with the application is that the mixed strategy nature of the equilibrium is awkward.

consumer learning less complete seems like a useful one to explore empirically.

2.2 Add-ons and adverse selection

Ellison (2005) provides a model with a somewhat different flavor—add-on pricing schemes can raise retailers' profits even if consumers correctly infer all prices in equilibrium. We develop this idea in more generality below to illustrate how it would work in an empirically-relevant setting.[5]

Suppose two firms $i = 1, 2$ can each produce two versions of a good $j = L, H$ at constant marginal costs c_L and c_H. They post prices p_{iL} for their low-quality goods on a price comparison site and simultaneously choose nonposted prices p_{iH} for their high-quality products. Consumers who visit the price-comparison site learn both low-quality prices. At a time-cost of s, consumers can visit a firm's website, learn its high-quality price, and buy or not buy. They can then visit the second firm's site at an additional cost of s if they so desire. We assume, however, that consumers wish to buy at most one unit.

As in Diamond (1971), the incremental price of the "upgrade" from good L to good H is priced at the *ex post* monopoly price in any pure strategy equilibrium. The argument is that at any lower price the firm will always be tempted to raise its upgrade price by ϵ. For $\epsilon < s$, no consumer will switch to the other firm, because that would require incurring s again and the other firm's product was less attractive at the prices that the consumer anticipated. Formally, if we write $p_{iU} \equiv p_{iH} - p_{IL}$ for the upgrade price, $c_U = c_H - c_L$ for the cost of the upgrade, and $x(p_{iU}, p_{iL}, p_{-iL})$ for the fraction of consumers who choose to upgrade, Diamond's argument implies that the equilibrium price p^*_{iU} satisfies

$$p^*_{iU}(p_{iL}, p_{-iL}) = p^m_{iU}(p_{iL}, p_{-iL}) \equiv \text{Argmax}_p (p - c_U) x(p, p_{iL}, p_{-iL})$$

Write $x^*(p_{1L}, p_{2L})$ for $x(p^*_{iU}(p_{iL}, p_{-iL}), p_{iL}, p_{-iL})$.

Write $D_1(p_1, p_2)$ for the number of consumers who visit firm 1.[6] Assume that this function is smooth, strictly decreasing in p_1, and otherwise well behaved. Firm 1's profits when it sets price p_{1L} and the other firm follows its equilibrium strategy are given by

$$\pi_1(p_{1L}, p^*_{2L}) = (p_{1L} - c_L + x^*(p_{1L}, p^*_{2L})(p^m_{1U}(p_{1L}, p^*_{2L}) - c_U))\, D_1(p_{1L}, p^*_{2L}).$$

[5] Ellison (2005) uses several special assumptions. The population consists of two types, demand for the low-quality good is linear, and all consumers of the same type have an identical willingness to pay to upgrade to the high quality good.

[6] In any pure strategy equilibrium, all consumers who visit firm i will buy from firm i. Otherwise they would be better off not visiting.

The first-order condition implies that the equilibrium prices satisfy

(1)

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

where $\epsilon = \frac{\partial D_1}{\partial p_{1L}} \frac{p_{1L}^* + x^*(p_{1L}^*, p_{2L}^*)p_{1U}^m}{D_1(p_{1L}^*, p_{2L}^*)}$. The left hand side of this expression is the firm's revenue-weighted average markup. The right-hand side is the product of a term that is like the inverse of a demand elasticity and a multiplier.

Suppose first that the fraction of firm 1's customers who buy the upgrade at any given price p_{1U} is independent of p_{1L}.[7] Then both of the right two terms in the multiplier are zero. Hence, the average markup satisfies an inverse elasticity rule. If total demand is highly sensitive to the low-quality price, then markups will be low. It does not matter whether the firm earns extremely high profits on add-on sales: these are fully competed away with below-cost prices if necessary in the attempt to attract consumers.

Although the constant-upgrade-fraction assumption might seem natural and has been made with little comment in many papers on competitive price discrimination, Ellison (2005) argues that it is not compelling. One way in which real-world consumers will be heterogeneous is in their marginal utility of income. In this case, price cuts disproportionately attract "cheapskates" who have a lower willingness to pay for upgrades. This suggests that it may be more common that both $\frac{\partial p_{1U}^m}{\partial p_{1L}} > 0$ and $\frac{\partial x^*}{\partial p_{1L}} > 0$. Ellison (2005) refers to such demand systems as having an adverse selection problem when add-ons are sold. With such demand, sales of add-ons will raise equilibrium profit margins above the inverse-elasticity benchmark. The factor by which profit margins increase is increasing in both the upgrade price and the fraction of consumers who upgrade. Hence, taking a low-cost, high-value feature out of the low-quality good and making them it available in the high-quality good may be a profit-enhancing strategy.

3 The Pricewatch universe and memory modules

We study a segment of e-retail shaped by the Pricewatch price search engine. It is comprised of a large number of small, minimally differentiated firms selling memory upgrades, CPUs, and other computer parts. The firms do little or no advertising and receive most of their customers through Pricewatch.

Pricewatch presents a menu containing a set of predefined categories. Clicking on one

[7]For example, suppose that the optimal price for good H is always \$25 above the price of good L and that 50% of consumers upgrade at this price differential.

returns a list of websites sorted from cheapest to most expensive in a twelve-listings-per-page format. The categories invariably contain heterogeneous offerings: some include products made by higher and lower quality manufacturers; and all include offers with varying return policies, warranties, and other terms of trade. Figure 1 contains the first page of a typical list, that for 128MB PC100 memory modules from October 12, 2000.

There is substantial reshuffling in the sorted lists, making Pricewatch a nice environment for empirical study. For example, on average three of the twenty-four retailers on the first two pages of the 128MB PC100 list change their prices in a given hour. Each price change can move several other firms up or down one place. Some websites regularly occupy a position near the top of the Pricewatch list, but there is no rigid hierarchy.

