Search, Obfuscation, and Price Elasticities on the Internet: Supplementary Material

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October 2007

1 Introduction

This document contains additional material related to our paper "Search, Obfuscation, and Price Elasticities on the Internet."

2 Theory of price search engines

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 creates Bertrand-like competition, then retailers cannot pay the search engine because they are making no profits, and consumers will not pay the search engine because if there is no price dispersion they can just go directly to any retailer. In this section we present a simple model to illustrate the incentives of search engines and retailers and note that it is easy to avoid these paradoxes if the search engine has adequate pricing instruments.

Consider a retail sector consisting of a large number of firms selling a single undifferentiated product. Suppose that the only way that retailers can reach consumers is via a monopoly price search engine. The search engine can monitor sales that are made as a result of its searches and charge retailers a referral fee of r for each sale made. Suppose that the outcome of the price competition game between the listed retailers depends on two parameters: the wholesale price w at which retailers acquire the good and a parameter s that we call the level of "search frictions." Assume that aggregate sales in this equilibrium 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 $\frac{\partial \pi^r}{\partial s} > 0$.[1] Assume that prices converge to marginal cost as s goes to zero so $Q^*(w,0) = D(w)$ and $\pi^r(w,0) = 0$.

Suppose for now that the price search engine can costlessly choose any level of search frictions s. Write c for the cost at which retailers acquire the good that they sell. The

[1] The one condition where one would expect "for small s" 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.

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 eliminate all search frictions (*i.e.,* set set $s=0$). The search engine's problem is then simply the standard monopoly pricing problem,

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

where $p \equiv c+r$. The search engine sets $r = p^m - c$ and gets the full monopoly profit. Retailers earn zero profits. This illustrates our first observation, that search engines would like to reduce frictions.

Our resolution to the search engine revenue paradox is that as long as search engines can charge per sale referral fees, firms pass the referral fees on to consumers and search engines can collect their revenues from retailers.[2] The model does have the Bertrand-paradox problem if retailers have fixed costs. In this case a couple of solutions would be natural: the search engine could make fixed payments to the retailers to cover their fixed costs, or, if that is not feasible, the search engine could choose the minimal level of search frictions that would let the retailers recover their fixed costs.

Now consider a model in which search engines and retailers must make costly investments to increase or decrease search frictions. Search frictions will then typically not be eliminated, and the effect of technological progress on the level of search frictions is indeterminate. This is our second observation. For example, the simplest balance-of-power game would have the search engine choose an investment level x_{se} at cost $g(x_{se};\theta)$ while retailers simultaneously choose x_r at cost $h(x_r;\theta)$, resulting in the level of search frictions being $s_0 - x_{se} + x_r$. The parameter θ indexes the state of technology. Whether increases in θ increase or decrease equilibrium search frictions in a model like this is obviously indeterminate: it depends on whether the technology aids search-improving or search-obfuscating more.

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

A couple variants of the model are worth mentioning. First, suppose the search engine could also charge fixed fees. It would then charge a fixed fee of $\pi^r(s^*) - h(x_r^*; \theta)$ to extract the retailers' profits. As long as the fixed and referral fees were chosen in a stage prior to when the x's were chosen, the determination of equilibrium search frictions would be unchanged—the only difference would be that the retailers' efforts at obfuscation would just help them achieve a zero profit. Second, suppose that there were multiple search engines competing to attract consumers. In a model with differentiation between search engines á là Hotelling, the degree of differentiation determines the utility consumers receive. The search engines will want to provide this utility level in the most efficient way possible. In many models this would give search engines an incentive to reduce search frictions and also lead them to charge lower referral fees than in the monopoly model.

The only full models of price search engines we are aware of are those of Baye and Morgan (2001, 2003). They do not consider the possibility of charging referral fees. They nonetheless avoid the revenue paradox. The key insight is that differences from the Bertrand model that one might think are trivial—the presence of an outside option for retailers and/or positive listing fees—make the standard argument that the Bertrand game has no mixed strategy equilibria inapplicable. It turns out that the model has a symmetric mixed strategy equilibrium in which firms randomize both over whether to list and over the prices to choose if they do. Both retailers and consumers are willing to pay positive fixed fees to the search engine.

