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

Glenn Ellison
MIT and NBER

and

Sara Fisher Ellison
MIT

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1 Introduction

In the past two years there has been a dramatic collapse in the market valuation of leading e-retailers. One reason is a growing belief that e-retailer's high costs will limit their ability to take market share away from traditional retailers. A second is the fear that there will be "destructive competition" for the business they do get. Initially, prices on the internet were very low mostly because e-retailers were willing to lose money to gain market share. With the growth of price search engines, however, it is feared that even short run profit-maximizing firms will find themselves in Bertrand-like competition and be unable to cover their fixed costs. In this paper we contribute to this discussion by examining the impact that price search is having on demand in one segment of the e-retail market.

We see our paper as an attempt to examine the impact that search engines may have on e-retail in the future. It is not as much about the present e-retail environment because while the leading price search sites, Dealtime and mySimon, have millions of unique visitors per month, so far only a small fraction of internet sales are made through price search engines and thus they are probably having little impact on most e-retail segments.[1] We nonetheless feel that the potential for price search to transform how consumers shop makes understanding its effects an important topic for research. Our approach to developing empirical evidence is to focus on one segment of the retail market (computer parts sold by small firms) where a price search engine (Pricewatch) has already taken on a dominant role.

We begin with a brief theoretical discussion of price search engines. We make the obvious point that the effect of technological progress on search costs is in principle a balance-of-power problem. Improvements in information technology could increase or decrease equilibrium search costs depending on how much the technology helps those who wish to lower search costs (e.g. consumers) and how much it helps those who wish to raise them (e.g. retailers). The internet is clearly a revolutionary search-facilitating technology –

[1] Among the other leading price search engines are Pricewatch, PriceScan, PriceGrabber, BottomDollar, Shopper and Qixo. See White (2000) for more on the impact of price search engines. Johnson et al (2000) note that in 1997-1998 70 % of the online shoppers in their panel used a single online retailer for all of their purchases within the book and CD categories. Why price search engines are not more popular is another interesting question.

internet price listings can be searched much more easily than Yellow Pages or newspaper advertisements, and the growth of XML and other standards may allow further improvements in the near future. Our motivation for mentioning the balance-of-power model, however, is the observation that e-retailers may simultaneously be able to exploit internet technology to thwart price search. For example, traditional retailers must hire a substantial number of articulate salespeople if they want to offer nonstandard sales contracts, to use "bait-and-switch" techniques, to sell extended warranties, or to personalize prices. This is expensive and hence these practices are usually associated with sales of fairly expensive products such as cars, appliances, and mattresses.[2] E-retailers, in contrast, can create automated sales pitches to cheaply implement all of these strategies.

The evidence part of our paper begins with an informal description of the Pricewatch retail universe and some of the obfuscation strategies we have observed there and elsewhere. Our empirical analyses of the competitive environment that Pricewatch creates uses data from two sources. First, we obtained a year-long hourly price series by conducting price searches on Pricewatch. In this draft we use three months of data for three classes of products: two types of computer memory upgrades and one computer motherboard. Second, we obtained cost and sales data from a private firm that operates several computer parts websites. The firm does little advertising and derives a substantial fraction of its sales from Pricewatch referrals.

Our first empirical result is a striking confirmation of the hypothesis that price search on the internet may lead to extremely elastic demand. We estimate that the firm faces a demand elasticity of -50 for its lowest quality memory modules! This is the largest demand elasticity we have seen empirically estimated, and for single product retailers it would lead to a "Bertrand paradox" where the equilibrium price would be so low as to prevent retailers from covering their fixed costs.

The primary obfuscation strategy we observe among the Pricewatch retailers is a variant of a "loss-leader" or "bait-and-switch" strategy where firms offer an (inefficiently) low quality product at a very low price to attract customers and then try to convince them to pay extra to get the product they want. For example, the retailer we study offers low quality

[2] The 'Do you want fries with that?' refrain is one exception to this general rule.

memory modules with an unattractive return policy, and then tries to convince consumers to instead purchase intermediate-quality (but still generic) or high-quality (private-label branded) memory.

Our second main empirical result is a demonstration that loss-leader/bait-and-switch techniques are effective. Low-quality goods and high-quality goods are substitutes and hence we would ordinarily expect that the cross-price elasticity of demand for a high-quality product with respect to the price of a low-quality product should be positive. Our empirical finding is that these cross price elasticities are, in fact, large and negative. Intuitively, the reason why low prices for low-quality products increase demand for high-quality products is that one cannot ask a search engine to find "decent-quality memory modules sold with reasonable shipping, return, warranty and other terms." Hence, consumers use the price search engine to find websites offering low prices for some memory module, and then search within some number of websites to find a product that best fits their preferences.

The third main question we address is how (if at all) obfuscation lets firms avoid destructive competition. Our first result on this is that, at least for the firm we study, competition is not destructive. Its average markup on memory upgrades is about 8%, which makes it plausible that fixed costs can be covered.[3] How are these makups sustained? One part of the answer is that consumers have limited patience for searching through retailers' websites and this makes the demand for intermediate- and high-quality memory chips less elastic. We estimate that the own-price elasticities for intermediate- and high-quality memory chips are around -6 to -8. This alone, however, is not sufficient to explain nontrivial average markups. For example, if firms are able to talk 50% of their customers into buying an upgraded product that is priced at $20 above cost, Bertrand-like competition could drive the price for the low-quality good down to about $20 below cost. The crucial second part of the explanation seems to be that bait-and-switch selling naturally creates an adverse selection problem that limits below-cost pricing. Our estimates of the cross-price elasticities suggest that consumers who buy from the firm with the lowest price are harder to talk into buying an upgraded product than consumers who are willing to consider buying from a firm with a slightly higher price. Firms would thus want to avoid having the lowest price if prices

[3]The current draft does not contain our markup calculations.

ever fell much below cost.

The one other empirical study of price search engines and demand that we know of is Brynjolfsson and Smith (2000). They 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.[4] They note that even book retailers appear to be differentiated and identify price premia that consumers are on average willing to pay to buy from branded retailers (Amazon, Barnes & Noble, and Borders) and from retailers they have patronized in the past.[5] They also present results on price dispersion that are suggestive of there being much less intense competition in books than in the market we study.[6] This should not be surprising. Very few book buyers currently use price search engines, so one would not expect the aggregate demand bookstores face to be highly elastic.