Several factors contribute to the reshuffling. One of these is the volatility of wholesale memory prices: wholesale price changes will make firms want to change retail prices. Memory prices declined by about 70% over the course of the year we study, but there were also two subperiods during which prices rose by at least 25%. A second complementary factor is a limitation of Pricewatch's technology: Pricewatch relied on retailers' updating their prices in its database. Most or all of the retailers were doing this manually in the period we study and would probably reassess each price one or a few times per day.[8] When wholesale prices are declining, this results in a pattern where each firm's price tends to slowly drift down the list until the next time it is reset.

Our sales and cost data come from a firm that operates several websites, two of which regularly sell memory modules.[9] We have data on products in four Pricewatch categories of memory modules: 128MB PC100, 128MB PC133, 256MB PC100, and 256MB PC133. PC100 vs. PC133 refers to the speed with which the memory communicates with the CPU. They are not substitutes for most retail consumers because the speed of a memory module must match the speed of a computer's CPU and motherboard. The second part of the product description is the capacity of the memory in megabytes. The 256MB modules are about twice as expensive. Each of our firm's websites sells three different quality products within each Pricewatch category. They are differentiated by the quality of the physical product and by contract terms. Figure 2 illustrates how a similar quality choice is presented to consumers on a website that copied site A's design. Making comparisons across websites would be much harder than making within-website comparisons because many sites contain minimal technical specifications and contractual terms are multidimensional.

[8] A retailer may have dozens or hundreds of products listed in various Pricewatch categories.

[9] We will call these Site A and Site B.

4 Observations of obfuscation

Pricewatch has made a number of enhancements to combat obfuscation. Practices that frustrate search nonetheless remain commonplace.

One of the most visible search-and-obfuscation battles was fought over shipping costs. In its early days Pricewatch did not collect information on shipping costs and sorted its lists purely on the basis of the item price. Shipping charges grew to the point that it was not uncommon for firms to list a price of $1 for a memory module and inform consumers of a $40 "shipping and handling" fee at check out. Pricewatch fought this with a two-pronged approach: it mandated that all firms offer UPS ground shipping for a fee no greater than a Pricewatch-set amount ($11 for memory modules); and added a column that displayed the shipping charge or a warning that customers should be wary of stores that do not report their shipping charges.[10] Many retailers adopted an $11 shipping fee in response, but uncertainty about the cost of UPS ground shipping was not completely eliminated: a number of retailers left the column blank or reported a range of charges. The meaning of "UPS ground shipping" was also subject to manipulation: one company explicity stated on its website that items ordered with the standard UPS ground shipping were given lower priority for packing and might take two weeks to arrive. More recently, Pricewatch mandated that retailers provide it with shipping charges and switched to sorting low-price lists based on shipping-inclusive prices. This appears to be working, but is only fully satisfactory for customers who prefer ground shipping: those who wish to upgrade to 3rd-, 2nd-, or next-day air must search manually through retailers' websites.

One model of obfuscation we discussed involved firms trying to increase customers' inspection costs and/or reduce the fraction of customers who will buy from the firm on the top of the search engine's list. We observed several practices that might serve this purpose. The most effective seems to be bundling low-quality goods with unattractive contractual terms, like providing no warranty and charging a 20% restocking fee on all returns. Given the variety of terms we observed, it would seem unwise to purchase a product without reading the fine print. Another is making advertised prices difficult to find. In 2001 it took us quite a bit of time to find prices listed on Pricewatch on several retailers' sites. In a few cases, we never found the listed prices. Several other firms were explicit that Pricewatch prices were only available on telephone orders. Given that phone calls are more costly for the retailers, we assume that firms either wanted people to waste time on hold or to make people sit through sales pitches. Pricewatch has fought these practices in several ways. For

[10]Our empirical work is based on data from the period when these policies were in effect.

example, it added a "buy now" button, which (at least in theory) takes customers directly to the advertised product.

The second obfuscation mechanism we discussed is the adoption of a "loss-leader" or "add-on" pricing scheme: damaged goods are listed on the search engine at low prices and websites are designed to convince customers attracted by the low prices to upgrade to a higher quality product. Such practices are now ubiquitous on Pricewatch. Figure 2 is one example. Customers who tried to order a generic memory module from Buyaib.com at the price advertised on Pricewatch.com were directed to this page. It illustrates several ways in which the low priced product is inferior to other products the company sells (at higher markups). Figure 3 is another example. A consumer who tried to order a generic module from Tufshop.com was taken to this page, on which a number of complementary products, upgrades, and services were listed. The figure shows the webpage as it initially appeared, defaulting the buyer to several upgrades. To avoid purchasing the various add-ons, the consumer must read through the various options and unclick several boxes. After completing this page, the customer was taken to another on which he or she must choose from a long list of shipping options. These include paying $15.91 extra to upgrade from UPS ground to UPS 3-day, $30.96 extra to upgrade to UPS 2-day, and $45.96 extra to upgrade to UPS next day.[11]

Our impression is that the practices are also consistent with the add-on pricing model in terms of the low-priced goods being of inefficiently low quality. In Pricewatch's CPU categories all of the listings on the first few pages were "bare" CPUs without fans attached. This seems highly inefficient: an experienced installer can attach a fan in less than a minute, whereas there is a nontrivial probability that a novice will snap off a pin and ruin a $200 chip. We were also told that most of the generic memory modules at the top of Pricewatch's memory lists are poor quality products that are much more likely to have problems than are other modules that can sometimes be purchased wholesale for just one or two dollars more. We know that the wholesale price difference is occasionally so small as to induce the retailer from which we got our data to ship "medium quality" generic modules to customers who ordered low quality modules (without telling the customers) because it felt the time cost and hassle of dealing with returns was not worth the cost savings.