3 Pricewatch universe and memory modules

One can actually use Pricewatch to locate a product in one of two ways. One can either type a technical product description, such as "Kingston PC2100 512MB," into a search box, or one can run through a multilayered menu to select one of a number of predefined product categories as discussed on our paper, *e.g.,* clicking on "System Memory" and then on "PC133 128MB SDRAM DIMM." We believe that the latter is much more common.

Two aspects of the time-series of memory prices are important to our paper. The first is that memory prices are quite volatile. Figure 1 graphs site A's prices for low-, medium-, and high-quality 128MB PC100 memory modules along with the lowest price available on

Pricewatch. The volatility is apparent in the lowest price listed on Pricewatch. Prices declined by about 70% over the course of the year, but the decline is far from steady, *e.g.* prices rose by about 50% between late May and early July 2000 and by about 25% in less than two weeks in November 2000. There are many instances of rapid short-term movement. The volatility of memory prices contributes to the turnover in Pricewatch's lists. The second is that our retailer's prices for medium- and high-quality memory tend to stay fixed for longer periods and then to change in discrete jumps. These discontinuities are an important source of information about demand elasticities.

4 Data

Summary statistics for each of the four categories are presented in Table 1. In all four categories the websites we study are consistently near the top of the Pricewatch list: the average prices for the low-quality products they sell are within 10% of the average lowest price. There is more price dispersion in the 256MB categories (part of which is due to a period when only a few firms had access to a low-cost supplier). The fraction of consumers who choose to upgrade to medium- or high-quality is higher in the 256MB categories.

One issue that comes up in interpreting our demand regressions is that the $PLowRank$ variable could proxy for the attractiveness of our firms' medium- and high-quality offerings relative to the offerings of its competitors. We cannot offer a study of this based on a full sample of firms for two reasons: first, there is no natural definition of "medium-quality" or "high-quality" that could be applied across websites to categorize the many diverse offerings; second, even if there were such definitions, we do not have the data. Collecting such data would have been difficult and we did not do it.

We can provide some relevant evidence by comparing our firm's two websites. We construct three daily variables giving the difference in logs between Site B's price for a product and Site A's: $\Delta \log(PLow)$, $\Delta \log(PMid)$, and $\Delta \log(PHi)$. The top part of Table 2 gives summary statistics for these variables from the 128MB PC100 category. The positive means reflect that site B typically has slightly higher prices. Prices usually differ by a few percent. (For low-quality memory, they could only differ by a few percent if they both were to appear on Pricewatch's list.) They are occasionally much farther apart. The bottom panel of the table gives pairwise correlations. The correlations of low-quality price differences with medium- and high-quality differences are 0.48 and 0.30. Correlations with $\Delta \log(1 + PLowRank)$ would be somewhat lower.

A second data issue is that we are aggregating hourly data to produce daily variables. In a nonlinear model this has the potential to cause bias. The one variable in our model for which this is a concern is $PLowRank$.[3] It does change at least once on most days: in the 128MB PC100 data $PLowRank$ only is constant throughout the day on 39% of the website-days. To give more a sense of the magnitude of the within-day variation, we computed the within-day range of $PLowRank$: $\max_h PLowRank_{ht} - \min_h PLowRank_{ht}$. In the 128MB PC100 category the mean range is 1.93. The frequencies of 0, 1, 2, 3, 4, and 5 are 39%, 24%, 14%, 6%, 5%, 2%, and 3%. The range is greater than 6 on 7% of the website-days.

If one knew the parameters of the demand model, then it would be possible to avoid aggregation bias in a daily regression. Suppose $Q = \sum_h Q_h$. If $E(Q_h) = (1 + Rank_h)^\gamma w_h$, then $E(Q) = \sum_h (1 + Rank_h)^\gamma w_h$. The ideal aggregate rank variable $\overline{Rank}$ is that which satisfies

$$E\left(Q(1 + \overline{Rank})^{-\gamma} \left(\sum w_h\right)^{-1}\right) = 1.$$

This gives

$$\log(1 + Rank) = \frac{1}{\gamma} \log\left(\frac{\sum_h (1 + Rank_h)^\gamma w_h}{\sum_h w_h}\right).$$

We computed the aggregate rank variable defined by this expression on our 128MB PC100 data using the estimated γ from our base demand model. The correlation of this variable with the one we use is 0.9946.

5 Demand estimates

In this section we discuss some variants on our demand estimation.