2 Theory of price search engines; search and obfuscation

Any model of price search engines must avoid two possible contradictions. The first is the Bertrand paradox. A price search engine that caused all retailers to go out of business would be of little use. The second is what we will call the search engine revenue paradox. If a price search engine directs all consumers to the lowest-priced firms, then the only firms receiving a benefit from being listed may be firms that are making no profits and will not pay much to be listed. If search engines create Bertrand competition, then there will be no price dispersion and consumers will be unwilling to pay for the information the search engine provides.

In this section, we provide a high-level reduced form discussion of price search engines. In the model, avoiding the potential paradoxes is straightforward. We leave a more detailed model of the particular price obfuscation strategies we report to future research.

We begin with the search engine revenue paradox. Consider a retail sector consisting of

[4] A disadvantage of their dataset is that they do not observe purchases and must use last clickthroughs as a proxy.

[5] The most recent draft we have seen does not report price elastiticies, but they could presumably easily be derived and reported separately for branded and generic online bookstores.

[6] The difference in price between the lowest and tenth lowest price in their data is over \$10 or more than 30% of the average purchase price. A comparable figure for generic memory modules in our sample is about \$4 or 4% of the average purchase price.

a large number of firms selling a single undifferentiated product. Suppose that the outcome for retailers depends on two factors: the wholesale price w at which they acquire the good and a parameter s describing the level of search frictions (which might also be taken to reflect retailer differentiation). Assume that the result of some pricing game between the fixed number of retailers is that aggregate sales are $Q^*(w, s)$ and aggregate retailer profits are $\pi^r(w, s)$. Assume that these functions are differentiable and that for small s we have $\frac{\partial Q^*}{\partial w} < 0$, $\frac{\partial Q^*}{\partial s} < 0$, $\frac{\partial \pi^r}{\partial w} < 0$ and $\frac{\partial \pi^r}{\partial s} > 0$.[7] In the limit as s goes to zero assume that competition converges to Bertrand. Firms set prices equal to w giving $Q^*(w, 0) = D(w)$ and $\pi^r(w, 0) = 0$.

Suppose first that the only way that retailers can reach consumers is via a monopoly price search engine. Suppose that the search engine can monitor sales that are made as a result of its searches and can thus charge retailers a referral fee of r for each sale they make.[8] Suppose that internet technology allows the price search engine to costlessly choose any level of the search friction s. Write c for the cost at which retailers acquire the good that they sell. The problem facing the search engine is now

$$\text{Max}_{r,s}\ rQ^*(c + r, s).$$

Given that Q^* is decreasing in s the optimal choice is to set $s = 0$. If we view the search engine's choice variable as being $p \equiv c + r$ its problem is now

$$\text{Max}_p (p - c)D(p).$$

This is the standard monopoly pricing problem. Hence the search engine sets $r = p^m - c$ and gets the full monopoly profit in the market. Retailers earn zero profits. Our resolution

[7] The one condition where one would expect the "for small s" condition to bind most quickly is the last one, but given the elasticities we report we feel comfortable assuming that the firms in our data would prefer somewhat less efficient search. A main observation of Diamond's (1971) search model is that profits can be discontinuous and jump to the monopoly price with a positive search cost. A large subsequent literature has explored variants of the model in which intermediate search costs lead to intermediate outcomes. See Varian (1980), Burdett and Judd (1983) and Stahl (1989). Bakos (1997) and Janssen and Moraga (2000) examine the effects of search costs on prices and welfare. Bakos examines a model with horizontally differentiated firms where consumers must pay a search cost to learn a firm's location as well as its price and notes that lower search costs lead to lower prices and improved match quality. Janssen and Moraga examine a Stahl-style model with undifferentiated products and two types of consumers and emphasize that in some cases prices may be higher with lower search costs.

[8] Yahoo! Shopping, for example, charges retailers 2% of their gross revenues on any sales made during the course of a browser session in which the consumer was referred to the website by Yahoo! Shopping.

to the search engine revenue paradox is that as long as search engines can charge per sale referral fees, e.g. by making them pay for each clickthrough, firms pass the referral fees on to consumers and search engines can collect their revenues from retailers.[9]

Rather than being able to choose s costlessly, assume now that the search engine needs to make a costly investment to reduce s. Specifically, assume that in the absence of any investments, search frictions will be s_0, but that these can be reduced to $s_0 - x$ if the search engine invests $g(x;\theta)$, where θ indexes the state of technology. Define $\pi^{se}(s) = \text{Max}_r\ rQ^*(c+r,s)$. Assume that π^{se} is decreasing and strictly concave and that g is increasing and strictly convex in x. The conclusion will then be that the search engine chooses to reduce s to zero if

$$\left|\frac{d\pi^{se}}{ds}(s)\right| > \frac{\partial g}{\partial x}(s_0 - s;\theta)$$

for all $s \in (0, s_0)$. Otherwise the equilibrium s^* is given by the first order condition

$$-\frac{d\pi^{se}}{ds}(s^*) = \frac{\partial g}{\partial x}(s_0 - s^*;\theta).$$

When search frictions are nonzero, they will be decreasing in the state of technology θ provided that $\frac{\partial^2 g}{\partial x \partial \theta} < 0$, i.e. as long as technological improvements reduce the marginal cost of reducing search frictions.

A simple game in which the equilibrium level of search frictions is determined by a balance of power between search engines and retailers is obtained by assuming that search engines and retailers make simultaneous investments. Assume that if the search engine chooses an investment level x_{se} at cost $g(x_{se};\theta)$ and retailers choose x_r at cost $h(x_r;\theta)$, then the resulting level of search frictions is $s_0 - x_{se} + x_r$. In addition to the assumptions above, assume that π^r is increasing and strictly concave in s and h is increasing and strictly convex in x. In an interior equilbrium, the investments x^*_{se} and x^*_r and the resulting level of search frictions $s^* = s_0 - x^*_{se} + x^*_r$ will be the solution to the first-order conditions

$$\begin{aligned}
-\frac{\partial \pi^{se}}{\partial s}(s^*) &= \frac{\partial g}{\partial x}(x^*_{se};\theta) \\
\frac{\partial \pi^{r}}{\partial s}(s^*) &= \frac{\partial h}{\partial x}(x^*_{r};\theta).
\end{aligned}$$

[9] As in the literature on vertical restraints, there may be many other contracts which search engines could use to extract the monopoly profits. For example, they could refuse to post any price offer below the monopoly price and charge each retailer a fixed fee equal to its expected market share times the monopoly profit.

