

# Consumer Search

Glenn Ellison

# Sorensen: “Price Dispersion in Retail Markets for Prescription Drugs,” *JPE* 2000

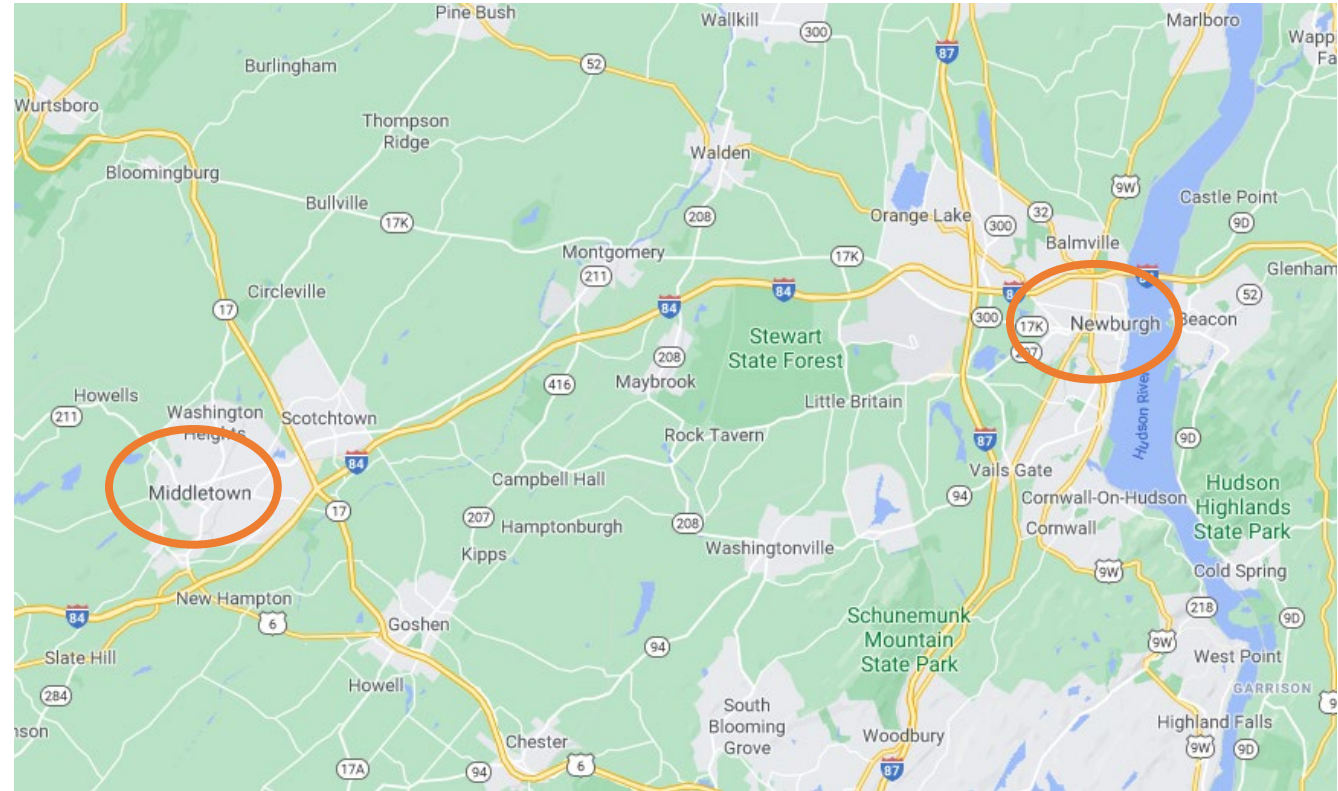
Wanted to examine price dispersion where perfect competition might be expected.

Retail prescription drugs were attractive for several reasons:

- Simple identical products fit Bertrand. (Insurance was uncommon.)
- Large number of drugs gives degrees of freedom.

He focused on two mid-sized towns in New York, Middletown and Newburgh.

- The cities can be treated as well-defined markets.
- A New York regulation facilitated collecting prices.



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This was part of Alan's thesis. The towns are not far from I-84. He drove there and collected data by hand.

# “Price Dispersion in Retail Markets,” Sorensen

Motivations for the study design include:

- The prescription drugs themselves are identical across pharmacies.
- We can identify all stores in each market.
- New York required that pharmacies display a poster with prices for 200+ prescription drugs.
- Cross-drug analyses can examine how dispersion relates to drug characteristics.
- Pharmacy amenities are plausibly common across drugs.