Our standard demand model includes three different variables related to low-quality prices: our firm's price, $\log(PLow)$, the lowest price on Pricewatch in the category, $\log(LowestPrice)$,

[3] The daily $\log(1 + PLowRank)$ variable used in our paper was constructed as the average across hours of $\log(1 + PLowRank_h)$, rather than as the log of one plus the average rank. Our hope was that this might help reduce the aggregation problem because it is a correct solution in a regression of $\log Q$ on $\log(1 + PLowRank)$.

and the rank of our firm on Pricewatch's list, $\log(1 + PLowRank)$. One limitation of our approach is that we have assumed a functional form for the effect of $PLowRank$. One could worry that this restriction misses important details or that it is driven by ranks that are outliers. For instance, Baye, Gatti, Kattuman and Morgan (2006) emphasize that the firm on the top of Kelkoo's lists receives many more clicks than the second-highest firm.

As one alternate approach, we estimate a model that is more flexible than our base model, but not so flexible as to make the estimates highly noisy. Specifically, we assumed that the demand function was rank-independent when a firm was not on the first page of Pricewatch's list and that when a firm was on the first page the relationship between $X\beta$ and $PLowRank$ was continuous and piecewise linear in $PLowRank$. We allowed the slopes to change at ranks of 2, 4, 6, and 12. (Note that this makes the estimation of demand when the firm is in the top position fully flexible.)

Coefficient estimates from this model are given in Table 3. Eleven of the twelve estimated slope coefficients are negative. Two of the estimates are very highly significant. Three others have t-statistics around 2.0. Figure 2 plots the fitted values from these estimates against our assumed parametric form.[4] The bold lines in the figure is our base model. The narrower lines are from the piecewise linear model. In general, the two sets of fitted values look similar. There is no evidence that are results are driven by outliers at the top rank.[5]

A second way to approach this issue is to estimate a more flexible functional form, even though we do not have enough data to get any precise estimates this way. To do this, we estimated a demand model on the 128MB PC100 data that is like our main specification but with twelve rank dummies instead of the $\log(1 + PLowRank)$ variable.[6] The top panel of Figure 3 plots the predicted low-quality demand levels in our model $(1 + PLowRank)^{\hat{\gamma}}$. Superimposed on the plot are the predicted values obtained from the model with rank

[4]The graph plots fitted values of $X\hat{\beta}$ with all dummy variables set equal to zero and other variables (apart from $PLowRank$) set to their sample means.

[5]The one apparent departure is that high quality sales appear to be greater than our base model indicates at ranks 6-12. The standard error on the coefficient estimate driving this result, however, is sufficiently large so that we could not reject the hypothesis that piecewise linear slope coefficient takes on the value that would make the two curves nearly coincide.

[6]The $RankX$ dummy is a dummy for observations with $\log(1+PLowRank)$ being between $\log(1+(X-\frac{1}{2}))$ and $\log(1 + (X + \frac{1}{2}))$ to accomodate the within-day rank changes.

dummies with two-standard-error bars.[7] The rank-dummy estimates are generally similar to our assumed functional form. Our base model lies within the standard error bars in all cases. The tendency of the flexible model to predict slightly higher sales at the low ranks appears to be a little more pronounced in this model. Again, there is no evidence of a jump in sales when moving to the top of the list, which one might have guessed would exist given Baye *et al.*'s (2006) results.

Our standard demand specification is not a constant elasticity specification. Table 3 in our main paper reports estimated elastiticities that apply when variables are set to their sample means. Elasticities with respect to changes in the low-quality price will differ at different prices both because of the assumed functional form for the effect of $PLowRank$ and because one would want to use a different value for $\frac{\partial PLowRank}{\partial PLow}$ to account for differences in density of the price distribution. The top half of Table 4 illustrates how the elasticities change with prices in our standard 128MB PC100 model. The left matrix assumes a rank of 2.5, the center matrix assumes a rank of 6 and the right matrix assumes a rank of 9.[8] Note that the estimated elasticities with respect to the low-quality price are much larger when a website is close to the top of the Pricewatch list. This is due both to the assumed functional form for demand and to prices being closer together at the top of the list than they are further down on the list. This pattern of elasticities is consistent with optimal pricing intuition: the inverse-elasticity pricing rule implies that firms with similar costs can only be indifferent to a range of positions on the list if demand elasticities are lower at the higher price levels.