If we differentiate these first order conditions with respect to θ, mulitiply the first equation by $\frac{\partial^2 h}{\partial s^2}$ and the second by $\frac{\partial^2 g}{\partial s^2}$ we find that condition

$$\frac{ds^*}{d\theta} = \frac{\frac{\partial^2 g}{\partial x \partial \theta}(x^*_{se})\frac{\partial^2 h}{\partial x^2}(x^*_r) - \frac{\partial^2 h}{\partial x \partial \theta}(x^*_r)\frac{\partial^2 g}{\partial x^2}(x^*_{se})}{\frac{\partial^2 g}{\partial x^2}\frac{\partial^2 h}{\partial x^2} - \frac{\partial^2 \pi^r}{\partial s^2}\frac{\partial^2 g}{\partial x^2} - \frac{\partial^2 \pi^{se}}{\partial s^2}\frac{\partial^2 h}{\partial x^2}}.$$

The denominator in this expression is positive, so s^* is decreasing in θ if and only if

$$\frac{\left|\frac{\partial^2 g}{\partial x \partial \theta}(x^*_{se})\right|}{\frac{\partial^2 g}{\partial x^2}(x^*_{se})} > \frac{\left|\frac{\partial^2 h}{\partial x \partial \theta}(x^*_r)\right|}{\frac{\partial^2 h}{\partial x^2}(x^*_r)},$$

i.e. technological improvements reduce search frictions if and only if the technology aids search-improving more than it aids search-obfuscating. When this is the case, the magnitude of the difference and the magnitude of the terms in the denominator determine how rapidly search frictions decline with technological improvement.

A less reduced-form model of search and obfuscation could potentially be quite interesting and help us think more about why technology might aid one side more than the other in this game. In this paper, of course, we'll be trying to help understand the effects by looking empirically at how they have played out in one price-search dominated market.

The one full model of a price search engine we are aware of is Baye and Morgan (2001). They do not consider the possibility that the search engine may charge referral fees. They nonetheless avoid the revenue because the presence of an outside option for retailers makes it possible to have a mixed strategy equilibrium in which firms randomly choose whether or not to list on the search engine. Because each retailer knows that there is a positive probability that it will be the only firm listed on the search engine, the pricing game has a mixed equilibrium where prices are bounded away from cost. The search engine is able to charge positive fixed fees to both retailers and consumers. The particular market we study has very thick listings, e.g. Pricewatch will return hundreds of price offers from a hundred different retailers in response to a request for a particular memory module. The low-priced firms also at times change their prices daily (or more often). A model in which the possibility that only one firm lists is important and in which firms would like to change their prices once they see the prices other firms are charging is probably not well-suited.

Bakos (1997) does not explicitly model a search engine, but does discuss a model in which consumers face different types of search costs in choosing between differentiated retailers and notes how consumers' and retailers' preferences over the level and type of search costs differ.

A second theoretical literature which develops complete models of practices similar to some of the obfuscation techniques we describe is the literature on loss leaders and bait-and-switch advertising. In Gerstner and Hess's (1990) and Lazear's (1995) bait-and-switch models the low priced goods that are advertised are actually unavailable (although the former create a link between the prices of other goods to prices of the bait by making rain checks available.)[10] In Hess and Gerstner's (1987) and Lal and Matutes's (1994) loss-leader models, consumers buy multiple products, and advertising a low price for one good allows the firm to commit to a low price for the full bundle of products. In Simester (1995) a low advertised price for one good may signal to consumers that the firm is very efficient and hence is likely to have low prices for other goods as well. In all of these models, in contrast to the obfuscation we observe, the set of products is exogenously specified rather than being endogenously invented by the firms. As in the price discrimination literature, an interesting question would be whether the creation of the damaged goods leads to lower welfare.[11]

3 The Pricewatch Universe

Our study will focus on small e-retailers selling memory upgrades, CPUs, and other computer parts. In contrast to Amazon.com or Pets.com, the firms we study have virtually no advertising or web development costs. Instead, customers find them by conducting price searches on Pricewatch.com. The firm which we have data, for example, has annual sales of over $10 million and spends perhaps $5000 on advertising — not enough to buy even one-tenth of one second of commercial time on the Super Bowl. There are a large number of small businesses in this segment. For example, a search for a 128MB PC133 SDRAM

[10] Lazear notes that for bait-and-switch ads to be profitable it must be that "enough actual buyers [are] induced into the showroom by advertising [product] B to make up for those lost from failing to advertise truthfully." Advertising memory prices on Pricewatch certainly satisfies this condition. There is really no way to inform Pricewatch of the quality of (unbranded) memory modules or the reasonableness of warranty etc. terms. A firm trying to advertise the product it wants consumers to switch to would have a price that is sufficiently far down Pricewatch's list so that no consumers would ever look at it.

[11] See Deneckere and McAfee (1996). In our memory module data a majority of consumers buy products that we understand to be inefficient.

memory module on Pricewatch returns a list of over 350 price quotes from more than 100 different websites. While some websites are clearly "big" players that regularly occupy a position near the top of the Pricewatch list, there is not a rigid hierarchy. Between mid-May and late-December of 2000 we observed 64 different websites appearing on the first page (which contains the twelve lowest prices) of the list mentioned above at least once.

The e-retailers in this universe are generally not VC-backed firms trying to gain market share. Our impression is that they are trying to earn profits and have no cash to burn through even if they wanted to. They are highly efficient firms. As a fraction of revenues, their sales, general, and administrative expenses are probably less than half of those at Amazon.com (and even below Wal-mart's).

Retailers in this universe often offer very low prices. For example, computers assembled and sold by some of these firms are offered for as little as $60 above the sum of the wholesale prices of the components that go into the computer. This makes them perhaps 20% cheaper than computers from Dell with similar specifications (which may however be superior in unobservable dimensions). Prices for memory modules are typically about half of what Dell charges for a comparable product. Pricewatch retailers typically would only sell a CPU which was boxed by the manufacturer for retail sale if they wanted to sell it as a "premium" product and charge a $40 higher markup than they apply to unboxed CPUs and fans. Even so, prices from Pricewatch firms are again about 20% below Dell's prices.