Obfuscation could presumably take many forms in addition to those we outlined in our theory section. One is that firms could try to confuse boundedly-rational consumers. Presumably, this would involve either tricking consumers into paying more for a product

[11] The incremental costs to Tufshop of the upgraded delivery methods were about $4, $6, and $20.

than it is worth to them or altering their utility functions in a way that raises equilibrium profits. Our impression is that many Pricewatch retailers' sites are intentionally confusing. For example, whereas several sites will provide consumers with product comparison lists like that in Figure 2, we did not see any that augmented such a comparison with a description of what "CAS latency" means to help consumers think about whether they should care about it.

Pricewatch requires that retailers enter their prices into a database. An alternate technology for running a price comparison site is to use shopbots to gather information automatically from retailers' sites. The shopbot approach may be even more prone to obfuscation. In 2001, for example, Yahoo! Shopping search engine should have had a much easier time gathering information than a general search engine because it only searched sites hosted by Yahoo. Yahoo collected a royalty on all sales made by merchants through Yahoo! Shopping, so there must have been some standardization of listing and ordering mechanics. Nonetheless, when we typed "128MB PC100 SDRAM DIMM" into the search box, the five lowest listed prices were from merchants who had figured out how to get Yahoo! Shopping's search engine to think the price is zero even though a human who clicks over to the retailer can easily see the price (and see that it is 50-100% above the Pricewatch price). The next hundred or so cheapest items on Yahoo's search results were also either products for which Yahoo's search engine had misinterpreted the price or misclassified items.

5 Data

Our price data were collected from Pricewatch.com. They contain information on the twelve or twenty-four lowest price offerings within each of the four predefined categories mentioned above.[12] They are at hourly frequency from May 2000 to May 2001.

In addition to the price data for these "low-quality" products, we obtained price and quantity data from an Internet retailer that operates two websites selling memory modules. The data contain the prices and quantities sold for all products that fit within the four Pricewatch categories. The websites usually offer three different quality products in each category. We aggregate data on individual orders to produce daily sales totals for each product-website pair.[13] Our primary price variables are the average transaction prices for sales of a given product on a given day.[14] We also record the daily average position of each

[12] We collected the twenty-four lowest prices for the 128MB PC100 and 128MB PC133 categories and the twleve lowest prices in the other two.

[13] Here, a "product" includes also the quality level, *e.g.,* a high-quality 128MB PC100 module.

[14] Transaction prices are unavailable for products which have zero sales on a given day. These are filled in

website on Pricewatch's price-ranked list.

The same Internet retailer also provided us with data on wholesale acquisition costs for each product.

Websites A and B have identical product lineups: they sell three products within each memory module category, which we refer to as the low-, the medium-, and the high-quality module. Our dataset contains between 575 and 683 observations in each category.[15] Summary statistics for the 128MB PC100 category in Table 1.[16] The data are at the level of the website-day, so the number of days covered is approximately half of the number of observations. $LowestPrice$ is the lowest price listed on Pricewatch (which is presumably for a low-quality memory module).[17] $Range$1-12 is the difference between the twelfth lowest listed price and the lowest listed price. Note that the price distribution is fairly tight. $PLow$, $PMid$ and PHi are the prices for the three qualities of memory modules at the two websites. $QLow$, $QMid$ and QHi are the average daily quantities of each quality of module sold by each website. The majority of the sales are the low-quality modules. $PLowRank$ is rank of the website's first entry in Pricewatch's sorted list of prices within the category.[18] This variable turns out to allow us to predict sales much better than we can with simple functions of the cardinal price variables.

We have not broken the summary statistics down by website. Website A's prices are usually lower than website B's, but there is no rigid relationship. In the 128MB PC100 category, website A has a lower low-quality price on 251 days and accounts for 70% of the combined unit sales.

using the data collected from Pricewatch or imputed using prices on surrounding days and prices charged by the firm's other websites.

[15]Data are occasionally missing due to failures of the program we used to collect data and missing data in the files the firm provided. The 256MB prices are missing for most of the last six weeks, so we chose to use mid-March rather than May as the end of the 256MB samples.

[16]Summary statistics for the other categories are presented in Ellison and Ellison (2004, 2007). We will present many results for the 128MB PC100 category and only discuss how the most important of these extend to the other categories. One reason for this choice is that the 128MB PC100 data are available for the longest time period and demand is less time-varying, which allows for more precise estimates.

[17]The Pricewatch data are hourly. Daily variables are constructed by taking a weighted average across hours using weights that reflect the average hourly sales volumes of the websites we study.

[18]We only know a site's Pricewatch rank if it is among the 12 or 24 lowest priced websites. When a site does not appear on the list we impute a value for $PLowRank$ using the difference between the site's price and the highest price on the list. In the 128MB category this happens for fewer than 1% of the observations. In the 256MB category this happens for 3% of the site A observations and 14% of the site B observations.

6 Demand patterns

In this section we estimate demand elastiticies and examine how consumers substitute between low-, medium-, and high-quality products. We do this both to provide descriptive evidence on search-engine influenced e-retail and to provide empirical evidence on theories of obfuscation.

6.1 Methodology for demand estimation

Assume that within each product category c, the quantity of quality q products purchased from website w on day t is

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

with

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

The effect of $PLowRank$ on demand is of interest for two reasons: it will contribute to the own-price elasticity of demand for low-quality memory; and it provides information on how the Pricewatch list is guiding consumers who buy other products. The price variables $PLow$, $PMid$, and PHi are used to estimate elasticities. We think of the other variables mostly as important controls. An important part of our estimation strategy is the inclusion of the $TimeTrend$ variables, which allow for a piecewise linear time trend with a slope that changes every 30 days.

We estimate the demand equations via GMM. Specifically, for most of our estimates we assume that the multiplicative error term u_{wcqt} satisfies $E(u_{wcqt}|X_{wct}) = 1$ so that we can estimate the models using the moment condition

$$E(Q_{wcqt} e^{-X_{wct}\beta_{cq}} - 1 | X_{wct}) = 0$$

These estimates are done separately for each product category and each quality level. Standard errors use a Newey-West style approach to allow for serial correlation.