The bottom half of the table presents corresponding estimates derived from our piecewise linear estimates.[9] The flexibly estimated elasticity matrices at the three ranks are

[7] The omitted category in the rank-dummies model is all ranks above 13. The predicted values again correspond to setting all continuous variables equal to their sample means and all other dummy variables equal to zero.

[8] The table in our main paper is quite close to the center matrix because it corresponds to an assumed rank of 5.4. For the first matrix $\frac{\partial PLowRank}{\partial PLow}$ was set to the three times the inverse of the average difference between the first and fourth-lowest prices, and prices and ranks were set to the means from the subset of observations when a site's rank was in this range. The second matrix uses 11 times the inverse of the average difference betweeen the lowest and 12^{th}-lowest price and full sample means (as does the matrix in our main paper). The third is based in differences between the seventh- and eleventh-lowest prices and means from observations with ranks in this range.

[9] The low-price elasiticities in the left and right matrix are derived using the $PLowRank$ (2-4) and $PLowRank$ (6-12) coefficients, respectively. Our piecewise linear specification has a kink at a rank of six,

remarkably close to the estimates from our standard model. Our model appears to be adequate to capture the main features of the demand-rank relationship.

6 Instrumental variable estimates

Our paper presents IV estimates using two sets of instruments, "cost-based" and "other-speed" instrument sets. In this section, we provide some information on the power of the instruments.

Table 5 presents regressions of $\log(PLow)$, $\log(PMid)$, and $\log(PHi)$ on the exogenous variables in our demand model and the cost-based instruments, in other words, the first stage regressions. The cost for the low and high quality modules is highly significant for the corresponding price in the regressions, and the $\mathcal{F}$-tests for the joint significance of the instruments are significant. The mid-quality cost is not significant in the mid-quality regression. In this regard, the the power of the cost-based instruments is less than what one would like.

Table 6 presents the analogous first stage regressions for the other-speed instruments. Note that we can and do instrument for $\log(1 + PLowRank)$ with these instruments, so we present four first stage regressions. This time, the coefficients on all of the instruments have very high t-statistics in the relevant regressions. The instruments, however, only capture a portion of the variation in $PLowRank$ and this will reduce the precision of our estimates of the effects of a site's low-quality rank on its sales.

so we have chosen to use the average of the $PLowRank$ (4-6) and $PLowRank$ (6-12) coefficients when calculating the slope of the demand-rank curve at six.

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Baye, Michael R., J. Rupert J. Gatti, Paul Kattuman, and John Morgan (2006): "Clicks, Discontinuities, and Firm Demand Online," mimeo.

Ellison, Glenn and Sara Fisher Ellison (2007): "Search, Obfuscation, and Price Elasticities on the Internet," mimeo.