Seeing these low prices the obvious first question to ask is "Are they too good to be true?" The answer is sometimes yes and sometimes no. None of the firms have 24/7 technical support. None would follow the lead Amazon set with *Harry Potter and the Goblet of Fire* and upgrade consumers to same day Federal Express service without even mentioning in advance that they would do this. The ones that do their own shipping (some may use distributors like Ingram Micro to ship products directly without ever taking possession) lack the automation necessary to have their websites automatically inform consumers of whether products are in stock and can be shipped immediately. A more relevant question is "Are they honest and do they do a decent job of shipping products on time and handling disputes fairly?" It is hard to find good information on very small firms. The best source we know of for this retail segment is ResellerRatings.com, which allows people to post eBay-like feedback on companies they deal with and rate them on a scale from zero to seven. On a recent day we looked up the ResellerRatings feedback of the twelve websites with the lowest Pricewatch prices for 128MB PC100 memory modules. Two websites were not listed there. Five had average ratings below 3.0, which we would take to indicate that the websites have significant honesty/competence problems.[12] The other five websites, however, all have scores of at least 4.5, which would suggest that they are reasonably honest. The two websites we study are in the latter category; website B has the single highest rating.[13]

Prices for computer parts decline rapidly over time. Memory prices, for example, have fallen by about 40-50% per year over the last decade. The cumulative effects of such a rate of price decline are huge. For example, memory prices were about $35 per megabyte when one of us bought a computer in 1992 (at the peak of a price cycle) and are about 40 cents per megabyte today. A short-run consequence of persistent price declines is that firms hold very little inventory and temporary supply shocks (which are for some reason common in the memory market) lead to large price swings. For example, In the past year and a half, prices for 128MB SDRAM modules rose from about $120 in the summer of 1999 to about $180 in the fall of 1999 (when one of us needed a computer); fell to about $80 at the start of our data in May 2000; rose to $120 in the summer of 2000 and have now fallen again to about $40. Figure 1 contains a graph of the lowest price for a 128MB PC133 SDRAM module found by Pricewatch between May and December of 2000. Given the volatility of wholesale prices, online retailers change their prices frequently. For example, this paragraph is being written on the afternoon of Saturday, December 30, 2000 and despite this being a holiday weekend four of the twelve lowest-priced firms on Pricewatch have changed their prices on 128MB PC1333 SDRAM modules today. Other semiconductor products (like CPU's and motherboards) that are branded tend to have more orderly price declines.

People who have not seen previous studies about price dispersion might think that it is remarkable that there are so many different prices listed for nearly identical items

[12] The firm with the lowest numerical rating is remarkable also for having 502 postings about it on ResellerRatings. None of the other nine sites has more than 61 postings. The websites we study make on the order of 10,000 sales a year. The fact that there are so few feedback items on ResellerRatings indicate that the ratings there are very, very far in information content from eBay feedback ratings.

[13] A measure of the limited information content of the ratings is that they vary across the three identically-run websites we study. The average ratings of websites A, B, and C are 4.7, 6.3 and 4.6, respectively.

on Pricewatch. In comparison with previous studies, we think it is remarkable how close together prices can be. For example, the lowest and tenth lowest prices for a 128MB memory module typically differ by about \$4 (or about 4% of the price.)

In this draft we will focus on three sets of products:

1. PC100 SDRAM Memory Modules. Consumers purchase memory modules to upgrade old computers or when building new computers. We are currently focusing on 128MB memory modules. The company from which we have sales data sells three different quality levels.

2. PC133 SDRAM Memory Modules. These are similar to PC100 modules. They are faster, but not a substitute good for most people. The speed of a memory module must match the speed of the motherboard around which a computer is built. At the time of our data collection motherboards using PC133 modules were very popular with hobbyists building Athlon-based computers.

3. Abit KA7 Motherboard. A popular motherboard for home built Athlon-based computers.

In the future we may expand the scope of this paper to also examine 256MB memory modules and AMD Athlon CPUs.

4 Observations of obfuscation

Pricewatch.com is a database-based facility. Firms directly enter prices and item descriptions into the Pricewatch database using a web-based interface whenever they desire to change them. It is easy to notice firms doing many things to allow them to advertise very low prices and to make it time-consuming for consumers to compare products.

Before Pricewatch cracked down on the practice (adding shipping fees to its main search page and threatening to ban firms charging unreasonable shipping fees) it had become standard for firms to charge about \$40 for shipping and handling on a memory module that when packaged still weighs just a few ounces. Most firms now have shipping and handling fees of about \$10 listed in Pricewatch's shipping fees column, but a substantial fraction give a range of shipping fees or put "and up" after the number. At about one-third of the websites one cannot find out the shipping fee without entering an address and other information. One company explicitly states (but not in its Pricewatch listing) that items ordered with the standard UPS ground shipping are given lower priority for packing than other orders and may take two weeks to arrive.

Many firms' low price offerings feature very unattractive contractual terms. For example, it is common for firms to make customers pay for return shipping and pay a 15-20% (plus depreciation) restocking fee on all returns. These restocking fees sometimes are explicitly noted to apply even if the retailer ships a defective product — a moral hazard problem in waiting that is so clear that it is hard to imagine that consumers will not notice. One merchant explicitly says that any CPU purchased without a fan (its lowest price offering) is sold on an "as is" basis with no returns allowed for any reason. Many retailers have very short warranty periods for low priced products. Higher priced products are are often advertised on the retailers' websites as having better warranty and return policies. Some websites make improved warranty terms an option on many products.

Some firms explicitly state on Pricewatch that the offered prices are not available through the website and require the consumer to call on the phone (and presumably wait on hold). At some retailers that do not explicitly require phone orders we could not find the prices listed with Pricewatch on the retailers' sites.[14] Other retailers state that the prices on Pricewatch are only available through the website and do not apply to phone orders.

In some cases the lowest prices listed on Pricewatch are for products of inefficiently low quality. For example, installing a CPU fan takes seconds for an experienced employee. For someone who does not do it regularly, it can be difficult, and one risks ruining the CPU. Nonetheless the low price offerings in Pricewatch's CPU category are all for CPUs without fans. Fans with attached CPUs are offered on these sites at higher prices. We are told that the lowest cost memory modules offered by many sites are also of inefficiently low quality. Apparently, they are far more likely to have problems than modules that can be purchased at wholesale for perhaps 1-2% more.

As mentioned above, Pricewatch is a database-based facility. This scheme for running a price search website seems to be gaining relative to the alternate technology of using

[14] Unsurprisingly, these were largely retailers with low ratings on ResellerRatings.com.

shopbots to search for prices when a consumer requests them. One explanation for this must be that the shopbot approach can result in substantial delays while the site searches. Another may be that the shopbot approach may be more prone to obfuscation. Yahoo! Shopping, for example, should have a much easier time organizing products than general price search engines.[15] Nonetheless, if one types "128MB PC100 SDRAM DIMM" into the search box and sorts on price, the five lowest listed prices are from merchants who have figured out how to get Yahoo! Shopping's search engine to think the price is zero even though a human visitor to those pages can easily see the price (and see that it is 50-100% above the Pricewatch price. Paging down from there the next hundred or so cheapest items will be incorrect matches that are not the desired memory module.[16]

Price search did not start with the internet. Telephones have long provided an effective method for comparing prices. Obfuscation has also been around for a long time. Mattress retailers are a classic example. We called two discount mattress stores and two furniture stores in Boston each of which sell four, seven, seven and ten models in the Sealy Posturepedic mattress line at prices ranging from $497 to $1439 for a queen-sized set. All twenty eight model names were, of course, distinct, so there was no easy way to figure out which model from one store corresponded to which model at each other store.[17] Many salespeople made getting this information an ordeal, so we cut off the experiment before calling the other fourteen Sealy dealers within ten miles of our house. We did, however, try calling a few stores in Birmingham, Alabama (where salespeople are more friendly and helpful) and looking at a few scattered dealers with internet listings. At seven stores we found forty four more Sealy Posturepedic mattresses at prices ranging from from $299 to $1399. Only two of the forty four model names matched names we had found in the Boston area.