This estimation approach presumes that the price variables and $PLowRank$ are not endogenous. In the case of $PLowRank$ we think this is a very good assumption: our e-retailer has little information on demand fluctuations and little analytic capability to assess whether idiosyncratic conditions affect the relative merits of different positions on the Pricewatch list. The person who sets prices told us that he checks some of the Pricewatch lists a few times a day and might change prices for a few reasons: if a rank has drifted too far from where he typically leaves it; if there has been a wholesale prices change; or occasionally if multiple employees have failed to show up for work and he needs to reduce volume.

The price variables are more problematic. The obvious endogeneity concern is that prices may be positively correlated with demand shocks and/or rivals' prices, which would bias estimates of own-price elasticities toward zero. The idea behind our base estimates, however, is that the unusual time-series properties of the variables may let us address this at least in part without instruments. The unusual aspect of the data is that our retailer tends to leave medium- and high-quality prices fixed for a week or two and then to change prices by \$5-\$10. Our hope is that demand shifts and rivals' prices are moving sufficiently smoothly so that much of the variation in them can be captured by the flexible time trends. The effect of our firm's prices on demand may be picked up in the periods around the discontinuous changes. In the next section we will see that we have some success with this approach, but in several categories it does not work very well.

We present alternate estimates derived from using two distinct sets of instruments for the price variables in Section 6.5.

6.2 Basic results on demand

Table 2 presents demand estimates from the 128MB PC100 memory module category. The first column of the table contains estimates of the demand equation for low-quality modules. The second and third columns contain estimates of the demand for medium- and high-quality modules.

Our first main empirical result is that demand for low-quality modules at a website is extremely price sensitive. Most of this is due to the effect of Pricewatch rank on demand. The rank effect is very strong: the coefficient on the $\log(1 + PLowRank)$ variable in the first column implies that moving from first to seventh on the list reduces a website's sales of low-quality modules by 83%. The estimates are highly significant—we get a t-statistic of 10.9 in a regression with only 683 observations. Table 3 presents demand elasticities derived from the coefficient estimates.[19] The upper left number in the upper left matrix

[19] Elasticities with respect to changes in the low quality price are a sum of two effects: one due to changes in the $PLow$ variable and one due to changes in the $PLowRank$ variable. We estimate the latter by treating $PLowRank$ as a continuous variable and setting the derivative of $PLowRank$ with respect to $PLow$ equal to

indicates that the combination of the two price effects in the model results in an own-price elasticity of -24.9 for low-quality 128MB PC100 modules.

A second striking empirical result in Table 2 is that low quality memory is an effective loss leader. The coefficients on $\log(1 + PLowRank)$ in the second and third columns are negative and highly significant. This means that controlling for a site's medium- and high-quality prices and other variables, a site sells more medium- and high-quality memory when it occupies a higher position on Pricewatch's (low-quality) list. The effect is very strong. The -0.77 coefficient estimate indicates that moving from first to seventh on the Pricewatch list for low-quality 128MB PC100 memory reduces a website's sales of medium-quality 128MB PC100 memory by 66%. The -0.51 coefficient estimate indicates that moving from first to seventh on the Pricewatch list for low-quality memory would reduces high-quality memory sales by 51%.[20]

A potential concern about this result is $PLowRank$ might be significant not because Pricewatch's low-quality list is guiding consumers' searches, but rather because of an omitted variable problem in our analysis: $PLowRank$ might be correlated with a ranking of our firm's medium- and high-quality prices relative to its competitors' prices for comparable goods. We think that this is unlikely given what we know of the time-series behavior of the different series: 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. One's first reaction to this concern would be to want to address it by including within-category rank variables $PMidRank$ or $PHiRank$ analogous to $PLowRank$. This is, however, not possible.[21] We can, however, provide a test robust to this concern by looking at choices conditional on buying from one of our websites. We discuss this and present results in section 6.3.

A third noteworthy result is that the coefficients on the site B dummy are negative and significant in all three regressions. Site B is particularly less successful at selling high-quality memory. This could indicate that website design is important.[22] Alternative explanations

the inverse of the average distance between the twelve lowest prices and setting the rank and other variables equal to their sample means.

[20]Although it is common in marketing to talk about loss leaders, the empirical marketing literature on the effectiveness of loss leaders has produced mixed results (Walters, 1988; Walters and McKenzie, 1988; Chevalier, Kashyap and Rossi, 2003). We are not aware of any evidence nearly as clear as our results.

[21]We did not collect data on other firms' full product lines. Even if we had done so, "medium" and "high" quality memory are not sufficiently well-defined concepts to make within-quality rank a well-defined concept: every website has a different number of offerings with (often undisclosed) technical attributes and service terms that do not line up neatly with the offerings of our retailer.

[22]Site A and site B are owned by the same firm. They share customer service and packing employees.

would include that people may prefer to buy memory from site A because it specializes in memory and that there may be reputational advantages we cannot directly observe.

We report elasticity matrices for the other memory categories in Table 3, but to save space we have not included full tables of demand estimates.[23] The elasticity tables reveal that our findings that 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 estimated own-price elasticities for low-quality modules range from -33.1 in the 128MB PC133 category to -17.4 in the 256MB PC100 category. The one way in which the results for the 128MB PC100 category are unusual is that the own-price elasticities of medium- and high-quality memory are precisely estimated. This problem is particularly severe in the 256MB categories where the effective sample size is reduced by the fact that most of the memory is sold toward the end of the data period.