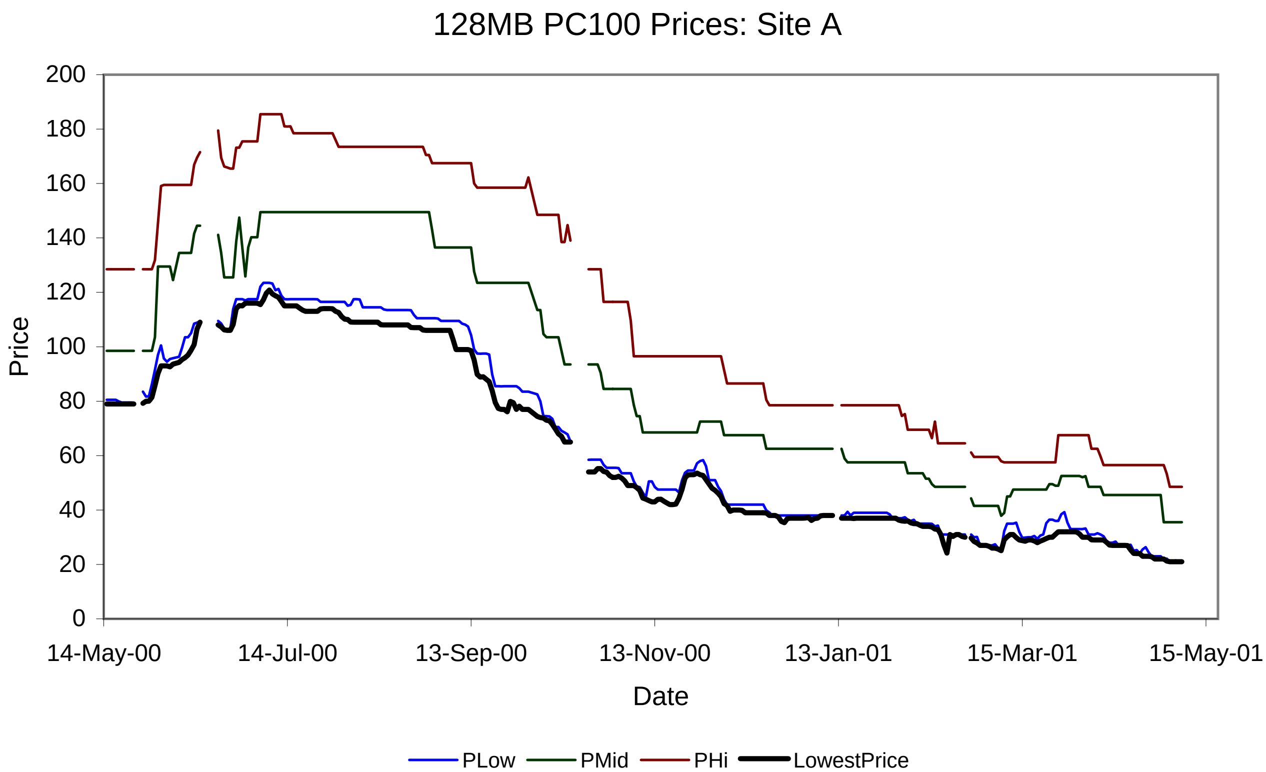
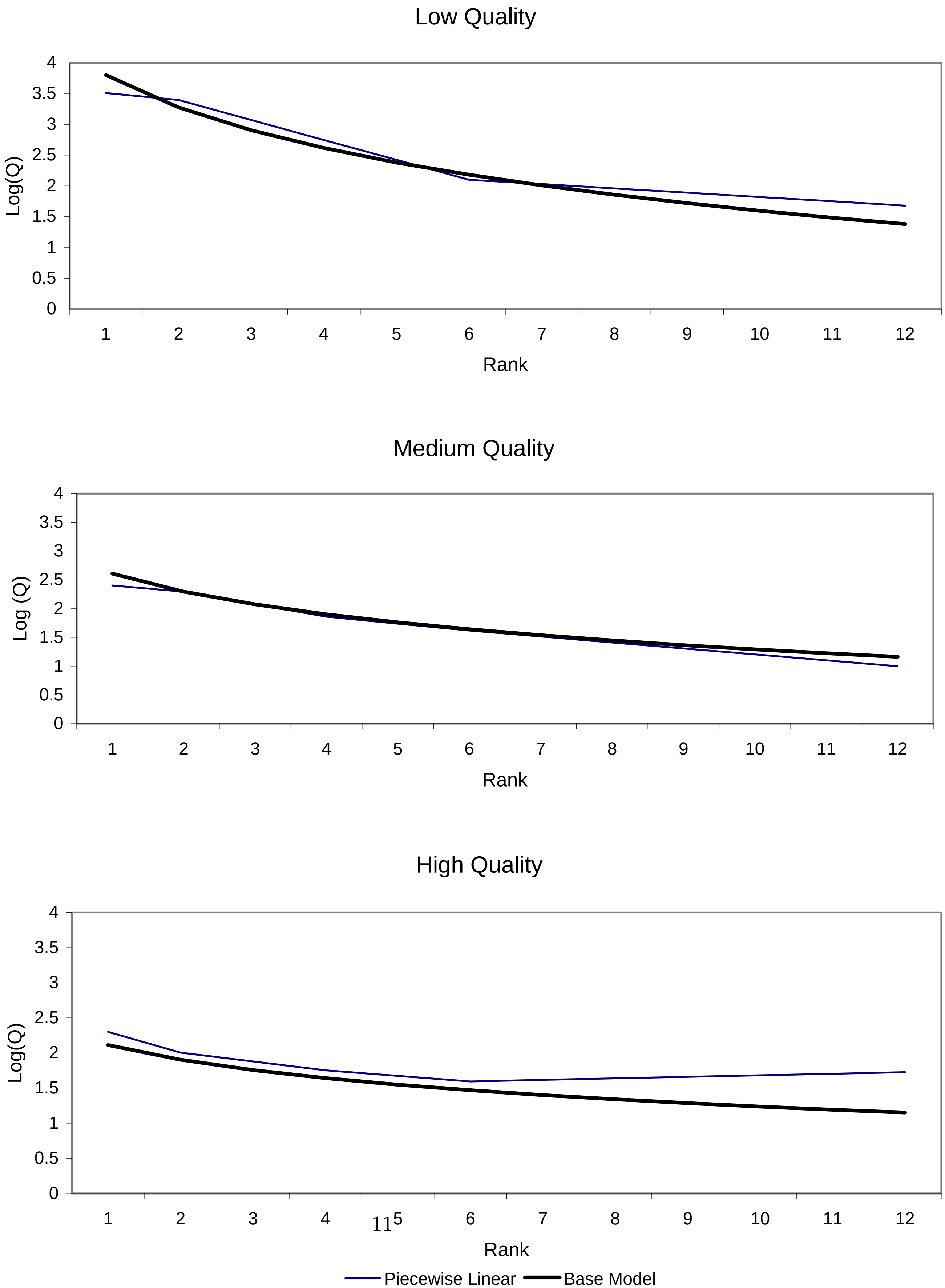