[15]Yahoo collects a fee on all sales made by merchants through Yahoo! Shopping (as well as a monthly fee based on the number of items offered for all Yahoo! Store merchants). For this reason there must be some standardization of listing and ordering mechanics.

[16]It is possible to use Yahoo! Shopping's search engine to get a well-sorted list and find low prices if one is experienced with it.

[17]That the models at the two stores with seven product lines are not directly comparable is suggested by the fact that in one of the two stores the three lowest prices were $497, $797 and $899, and in the other the three lowest prices were $569, $669 and $779.

5 Data

We have hourly price data on a number of products obtained by using Go!Zilla to regularly download price search results from Pricewatch.com. The price data run from May 2000 to the present (with some holes). For each product we have collected either the lowest twelve prices or the lowest twenty four prices each hour. By product here, we mean, for example, a 128 MB PC-100 SDRAM module. Pricewatch's category lists do not allow one to specify a quality level (or to specify desired return and warranty terms, etc.).

We obtained sales data for the products from one internet retailer. It does little advertising and gets most of its traffic from Pricewatch. It operates a few different (but similar) websites, which typically have different prices for the products studied.[18] We currently have sales data for May 15, 2000 - August 9, 2000.[19]. The raw sales data are at the level of the individual order and indicate from which website the customer made the purchase. We aggregate the individual orders to produce daily sales totals for each product at each website.[20] Our primary price variables are the average transaction prices for sales of a given product on a given day.[21] We also record the daily average position of each website on Pricewatch's price ranked list.

We focus on three sets of products: 128MB PC100 memory modules; 128MB PC133 memory modules; and the Abit KA7 motherboard. Websites A and B offer identical memory modules with identical contractual terms (but different prices). Three quality levels of each memory module are offered which we'll describe as low, mid and high quality. Websites B and C sell the Abit KA7.

Our current dataset on memory modules contains 67 days of matched data. Sum-

[18] Among the motivations for having several websites are that different websites may be given different looks and consumers may have heterogeneous reactions, that it allows the websites to be more specialized (which seems to be attractive to some consumers), that it facilitates experimentation, that it may help promote private-label branded products and that the firm may occupy multiple places on the Pricewatch screen.

[19] We expect to add more data later

[20] Here, a "product" includes also the quality level, e.g. a high-quality PC-100 SDRAM module.

[21] Transaction prices are unavailable for products which have zero sales on a given day. The most volative prices are those for generic memory modules. If these products ever have zero sales we fill them in prices using the listed prices from Pricewatch. Prices for the other products change less often and can be filled in fairly completely by just assuming that prices are constant in the gaps between times when we observe identical transaction price observations. We also fill in a few other values by looking at when generic prices and prices at other websites changed.

mary statistics for the data appear in Table 1. $LowestPrice$ is the lowest price listed on Pricewatch (which is presumably for a low-quality memory module.)[22] $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. P_{low}, P_{mid} and P_{hi} are the prices for the three qualities of memory modules at the two websites. Note that we have two observations on each day for these variables. $LowPRank$ is rank of the website's first entry in Pricewatch's sorted list of prices for 128MB memory modules of the appropriate speed. This variable turns out to allow us to predict sales much better than we can with simple functions of the cardinal price variables. Note that the websites we study are consistently near the top of the Pricewatch list (i.e., have lowest prices), especially for PC133 modules. To give a feel for how the prices differ across websites, we report also summary statistics for the differences between the low-quality prices and the price ranks across the two websites, ΔP_{low} and $\Delta PRank_{low}$. Website A's prices are about 62 cents lower on average for the PC100 modules and the prices are more similar for the PC133 modules. Q_{low}, Q_{mid} and Q_{hi} are the average daily quantities of each quality of module sold by each website. Note that the majority of the sales are the low-quality modules. Website A generates 70% of the total unit sales of PC100 modules and 49% of the total unit sales of PC133 modules.

Our current dataset on Abit KA7 motherboard sales contains 82 days of matched data. Note that the prices for the Abit KA7 are much less volatile than memory prices. Websites B and C also rarely change their prices. In the first two months of our data website B charges substantially more than website C. In the last month the two prices are virtually identical. We thus cannot expect to estimate the elasticites as sharply. Another complication that arises here is that (because we only recorded the first page of Pricewatch's list and website B's price is quite high at times) we often do not know the order of website B in Pricewatch's list. When this happens we fill in an estimated order by taking the difference between website B's price and the highest price in the list we obtained from Pricewatch, dividing by the average distance between adjacent prices on the Pricewatch list and imputing that website B's price would have appeared this many places below the highest listed price.

[22]The Pricewatch data is 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.

6 Estimation

Our empirical work aims to improve understanding of how consumers search and of a price-search-dominated retail environment by estimating elasticites and cross-elasticities of demand.

Our basic approach to estimating demand elasticities is to regress daily quantities on prices. We do not feel that there is a real need to instrument in these regressions. We think that the best model of the variation in relative prices is that it is mostly a random process where the ranks and relative prices of our websites drift up and down as they and other firms periodically update prices, not one in which prices are optimally set given information the retailer possesses about demand.[23]

We estimate daily demand using negative binomial regressions. In a standard regression randomness in demand is attributed to idiosyncratic random factors unobservable to us that (additively) affect daily demand. A Poisson model for count data attributes randomness in a discrete random variable (like the number of purchases made in a day) to the fact that the realization of a Poisson random variable with a given mean will be different each time. The negative binomial regression is the most tractable model that allows for both of these sources of variation.