6.3 The mechanics of obfuscation: incomplete consumer search

One way to think about obfuscation discussed in Section 2 is as an increase in search costs that made search less complete. We noted in Section 6.2 that the finding that $PLowRank$ affects medium- and high-quality sales suggests that consumers are conducting a meaningfully incomplete search with the omissions being influenced by Pricewatch's list, but that an alternate explanation for the finding could be that $PLowRank$ is correlated with the rank of a site's higher quality offerings. In this section we note that the structure of our dataset provides an opportunity to avoid this confounding. Our two websites offer identical products. If all consumers learned about all prices, then conditioning on a consumer's decision to purchase from one of our sites, the relative position of the two sites on Pricewatch's list should not help predict which site a consumer will purchase from.[24]

To provide a straightforward analysis of conditional choices, we estimate simple logit models on the consumer-level data using a dummy for whether each consumer chose to buy from site A (versus site B) as the dependent variable. As explanatory variables we include

A few attributes should make site B more attractive: it had slightly lower shipping charges for part of the sample, it offers more products other than memory, and at the time it had a higher customer feedback rating at ResellerRatings.com, which was probably the most important reputation-posting site for firms like this.

[23]Significance levels in the other categories are generally similar to those in the 128MB PC100 category. The $\log(1 + PLowRank)$, $Weekend$, and $SiteB$ variables are usually highly significant. The other variables are usually insignificant.

[24]This would be exactly true in a discrete-choice model with the IIA property. In a random-coefficients model where consumers had preferences over websites and over quality levels, one would expect $PLowRank$ to have the opposite effect from the one we find: when site A has a low price for low-quality memory then fewer consumers with a strong site A preference will buy medium-quality memory, which makes the pool of consumers buying medium-quality memory tilted toward site B.

the difference across sites in $\log(1 + PLowRank)$, $\log(PMid)$, and $\log(PHi)$, and a set of time trends.

The two columns of Table 4 reports estimates from the sample of all consumers who purchased medium- and high-quality memory, respectively.[25] The significant coefficients on the $\Delta \log(PMid)$ variable in the first column and on the $\Delta \log(PHi)$ variable in the second column indicate that consumers are influenced by the prices of the product they are buying. Interestingly, however, the significant coefficients on $\Delta \log(1 + PLowRank)$ in both columns indicate that consumers are also more likely to purchase from the site with a lower low-quality price. Considering the standard deviations of the two variables, we find that the rank of a firm's low-quality product has about as much influence on consumer decisions as the price of the product consumers are buying. Overall, the regressions support the conclusion that consumer learning about prices is incomplete.

6.4 The mechanics of obfuscation: add-ons and adverse selection

The second model in Section 2 noted that creating inferior versions of products to advertise could raise equilibrium markups by creating an adverse selection problem. More concretely, this occurs if a decrease in a firm's low-quality price decreases the fraction of consumers who buy upgrades. In other words, 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. This feature is present in all four of our elasticity matrices.[26]

An alternate way to get intuition for the magnitude of this adverse selection effect without relying on the functional form assumptions is to look at the firm's quality mix using sample means. For example, we find that when one of our sites is first on one of the Pricewatch lists for 256MB memory, 63% of its unit sales are low-quality memory. On days when one of them is in tenth place, only 35% of the unit sales are low-quality memory.

6.5 Instrumental variables estimates

We noted above that an obvious source of potential difficulty for our elasticity estimates (especially with respect to changes in medium- and high-quality prices) is that our price variables may be correlated with demand shocks, rival firms' prices, or both. In this section we present two sets of instrumental variables estimates.

[25] We have pooled observations from all four memory categories.

[26] See Ellison and Ellison (2004) for additional evidence on this point, including similar estimates from CPUs.

Our first set of instruments are cost-based. We instrument for $PLow$, $PMid$, and PHi with our firm's acquisition costs for each product. Many textbooks use costs as the prototypical example of an instrument for price in a demand equation. In retail, however, the case for instrumenting with acquisition costs is tenuous: "costs" are really wholesale prices and will therefore be affected by broader demand shocks; and they may be correlated with retail prices charged by our firm's rivals. Two features of the memory market make correlation with demand shocks less of a worry than they would be in other retail industries: sales of aftermarket memory are small compared to the use of memory in new computers, so aftermarket memory prices will not be much affected by aftermarket demand shocks; and some of the variation in wholesale prices in the period we study is due to collusion among memory manufacturers.[27] The correlation with rival's prices is clearly a potential problem.

The first three columns of Table 5 report estimates of the demand equations for 128MB PC100 memory modules (comparable to those in Table 2) obtained using the cost-based instruments for $PLow$, $PMid$, and PHi.[28] Our primary results about own-price elasticities and loss-leader benefits are robust to this change: The effect of $PLowRank$ on sales remains large, negative, and significant in all three categories. The biggest difference between the IV estimates and our earlier estimates is that the cross-price terms are all positive and many are much larger. The standard errors, however, are also generally larger in these regressions so few of the own-price and cross-price estimates are significant.

We refer to our second set of instruments as the "other-speed" set. We instrument for $PLow$, $PMid$, PHi, and $\log(1 + PLowRank)$ in the 128MB PC100 category using a website's prices for low-, medium-, and high-quality 128MB PC133 modules and its rank in this category.[29] These may be useful in identifying exogenous shifts in medium- and high-quality prices if these tend to occur in both categories simultaneously either because prices are reviewed sporadically or if prices are adjusted in response to unexpected labor shortages. Another attractive aspect of this strategy is that the availability of the other-speed rank gives us a fourth instrument, whereas in our cost-based instrument set we had to

[27]Demand shocks in the new computer and memory upgrades markets may be correlated, of course, if both are driven by the memory requirements of popular applications. Samsung, Elpida, Infineon, and Hynix plead guilty in separate cases to collusion charges covering the period from April 1999 to June 2002. Executives from these companies and a Micron sales representative were also prosecuted individually and received jail sentences.

[28]First-stage regressions are presented in Ellison and Ellison (2007). The cost of medium-quality memory has less predictive power than one might hope.

[29]Ellison and Ellison (2007) present first-stage regressions showing that the instruments are not weak, although predictive power is better for the prices than for the rank.

maintain the assumption that $\log(1 + PLowRank)$ was exogenous. There are still potential concerns. For example, prices in the other category may not be completely orthogonal to demand conditions if demand in both categories is driven by a common shocks, like the memory requirements of popular software applications.