Figure 1: Prices for 128MB PC100 memory modules: the lowest price on Pricewatch and website A's low-, medium- and high-quality prices


Low Quality
Log(Q)
Rank
Medium Quality
Log (Q)
Rank
High Quality
Log(Q)
Rank
Piecewise Linear
Base Model

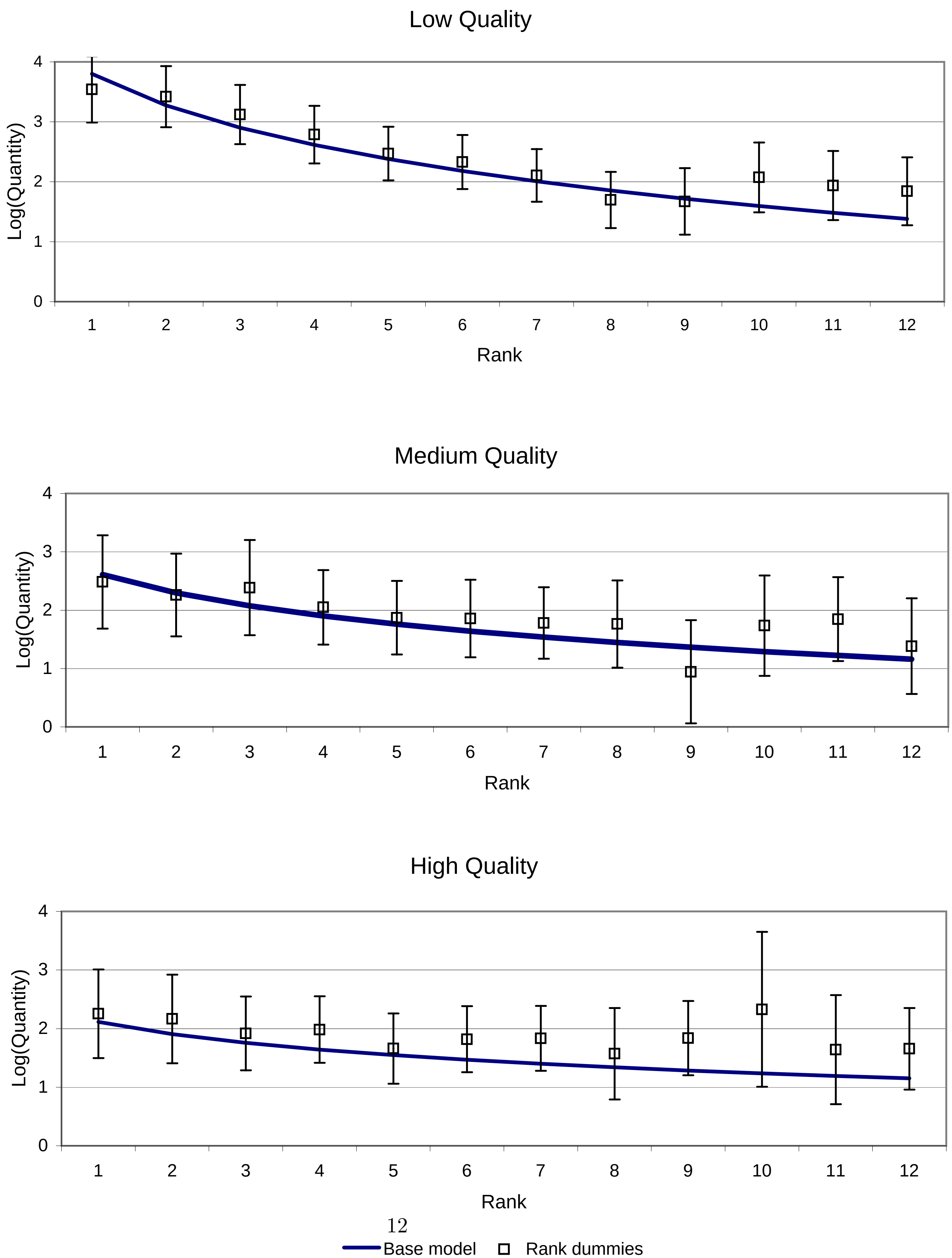


Figure 3: Functional forms for demand: standard model vs. flexible rank-by-rank estimates

Variable	Mean	Stdev	Min	Max
128MB PC100 Memory Modules 683 website-day observations				
$LowestPrice$	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
128MB PC133 Memory Modules 608 website-day observations				
$LowestPrice$	71.02	37.02	21.00	131.00
$Range$1-12	5.92	2.74	2.00	15.00
$PLow$	73.65	36.72	21.00	131.49
$PMid$	98.70	41.78	35.45	154.00
PHi	123.46	47.56	48.50	189.50
$\log(1 + PLowRank)$	1.77	0.64	0.69	3.40
$QLow$	10.10	12.11	0	99
$QMid$	2.15	4.91	0	100
QHi	4.79	3.93	0	35
256MB PC100 Memory Modules 575 website-day observations				
$LowestPrice$	130.30	58.17	32.46	215.00
$Range$1-12	28.95	15.78	6.39	75.80
$PLow$	143.40	67.19	47.67	283.49
$PMid$	206.36	85.91	77.49	372.89
PHi	250.13	93.13	98.50	417.18
$\log(1 + PLowRank)$	1.90	0.55	0.69	2.91
$QLow$	2.87	4.61	0	33
$QMid$	1.00	1.88	0	18
QHi	0.87	1.63	0	16
256MB PC133 Memory Modules 575 website-day observations				
$LowestPrice$	143.90	71.97	32.46	269.00
$Range$1-12	25.49	14.01	6.60	67.00
$PLow$	156.08	78.22	43.00	291.45
$PMid$	213.16	91.89	78.49	345.45