We estimate a separate negative binomial regression for each of the four products we study: low-quality memory modules, intermediate-quality memory modules, high-quality memory modules, and Abit KA7 motherboards. Our model of the demand for speed s memory modules of quality q at website w on date t is

$$\begin{aligned}
Q_{qwst} &\sim \text{Poisson}(\mu_{qwst}) \\
\log(\mu_{qwst}) &= \beta_0 + +\beta_1 \log(1 + LowPRank_{wst}) + \beta_2 \log(P_{midwst}) + \beta_3 \log(P_{hiwst}) \\
&\quad +\beta_4 \log(LowPrice_{st}) + \beta_5 Weekend_t + \beta_6 Time_t + \beta_7 SiteB_w \\
&\quad +\beta_8 PC133_s + \beta_9 SiteB_w PC133_s + \epsilon_{qwst},
\end{aligned}$$

where the ϵ_{qwst} are independent random variables with $e^{\epsilon_{qwst}} \sim \Gamma(\theta, \theta)$. The control variables in the regression that we did not include in our summary statistics table are a dummy

[23] We are, however, attempting to collect daily cost data that could provide instruments.

for weekend days, a linear time trend (which increases by one each day), dummy variables for the website and the speed of memory chip, and an interaction of these dummies.

The Poisson regression model is the special case of the negative binomial with $\theta = \infty$. In applied work it is common to find that a specification test can reject the Poisson model in favor of other models that allow for more dispersion. The particular assumption that the errors are distributed like the logarithm of a gamma random variable (as opposed to being normally distributed for example) is motivated by the fact that a relationship between Poisson and gamma random variables allows the likelihood to be evaluated without a numerical integration.[24]

The primary estimates of interest are those on the first three variables. We use the (concave function of) the rank of the firms lowest price in the Pricewatch list rather than the price itself, because preliminary estimates indicated that the rank was a far more powerful predictor of demand. We include variables for the impact of the prices of all three quality levels in each regression in order to freely estimate a full set of cross-elasticities. The coefficient on $\log(LowPrice)$ will be difficult to interpret in intermediate- and high-quality demand regressions as it reflects both the overall elasticity of demand for memory and that individuals' decisions are likely based on a comparison of mid- and high-quality prices with low-quality prices.

The coefficients on the logs of the prices of the intermediate- and high-quality modules can be directly interpreted as elasticities. To construct elasticities of demand with respect to a website's low-quality price we treat $\log(1 + LowPRank)$ as a continuous variable and compute estimated elasticities when all variables are at their means by setting the average change in $LowPRank$ with respect to a change in P_{low} equal to the inverse of the average distance between each of the twelve lowest prices.

Our model of demand for Abit KA7 motherboards is very similar. We use the website's position in Pricewatch's list of Abit KA7 prices as our explanatory variable. We use the same control variables as above (except of course for the memory speed dummies and the prices of other qualities of memory which have no direct analogue).

[24] The distribution of Q_{qwst} turns out to be negative binomial which is what gives the model its name. Section 19.9.4 of Greene (1997) provides a clear description of the model. Hausman, Hall and Griliches (1984) discuss a number of models for count data.

7 Results

In this section we would like to highlight a few aspects of the demand for goods in the Pricewatch universe that are apparent in our data. Table 2 presents coefficient estimates from our negative binomial regression. Coefficient estimates are presented with t-statistics in parentheses below them. Many of the coefficient estimates are highly significant. Likelihood ratio tests of the model relative to the Poisson special case strongly reject the Poisson model. Table 3 presents elasticity estimates derived from the regression coefficients.

The first observation that we would like to highlight is that demand for low-quality memory modules is extremely elastic. We estimate the own price elasticity for low-quality memory modules to be -51.8! The coefficient on $\log(1 + LowPRank)$ in the first column of Table 2 that is responsible for this estimate is extraordinarily significant — it has a t-statistic of 12 in a regression with only 268 observations! The elasticity is thus estimated fairly precisely. This extreme elasticity is a powerful illustration of the potential that price search has to produce a retail environment that is very different from any that has been seen before. Static Nash equilibrium prices would follow from the familiar Lerner index formula: $(P - MC)/P = 1/51.8$. An environment in which prices were only 2% above marginal cost would create a real Bertrand paradox where even efficient, budget-concious retailers that did not advertise could not survive.

The second striking observation in Table 3 is that the cross-elasticities of demand for intermediate- and high-quality memory modules with respect to a change in the price of low-quality modules are large and negative. Normally, we expect cross-price elasticities between substitutes to be positive. What we are seeing here is that in a price-search world, prices have advertising value. Apparently, what many consumers are doing is using Pricewatch to find the set of websites or perhaps a single website, offering the lowest prices for low-quality memory, clicking through to that website or websites, and then purchasing a higher quality product after looking over the full set of products offered on the websites. The estimates provide clear evidence of the effectiveness of loss-leader/bait-and-switch techniques on the internet. While it is common in marketing to talk about loss leaders, the empirical marketing literature on the effectiveness of loss leaders has produced very mixed results (Walters, 1988; Walters and McKenzie, 1988; Chevalier, Kashyap and Rossi, 2000). We noted earlier that the low memory prices advertised by the firms we study are below cost (though this is not necessarily true once the difference between shipping fees and shipping and labor costs are included). Further circumstantial evidence that most firms regard their low prices as loss leaders is that virtually all of the websites on the first page of Pricewatch's memory price lists only allow customers to purchase one unit at the stated price.

The third main fact we want to comment on is that the estimated own-price price elasticities for intermediate- and high-quality memory modules are -6.6 and -8.6 respectively. Each estimate is significant at the 1% level. Our first comment is that obfuscation is having only a limited effect — these are substantial elasticites. If in the future price search engines come to be the dominant mode of shopping online and these elasticities become typical, then in equilibrium markups would be about 12-15%. Currently well-known e-retailers with their high advertising and website development expenses would not be able to survive. Of course, the websites that we observe to face these elasticities are not websites that have invested in brand image and reaching unsophisitcated consumers. They are part of a low-advertising, low-website-development retailer. At the margins these elasticities allow, there is no Bertrand paradox and an efficient retailer we're studying can easily cover its fixed costs.

A few other aspects of the memory demand regressions also seem worth mentioning. First, the coefficient on the *SiteB* dummy is significantly negative in all three regressions. The magnitude of the difference is striking given that website B is designed, owned and operated by the same people that run website A. Part of the difference may reflect consumers preferring to order memory from a website specializing in memory as opposed to a website that also sells other computer parts. We feel, however, that it probably reflects more that designing an effective website is something of an art. In the long run this retail segment is clearly a free entry industry. We would expect, however, that there will be enough heterogeneity in the ability of firms to design honest websites that induce consumers to buy higher margin products to allow some retailers to earn substantial profits. Second, retailers seem to face what might be thought of as an adverse selection problem when they charge very low prices. The fact that the own-price elasticity of low-quality modules is larger than the cross-price elasticities of the higher quality modules with respect to the low-quality price means that the marginal customers that are attracted by the lowest prices are disproportionately people who will not decide to upgrade to a higher-quality product. This effect may dissuade retailers from pricing much below cost. In the extreme it might lead to a situation where (in contrast to what happens in most demand models) retailers want to avoid being the low priced firm in a market.