The second three columns of Table 5 present estimates from the other-speed instruments. Instrumenting for $\log(1 + PLowRank)$ makes the standard errors on the estimates much larger. Two of the estimates become more negative and one less negative. The cross price effects between low- and high-quality memory are much larger than in our noninstrumented results. Standard errors on all the price effects are also much larger. Overall, we see the IV results as indicating that cross-price terms probably are larger than in our noninstrumented results. There is nothing to cause concern about any of our main results, although the limited quality of the instruments does not let us provide strong additional support either.

7 Markups

This section examines price-cost margins. It is intended both to provide descriptive evidence on price search-dominated e-commerce and to give insight on how obfuscation affects markups.

Table 6 presents revenue-weighted average percentage markups for each of the four categories of memory modules.[30] In the two 128 MB memory categories, the markups for low-quality products are slightly negative. Prices have not, however, been pushed far below cost by the desire to attract customers who can be sold upgrades. Markups are about 16% for medium-quality modules, and about 27% for high-quality modules. Averaging across all three quality levels, markups are about 8% and 12% in the two categories. This corresponds to about five dollars for a PC100 module and ten dollars for a PC133 module.

The firm's average markups in the 256MB memory categories were higher: 13% and 16% in the two categories. Part of the difference is due to the fact that a higher fraction of consumers buy premium quality products, but the largest part comes from the markups on low-quality memory being substantially higher.

It is interesting to examine how the actual markups compare to what one would expect given the overall demand elasiticity and the strength of the adverse selection effect. The

[30] The percentage markup is the percentage of the sale price, i.e. $100(p - mc)/p$. Dollar markups were obtained by adding the standard shipping and handling charge to the advertised item price, and then subtracting the wholesale acquisition cost, credit card fees, an approximate shipping cost, an estimate of marginal labor costs for order processing, packing, and returns, and an allowance for losses due to fraud. The labor and shipping costs were chosen after discussions with the firm, but are obviously subject to some error.

sixth row of the the table reports the inverse demand elasiticity $1/\epsilon$ defined in Section 2.2. Absent any adverse selection effects, these would be the expected markups. They range from 3.6% to 6.3% across the categories. Although these are small numbers and we have emphasized that demand is highly elastic, one channel by which obfuscation may be affecting markups is by preventing elasticities from being even higher than they are. We do not know how elastic demand would be absent the obfuscation, but it is perhaps informative to note that our estimates imply that fewer than one-third of consumers are buying from the lowest-priced firm. If Pricewatch ads were more standardized and consumers did not need to worry about restocking policies, etc., then one might imagine that many more consumers would buy from the lowest-priced firm and demand could be substantially more elastic.

The second mechanism by which we noted that obfuscation could affect markups is through the adverse selection effect that arises when firms sell addons. The seventh row reports the markup multiplier we would expect given the degree of adverse selection we have estimated to be present. Specifically, we report an estimate of the rightmost term in parentheses in equation (1), obtained by assuming $\frac{\partial \pi_{1U}^m}{\partial p_{1L}} = 0$ and computing the multiplier term as $1 + \frac{\partial x^*}{\partial p_{1L}}(p_{1U} - c_{1U})$.[31] The multipliers range from 1.7 to 3.5 across the four categories. This indicates that the adverse selection we have identified is sufficiently strong so that one would expect it to have a substantial effect on equilibrium markups.

The actual and predicted markups are roughly consistent. In three of the four categories the actual markups are within two percentage points of the predicted markups. This implies, for example, that prices are within $2 of what we would predict on a $100 product. The actual and predicted markups are both lowest in the 128 MB PC100 category. The difference between the actual and predicted markups is largest in the 256MB PC133 category, where actual markups are four percentage points higher than the prediction. Looking further into the data we note that the positive average markups for low-quality 256 MB modules are entirely attributable to two subperiods: low-quality 256MB modules were sold at about ten dollars above cost in September-October 2000 and at about five dollars above cost in February-March 2001. We think we understand what happened in the former period. A small number of retailers found an obscure supplier willing to sell them 256MB modules at a price far below the price offered by the standard wholesale distributors.[32] As

[31] The effect of the low-quality price on the fraction upgrading comes from the demand system and the markup on the upgrade is set to its sample mean.

[32] The first retailer to have found the supplier appears to have found it on July 10. On that day, when the firm that supplied us with data bought modules wholesale for $270, PC Cost cuts its retail price to $218—a full $51 below the next lowest price.

a result, there were effectively six or fewer retailers competing in these two months rather than dozens.

8 Conclusion

In this paper we have noted that the extent to which the Internet will reduce consumer search costs is not clear. Although the Internet clearly facilitates search, it also allows firms to adopt a number of strategies that make search more difficult. In the Pricewatch universe, we see that demand is sometimes remarkably elastic, but that this is not always what happens.

The most popular obfuscation strategy for the products we study is to intentionally create an inferior quality good that can be offered at a very low price. Retailers could, of course, avoid the negative impact of search engines simply by refusing to let the search engines have access to their prices. This easy solution, however, has a free rider problem—if other firms are listing, a firm will suffer from not being listed. What may help make the obfuscation strategy we observe popular is that it is hard not to copy it—if a retailer tries to advertise a decent quality product with reasonable contractual terms at a fair price it will be buried behind dozens of lower price offers on the search engine's list. The endogenous-quality aspect of the practice makes it somewhat different from previous bait-and-switch and loss-leader models, and it seems that it would be a worthwhile topic for research.[33] We would also be interested to see more work integrating search engines into models with search frictions, exploring other obfuscation techniques (such as individualized prices), and trying to understand why adoption of price search engines has been slow.

[33] Simester's (1995) model seems the most similar to the practice. We would imagine, however, that what makes the low prices on Pricewatch have advertising value is that the offerings are sufficiently attractive so as to force a retailer to set low prices for its other offerings to avoid having everyone buy the advertised product.