PHi	249.95	92.26	104.37	392.21
$\log(1 + PLowRank)$	1.97	0.49	0.69	2.73
$QLow$	5.29	10.24	0	136
$QMid$	1.10	1.93	0	12
QHi	3.61	3.86	0	19

Table 1: Summary statistics for memory module data

128 MB PC100 memory modules: Differences between Site B and Site A prices				
Variable	Mean	Stdev	Min	Max
$\Delta \log(PLow)$	0.034	0.045	-0.058	0.244
$\Delta \log(PMid)$	0.015	0.043	-0.099	0.208
$\Delta \log(PHi)$	0.024	0.041	-0.098	0.288

Correlations

	$\Delta \log(PLow)$	$\Delta \log(PMid)$	$\Delta \log(PHi)$
$\Delta \log(PLow)$	1.00		
$\Delta \log(PMid)$	0.48	1.00	
$\Delta \log(PHi)$	0.30	0.26	1.00

Table 2: Price differences between Site A and Site B: summary statistics and correlations across qualities

Independent Variables	Dep. var.: quantities of each quality level		
	Low q	Mid q	High q
$PLowRank$ (1-2)	-0.11	-0.11	-0.30
	(1.0)	(0.5)	(1.2)
$PLowRank$ (2-4)	-0.32*	-0.22*	-0.13
	(6.2)	(2.4)	(1.0)
$PLowRank$ (4-6)	-0.32*	-0.12	-0.08
	(5.8)	(1.5)	(1.1)
$PLowRank$ (6-12)	-0.07*	-0.10	0.02
	(2.0)	(1.8)	(0.4)
Dum$PLowRank$ >12	-0.65*	0.14	-0.61
	(3.0)	(0.4)	(1.8)
$\log(PLow)$	-3.29*	1.02	1.00
	(2.4)	(0.6)	(0.5)
$\log(PMid)$	0.33	-6.80*	2.21
	(0.4)	(5.8)	(1.6)
$\log(PHi)$	0.38	2.58	-4.29*
	(0.4)	(1.7)	(3.0)
$SiteB$	-0.25*	-0.30*	-0.64*
	(3.2)	(2.8)	(6.2)
$Weekend$	-0.48*	-0.94*	-0.72*
	(8.4)	(8.3)	(5.8)
$\log(LowestPrice)$	1.20	0.53	0.00
	(1.0)	(0.3)	(0.0)
Number of Obs.	683	683	683