The one aspect of the demand for the Abit KA7 motherboard that we wanted to highlight is that, despite the fact that the Abit KA7 is easy to describe completely and is as expensive as the memory upgrades, the demand for the Abit KA7 is less elastic than the demand for low-quality memory modules. The coefficient on $\log(PRank)$ in the fourth column of Table 2 corresponds to an own-price elasticity of -7.8.[25] Further evidence that is also suggestive of a lower price elasticity is that the distribution of prices of Pricewatch is much less tight and that even the lowest prices rarely have the "Limit 1 per order" notes that appear throughout the memory price screens. The average difference between adjacent Abit KA7 prices on the page we downloaded from Pricewatch was 62 cents as compared to about 40 cents for low-quality memory modules.[26]

Our interpretation of the lower elasticity is that motherboards are somehow less focal to searchers than are memory chips and CPUs. People who are building computers have a preference for buying components from as few stores as possible. Search engines are not good at finding the best bundle of products for a consumer, because the consumer would typically be willing to make substitutions to each component of the bundle given the prices offered at each retailer. Apparently, the way many consumers react is to search intensiviely for low prices for memory modules and CPUs (which are two of the most costly components

[25]As noted above, in many cases we had to fill in missing values of the $PRank$ using the price data. If we instead estimate the demand elasticity by just using $log(P)$ in as an explanatory variable, then the estimated demand elasticity is -8.9.

[26]We do not report the average difference between the lowest and twelfth lowest price for motherboards in our summary statistics because of an obfuscation problem. Unlike the memory searches which are a predefined list on Pricewatch, the way in which one searches for Abit KA7 prices is to type Abit KA7 into a search box. An increasing number of firms have noticed that if they put comments like "for use with Abit KA7 motherboards" in the description of a memory module or fan that costs less than an Abit KA7 it will occupy one of the fifteen spots on the screen whenever a customer tries to use Pricewatch to find an Abit KA7. As a result, our data may contain as few as eight price quotes for the KA7. Another observation is that one firm has taken a (low quality) motherboard that is so generic as to lack a name and named it the KA771 so that it would also show up in the results of such a search.

of a new computer) and to search less intensively for other products.

8 Conclusion

In this paper we've noted that the extent to which the internet will reduce consumer search costs is not clear. While 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 and I 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.[27] We would also be interested to see more work integrating search engines into models with search frictions, exploring other obfucation techniques (such as individualized prices) and trying to understand why price search engines have not yet caught on.

Large online retailers have very high expenses. While they can avoid the expense of setting up hundreds of retail locations, they have to handle every item they ship individually. It is much cheaper to ship a truckload of merchandise to a store than to ship a similar number of individual packages with UPS. It is cheaper to have a customer take packages off the shelf and bring them to a cashier than it is to hire someone to pick packages off shelves and put them in boxes. Large online retailers also have very high expenses of other types: they have been very intensive users of managerial talent; they have spent alot on

[27] 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.

advertising; and they have enormous website development costs.[28]

Given these expenses, large e-retailers cannot be competitive with Walmart's prices. This is not necessarily worrisome. Many people may be willing to pay a premium to avoid going to the mall and to take advantage of superior product variety. A more serious problem is that managerial, advertising and website development costs seem more like fixed costs than marginal costs. If price search engines become more popular and better sources of information develop on the reliability of retailers, then vigorous price competition may push online prices well below the level necessary to sustain current costs.

What will happen to e-retail if price search flourishes? One thing we have seen can happen is that demand can become incredibly elastic — so elastic that retailers could never break even. While this is a frightening possibililty to retailers, it doesn't seem very likely to us. Another possibility is that retailers will make significant efforts to ensure that price search engines never work too well. Many price elasticites may end up being closer to the -8 level we estimate for the higher quality memory chips and motherboards. Such demand elasticities would force large retailers to cut back substantially on management, advertising, and website costs, but it is certainly plausible that they could do so. Another possibility is that e-retail could end up with a very different market structure that traditional retail. Small e-retailers without venture capital realized long ago that the internet allows one to operate a retail store with virtually no advertising or website development costs. At present, small e-retailers are far more efficient than their more famous competitors. Whether they will remain more efficient and come to dominate price-search mediated markets or whether they will be pushed aside as larger firms copy their model is an interesting question.

[28]Amazon, for example, will report more than $250 million in R&D costs in 2000.

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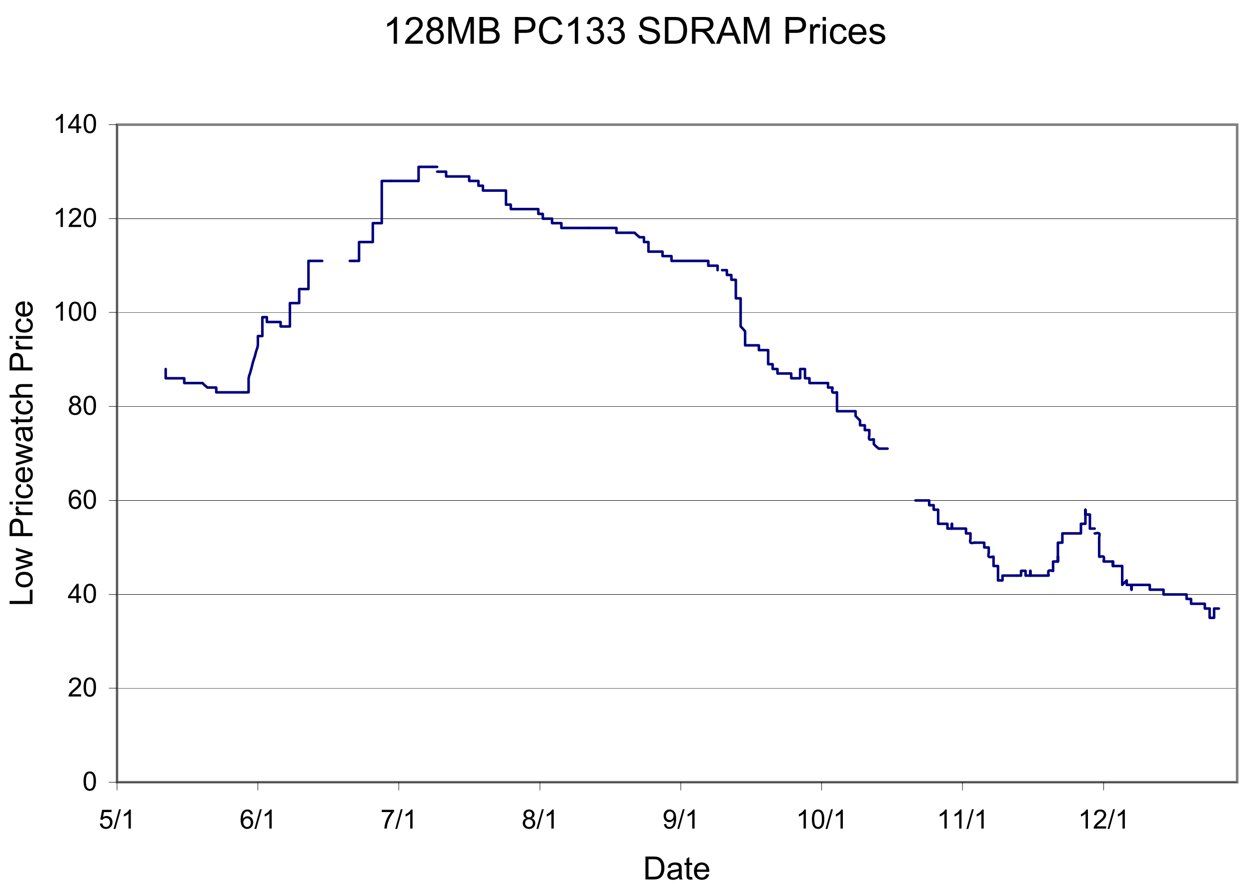