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128MB PC100 Memory Modules 683 website-day observations				
Variable	Mean	Stdev	Min	Max
$LowestPrice$	62.98	33.31	21.00	120.85
$Range$1-12	6.76	2.52	1.00	13.53
$PLow$	66.88	34.51	21.00	123.49
$PMid$	90.71	40.10	35.49	149.49
PHi	115.19	46.37	48.50	185.50
$\log(1 + PLowRank)$	1.86	0.53	0.69	3.26
$QLow$	12.80	17.03	0	163
$QMid$	2.44	3.33	0	25
QHi	2.02	3.46	0	47

Table 1: Summary statistics for memory module data

Independent Variables	Dep. var.: quantities of each quality level		
	Low q	Mid q	High q
$\log(1 + PLowRank)$	-1.29*	-0.77*	-0.51*
	(10.9)	(4.6)	(2.9)
$\log(PLow)$	-3.03	-0.59	1.49
	(2.3)	(0.4)	(0.9)
$\log(PMid)$	0.68	-6.74*	2.38
	(0.8)	(5.9)	(1.7)
$\log(PHi)$	0.17	2.72	-4.76*
	(0.2)	(1.8)	(3.3)
$SiteB$	-0.25*	-0.31*	-0.59*
	(3.5)	(2.9)	(5.6)
$Weekend$	-0.49*	-0.94*	-0.72*
	(8.4)	(8.3)	(5.8)
$\log(LowestPrice)$	1.20	0.83	-0.14
	(1.1)	(0.6)	(0.1)
Number of Obs.	683	683	683

Absolute value of t-statistics in parentheses. $*$ denotes significance at the 5% level.

Table 2: Demand for 128MB PC100 Memory Modules

PRICE WATCH® Query = System Memory PC100 128MB

Back To - New Components Home

Back To - "Not Exactly New" Home

BRAND	PRODUCT	DESCRIPTION	PRICE	SHIP	DATE/HR	DEALER/PHONE	ST	PART#
Generic	PRICE FOR ONLINE ORDERS ONLY - 128MB PC100 SDRAM DIMM - 8ns Gold leads	.- * LIMIT ONE - Easy installation - in stock	$ 68	9.69 INSURED	10/12/00 12:40:05 AM CST	Computer Craft Inc. 800-487-4910 727-327-7559 Online Ordering	FL	MEM-128-100PCT
Generic	ONLINE ORDERS ONLY - 128MB SDRAM PC100 16x64 168pin	- * LIMIT ONE	$ 69	INSURED$9.95	10/11/00 10:59:56 PM CST	Connect Computers 888-277-6287 949-367-0703 Online Ordering	CA	-
Generic	PRICE FOR ONLINE ORDER - 128MB PC100 SDRAM DIMM	- * LIMIT ONE - - InStock, 16x64-Gold Leads	$ 70	10.75	10/11/00 2:11:00 PM CST	1st Choice Memory 949-888-3810 -- P.O.'s accepted Online Ordering	CA	-
Generic	PRICE FOR ONLINE ORDER - 128mb True PC100 SDRAM EEPROM DIMM16x64 168pin 6ns/7ns/8ns Gold Leads	- * LIMIT ONE - in stock - with Lifetime Warranty	$ 72	9.85	10/10/00 11:30:39 AM CST	pcboost.com 800-382-6678 -- P.O.'s accepted Online Ordering	CA	-
Generic	IN STOCK, 128MB PC100 3.3volt unbuffered SDRAM Gold Lead 168 Pin, 7/8ns - with Lifetime warranty	- * LIMIT ONE Not compatible with E Machine	$ 74	10.95- UPS INSURED	10/11/00 12:44:00 PM CST	Memplus.com 877-918-6767 626-918-6767	CA	- 880060
Generic	PRICE FOR ONLINE ORDERS ONLY - 128MB True PC100 SDRAM DIMM - 8ns Gold - warranty	- * LIMIT ONE	$ 74	10.25	10/9/00 6:53:25 PM CST	Portatech 800-487-1327 .	CA	-
House Brand	128MB PC100 3.3volt SDRAM 168 Pin, 7/8ns - with LIFITIME WARRANTY	- * LIMIT ONE	$ 74	10.50 FedEx	10/11/00 10:20:23 AM CST	1st Compu Choice 800-345-8880 800-345-8880	OH	-
Generic	128MB 168Pin TRUE PC100 SDRAM - OEM 16X64	DIMM16x64 168pin 6ns/7ns/8ns Gold Leads	$ 75	$10	10/11/00 2:37:00 PM CST	Sunset Marketing, Inc. 800-397-5050 410-626-0211 -- P.O.'s accepted	MD	-
Generic	128MB 16x64 PC100 8ns SDRAM.	- * LIMIT ONE	$ 77	10.90	10/12/00 9:37:45 AM CST	PC COST 800-877-9442 847-690-0103 Online Ordering	IL	-
Generic	IN STOCK, PC100, 128MB, 168pins DIMM NonECC, - with Lifetime warranty	- * LIMIT 5	$ 77	$10.95 & UP For UPS Ground	10/9/00 5:11:10 PM CST	Augustus Technology, Inc 877-468-5181 909-468-1883 Online Ordering	CA	-
Generic	128MB PC100 8NS 16x64 SDRAM - one year warranty	- * LIMIT ONE	$ 78	Ups Ground $10.62	10/11/00 5:16:36 PM CST	Computer Super Sale 800-305-4930 847-640-9710 Online Ordering	IL	-
Generic	PRICE FOR ONLINE ORDERS ONLY - PC100 128MB NonBuffered, NonECC 16x64 SDRAM DIMM 3.3V 8ns mem module	- * LIMIT ONE - with lifetime warranty	$ 78	10.95	10/5/00 6:29:59 PM CST	Jazz Technology USA, LLC 888-485-8872 909-869-8859	CA	ME-GBP100128

Page 1 of 30

1 5 10 15 20 25 30 Next

Figure 1: A sample Pricewatch search list: 128MB PC100 memory modules at 12:01pm ET on October 12, 2000.