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

Table 3: Piecewise linear demand model for 128MB PC100 memory modules

Standard Demand Model

	$PLowRank = 2.5$		
	Low	Mid	Hi
$PLow$	-58.0	-32.3	-20.4
$PMid$	0.7	-6.7	2.4
PHi	0.2	2.7	-4.8

	Mean $PLowRank$		
	Low	Mid	Hi
$PLow$	-23.1	-11.4	-6.5
$PMid$	0.7	-6.7	2.4
PHi	0.2	2.7	-4.8

	$PLowRank = 9$		
	Low	Mid	Hi
$PLow$	-16.7	-7.6	-4.0
$PMid$	0.7	-6.7	2.4
PHi	0.2	2.7	-4.8

Piecewise Linear Demand Model

	$PLowRank = 2.5$		
	Low	Mid	Hi
$PLow$	-51.6	-31.3	-17.8
$PMid$	0.3	-6.8	2.2
PHi	0.4	2.6	-4.3

	Mean $PLowRank$		
	Low	Mid	Hi
$PLow$	-24.7	-11.2	-2.1
$PMid$	0.3	-6.8	2.2
PHi	0.4	2.6	-4.3

	$PLowRank = 9$		
	Low	Mid	Hi
$PLow$	-10.7	-9.9	3.3
$PMid$	0.3	-6.8	2.2
PHi	0.4	2.6	-4.3

Table 4: Price elasticities at different price levels: the standard model and a piecewise linear model

Independent Variables	Dependent Variable: log($PLow$)	log($PMid$)	log(PHi)
log($CostLow$)	0.14	-0.02	-0.08
	(4.7)	(0.4)	(2.5)
log($CostMid$)	0.01	0.02	0.02
	(0.3)	(0.8)	(0.9)
log($CostHi$)	0.05	0.11	0.35
	(2.0)	(3.2)	(11.7)
log($LowestPrice$)	0.45	0.21	0.14
	(12.1)	(4.0)	(3.4)
log($1 + PLowRank$)	0.06	0.02	0.01
	(22.4)	(6.5)	(4.6)
$SiteB$	0.002	0.000	0.01
	(0.7)	(0.0)	(2.6)
$Weekend$	0.004	0.003	0.001
	(1.9)	(1.3)	(0.5)
Number of Obs.	683	683	683
R-squared	0.997	0.994	0.996

Absolute value of t-statistics in parentheses. Regressions also include time-trends with slopes changing every 30 days.

Table 5: First stage regressions: Cost-based instruments

Independent Variables	Dependent Variable: $\log(PLow_{100})$	$\log(PMid_{100})$	$\log(PHi_{100})$	$\log(1{+}PLowRank_{100})$
$\log(PLow_{133})$	0.72	0.02	0.04	3.16
	(23.3)	(0.4)	(0.9)	(6.7)
$\log(PMid_{133})$	-0.00	0.56	0.15	0.41
	(0.0)	(15.4)	(4.2)	(1.0)
$\log(PHi_{133})$	0.05	0.31	0.49	0.87
	(1.7)	(7.2)	(11.7)	(1.8)
$\log(1 + PLowRank_{133})$	0.004	0.001	0.002	0.29
	(1.7)	(0.4)	(0.6)	(7.9)
$\log(LowestPrice)$	0.17	0.04	0.06	-1.63
	(5.9)	(0.9)	(1.7)	(3.7)
$SiteB$	0.006	-0.001	0.01	0.29
	(2.4)	(0.3)	(3.4)	(5.5)
$Weekend$	0.003	0.001	0.001	0.002
	(2.3)	(0.6)	(0.4)	(0.1)
Number of Obs.	608	608	608	608
R-squared	0.999	0.997	0.997	0.543

Absolute value of t-statistics in parentheses. Regressions also include time-trends with slopes changing every 30 days.

Table 6: First stage regressions: Other-speed instruments