Figure 1: SDRAM prices

Variable	Mean	St.Dev	Min	Max
128MB PC100 Memory Modules				
$LowestPrice$	103.46	13.62	79.00	120.85
$Range1$-12	4.33	1.39	1	7.74
P_{low}	107.18	14.42	79.45	123.49
P_{mid}	134.58	18.65	98.49	149.49
P_{hi}	165.26	19.52	127.75	185.5
$LowPRank$	5.61	3.77	1.00	18.79
ΔP_{low}	0.62	1.37	-1.68	4.96
$\Delta LowPRank$	1.82	3.19	-3.30	15.00
Q_{low}	6.45	5.96	0.00	30.00
Q_{mid}	1.96	2.88	0.00	12.00
Q_{hi}	1.45	1.78	0.00	9.00
128MB PC133 Memory Modules				
$LowestPrice$	112.32	16.42	83.00	131.00
$Range1$-12	6.51	1.74	3.59	12.00
P_{low}	113.97	16.27	83.49	131.49
P_{mid}	142.05	13.37	116.45	153.45
P_{hi}	171.92	16.86	141.75	189.50
$PRank_{low}$	3.00	1.47	1.00	8.00
ΔP_{low}	0.18	0.85	-3.00	3.53
$\Delta PRank_{low}$	-0.16	1.79	-6.00	3.97
Q_{low}	5.53	4.19	0.00	21.00
Q_{mid}	1.50	1.68	0.00	8.00
Q_{hi}	2.71	2.44	0.00	12.00
Abit KA7 Motherboards				
$LowestPrice$	128.55	2.02	126.00	132.00
P	134.80	7.66	127.25	144.49
$PRank$	12.29	11.51	1.19	40.20
ΔP	8.53	6.71	0.24	17.24
$\Delta PRank$	14.97	12.34	2.84	36.20
Q	2.91	2.55	0.00	10.00

Table 1: Summary Statistics

Independent Variables	Dependent variables: daily quantities			
	Memory modules			Abit KA7
	Low q	Mid q	High q	Motherboard
$\log(1 + LowPRank)$	-1.22†	-0.60*	-0.45*	
	(11.99)	(3.05)	(2.78)	
$\log(P_{mid})$	-1.00	-6.57*	-0.32	
	(0.78)	(2.61)	(0.16)	
$\log(P_{hi})$	0.41	-1.54	-8.59	
	(1.89)	(0.42)	(2.94)	
$\log(LowestPrice)$	-1.11	2.97	4.33*	-22.38
	(1.06)	(1.49)	(2.88)	(2.17)
$Weekend$	-0.39*	-1.14*	-0.65	-0.29
	(4.69)	(6.26)	(4.72)	(2.21)
$Time$	0.005	0.017*	0.012*	-0.017*
	(1.96)	(3.30)	(2.78)	(-2.61)
$SiteB$	-0.45*	-0.56*	-0.61*	-0.71*
	(4.20)	(2.87)	(3.23)	(4.20)
$PC133$	-0.77*	-0.31	0.50*	
	(7.40)	(1.55)	(3.07)	
$PC133 \cdot SiteB$	0.68*	0.36	0.19	
	(4.52)	(1.28)	(0.77)	
$\log(1 + PRank)$				-0.44*
				(3.53)
$Constant$	-67.82	-224.34*	-144.04	364.72
	(1.73)	(3.04)	(2.45)	(2.53)
θ	8.21	2.35	4.34	8.71
	($\chi^2_1 = 51.4$)	($\chi^2_1 = 53.4$)	($\chi^2_1 = 23.8$)	($\chi^2_1 = 7.0$)
Number of Obs.	268	268	268	164
Pseudo R^2	0.14	0.11	0.10	0.13

The table presents coefficient estimates from negative binomial regressions of daily sales on prices and other variables. The dependent variables in the first three columns are sales of different qualities of memory modules. These regressions have four observations per day — sales of two speeds (PC100 and PC133) of memory by two websites. The regression has sales of the Abit KA7 motherboard as its depedent variable It has two observations per day — sales of the motherboard at two websites. Absolute values of t-statistics are in parentheses under each coefficient estimate. Chi-squared test statistics under the estimated values of θ are likelihood ratio tests for the significance of the negative binomial regression relative to the Poisson model ($\theta = \infty$). $*$ denotes significance at the 1% level. † denotes significance at the 10^{-30}% level.

Table 2: Estimated demand for memory modules and motherboards

		Product		
		Low q	Mid q	High q
	P_{low}	-51.8†	-25.2*	-19.0*
Price	P_{mid}	-1.0	-6.6*	-0.3
	P_{hi}	0.4	-1.5	-8.6*

The table presents estimates of the elasticities of demand for low-, intermediate-, and high-quality memory modules with respect to the prices of the three goods. $*$ denotes significance at the 1% level. $\dagger$ denotes significance at the 10^{-30}% level.

Table 3: Cross-price elasticities for memory modules