Memory Spec. Chart - PC3200 DDR 512MB (Select Your Memory Module)		
Samsung/Micron or Major 512MB PC3200 [ADD $25]	**Industry Standard 512MB PC3200 [ADD $15]**	**OEM 512MB PC3200**
• CAS 2.5 Latency • Hand Picked 5ns • 6 Layer Low Noise Shielded PCB Board • 32x8 DRAM Type • Samsung/Micron or Major Brands • Return Shipping Paid • No Restocking Fee • Satisfaction & Compatibility Guaranteed • Lifetime Warranty • 15 Days Full Refund • Memory Tested Before Ship Out • Copper Heat Sink - Cool Down the Memory up to 40%	• CAS 2.5 Latency • Hand Picked 5ns • 6 Layer Low Noise Shielded PCB Board • 32x8 DRAM Type • Industry Standard DRAM Chips • 7 Days No Restocking Fee • Return Shipping not Paid • Improved Compatibility • Lifetime Warranty • Aluminum Heat Sink - Cool Down the Memory up to 35%	• CAS 3 Latency • 4 Layer Module Board • 64x4 DRAM Type • OEM DRAM Downgrade Chips • 20% Restocking Fee According to the Market Value • Verify Compatibility with Memory Configurator • Return Shipping not Paid • 9 Months Warranty

Figure 2: A website designed to induce consumers to upgrade to a higher quality memory module.

128MB PC100 Modules

	Low	Mid	Hi
$PLow$	-24.9*	-12.5*	-7.2*
$PMid$	0.7	-6.7*	2.4
PHi	0.2	2.7	-4.8*

128MB PC133 Modules

	Low	Mid	Hi
$PLow$	-33.1*	-11.2*	-4.9*
$PMid$	0.8	-3.6*	0.5
PHi	0.2	-4.8*	-4.8*

256MB PC100 Modules

	Low	Mid	Hi
$PLow$	-17.4*	-8.1*	-4.1
$PMid$	5.7	-7.8	-4.1
PHi	0.7	6.4	-3.8

256MB PC133 Modules

	Low	Mid	Hi
$PLow$	-24.8*	-12.5	-6.6
$PMid$	0.3	3.3	3.9*
PHi	-0.9	-7.2	-0.8

$*$ denotes significance at the 5% level.

Table 3: Price elasticities for memory modules: three qualities in each of four product classes

Figure 3: Another website designed to induce consumers to upgrade and/or buy add-ons

Independent Variables	Dependent variable: Dummy for choice of site A	
	Medium quality	High quality
$\Delta \log(1 + PLowRank)$	-0.64*	-0.31*
	(4.2)	(4.0)
$\Delta \log(PMid)$	-3.08*	1.48
	(2.2)	(1.4)
$\Delta \log(PHi)$	-1.43	-5.73*
	(1.2)	(3.4)
Number of Obs.	4118	6768

The table presents estimates of logit models. The dependent variable for the transaction-level dataset is a dummy for whether a consumer chose to buy from site A (versus site B). The samples are all purchases of medium- or high-quality modules from site A or site B. Absolute values of z-statistics in parentheses. * denotes significance at the 5% level. The regressions also include unreported category dummies, a linear time trend, and the difference between dummies for appearing on Pricewatch's first screen.

Table 4: Evidence of incomplete consumer learning: conditional site choices of consumers of medium- and high-quality memory.

Independent Variables	Dependent variables: Quantity of 128MB PC100 memory modules of each quality level					
	Cost instruments			Other speed instruments		
	Low	Mid	Hi	Low	Mid	Hi
$\log(1 + PLowRank)$	-1.99*	-1.06*	-1.19*	-1.75*	-0.25	0.02
	(3.8)	(2.2)	(3.1)	(3.0)	(0.4)	(0.0)
$\log(PLow)$	0.94	3.54	12.75*	2.68	-1.58	2.39
	(0.1)	(0.6)	(2.3)	(0.6)	(0.4)	(0.5)
$\log(PMid)$	12.61	-6.88	0.76	-1.72	-7.14*	-0.50
	(1.6)	(0.9)	(0.1)	(1.1)	(4.1)	(0.1)
$\log(PHi)$	6.41	6.38	-4.69	5.21*	2.03	-3.45
	(1.3)	(1.4)	(1.4)	(2.5)	(0.8)	(0.9)
$SiteB$	-0.40*	-0.36*	-0.59*	-0.25*	-0.51*	-0.66*
	(2.6)	(3.0)	(4.4)	(2.1)	(2.8)	(2.6)
$Weekend$	-0.55*	-0.95*	-0.76*	-0.48*	-0.95*	-0.64*
	(5.1)	(8.0)	(4.7)	(7.3)	(8.2)	(4.6)
$\log(LowestPrice)$	-5.91	-2.47	-8.26	-3.89	2.17	2.37
	(1.0)	(0.5)	(1.6)	(1.1)	(0.7)	(0.7)
Number of Obs.	683	683	683	608	608	608

Absolute value of t-statistics in parentheses. * denotes significance at the 5% level.

Table 5: Instrumental variables estimates of PC100 128MB Memory Demand Model

	Product Category			
	128 MB Memory		256 MB Memory	
	PC100	PC133	PC100	PC133
Actual low markup	-0.7%	-2.5%	4.3%	2.9%
Actual mid markup	17.3%	15.6%	16.2%	19.9%
Actual hi markup	27.3%	26.9%	24.3%	24.9%
Overall markup	7.7%	11.5%	12.7%	15.8%
Overal elasticity ϵ	-23.9	-27.7	-16.0	-21.2
$1/\epsilon$	4.2%	3.6%	6.3%	4.7%
Adverse selection multiplier	2.0	3.5	1.7	2.4
Predicted markup	8.3%	12.8%	10.9%	11.4%

The table presents revenue-weighted mean percentage markups for products sold by websites A and B in each of four product categories along with predicted markups as described in sections 2.2 and 7.

Table 6: Mean percentage markup in six product classes