DRUG	QUANTITY	PRICE	DRUG	QUANTITY	PRICE
ACCUPRIL 10 MG TABS	30		BUTALB/ACETAMIN/CAF	30	
ACCUPRIL 20 MG TABS	30		CEFADROXIL 500 MG	20	
ACETAM.COD.#3 TABS	20		CELEBREX 200 MG	30	
ACIPHEX 20 MG	30		CEPHALEXIN 250 MG	28	
ADDERALL XR 20 MG	30		CEPHALEXIN 500 MG	8	
ADVAIR 250/50	60		CELEXA 20 MG	30	
ALTACE 5.0 MG	30		CELEXA 40 MG	30	
ALBUTEROL 0.083%	75		CHLORHEXIDINE 0.12%	473	
ALLEGRA – D	60		CILOXAN 0.3% OPH SOLUTION	5	
ALLEGRA TABS 60 MG	60		CIPRO HC OTIC	10	
ALLEGRA 180 MG TAB	30		CIPRO 250 MG	20	
ALBUTEROL INHALER	17		CIPRO 500 MG	20	
ALPRAZOLAM 0.5 MG	30		CLARINEX 5 MG	30	
ALLOPURINOL 300 MG	30		CLINDAMYCIN 150 MG	30	
ALTACE 2.5 MG	30		CLONAZEPAM 0.5 MG	60	
AMOXICILLIN CHEW 400	20		CLONAZEPAM 1 MG	60	
AMOXICILLIN 500 MG CAPSULE	30		COMBIVENT AEROSOL	14.7	
AMOXICILLIN 250/5ML	150		COUMADIN 5 MG TABLETS	30	
AMBIEN 5 MG	30		COZAAR 50 MG	30	
AMBIEN 10 MG	30		COLCHICINE 0.6 (WW)	60	
AMOXIL 250 MG CAP	30		CONCERTA 18 MG	30	
AMOXIL 875 MG TABS	20		CONCERTA 36 MG	30	
AMOXIL SUSP 400 MG/5ML	100		CYCLOBENZAPRINE 10 MG	30	
ATENOLOL 50 MG	30		DEXAMETHASONE 4 MG	21	
ATENOLOL 25 MG	30		DEXEDRINE 10 MG SPANSULE	30	
AUGMENTIN 500 MG TABS	20		DEPAKOTE 250 MG	60	
AUGMENTIN 875 MG TABS	20		DEPAKOTE 500 MG	90	
AUGMENTIN 400 MG/ 5ML	100		DIAZEPAM 5 MG	90	
AUGMENTIN ES 600 MG/5ML	125		DIAZEPAM 10 MG	90	
AVELOX 400 MG	10		DIFLUCAN 150 MG	1	
BENZAFLIN GEL	25		DOXYCYCLINE 100 MG CAPSULE	20	
BIAXIN 500 MG	20		DURICEF 250/5 ML	100	
BIAXIN XL 500 MG	20		ENALAPRIL 10 MG	30	

Can treat each drug as a separate market, since no cross elasticity.

# “Price Dispersion in Retail Markets,” Sorensen

## Results:

1. There is substantial price dispersion. The difference between the highest and lowest price for a drug across the drugstores in each town is about \$13 for the average drug. The range is \$5 for the 10<sup>th</sup> percentile drug and \$25 for the 95<sup>th</sup> percentile drug. (The towns have about ten drugstores each.)

# “Price Dispersion in Retail Markets,” Sorensen

Results:

2. Price dispersion does not appear to be due to pharmacy amenities:

- Most pharmacies are in the top third for many drugs and in the bottom third for many others.
- Pharmacy fixed effects explain about one-third of the residual variance in a model with drug and city fixed effects.
- Pharmacy fixed effects do not align with a casual assessment of pharmacy amenities.

TABLE 1  
PRICE RANKINGS BY PHARMACY  
A. MIDDLETOWN

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

B. NEWBURGH

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

NOTE.—Groupings are based on price orderings across stores in each city. Only prescriptions for which prices were posted at all stores are included.



# “Price Dispersion in Retail Markets,” Sorensen

Results:

2. Price dispersion does not appear to be due to pharmacy amenities:

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- Pharmacy fixed effects do not align with a casual assessment of pharmacy amenities.

Alan-assessed

TABLE 4  
EXPLAINING PRICE VARIATION WITH PHARMACY FIXED EFFECTS

REGRESSOR	$\bar{R}^2$ (1)	$\epsilon$	
		Mean (2)	Standard Deviation (3)
Drug effects	.907	3.47	3.78
Drug and pharmacy effects	.938	2.74	3.13
Drug and pharmacy effects, with drug type interactions	.942	2.51	2.86

NOTE.—Based on regressions with price as the dependent variable. Each regression also includes a city dummy and a generic dummy. The means and standard deviations pertain to the absolute magnitudes of the regression residuals. The  $F$ -statistic testing the hypothesis that the pharmacy effects are all jointly zero in the second regression is 112.31 ( $p = .000$ ); the  $F$ -statistic for the interaction terms in the third regression is 1.535 ( $p = .000$ ).

# “Price Dispersion in Retail Markets,” Sorensen

4. The magnitude of the price dispersion for a drug is related to a measure of search costs: drugs that tend to be purchased multiple times, e.g. anti-hypertensives, have lower dispersion than single-use drugs, e.g. antibiotics.

Consumers can amortize their search costs over multiple purchases.

measured four ways

$$\text{RANGE}_{ij} = \beta_0 + \beta_1 \text{PFREQ}_i + \beta_2 \text{AWP}_i + \beta_3 \text{BR1}_i + \beta_4 \text{BR2}_i + \beta_5 \text{NEWB}_i + \sum_{k=6}^{25} \beta_k D_{ik} + \epsilon_{ij}$$

5. Average markups are also lower for frequently purchased drugs.
6. Drugs with unexpectedly high average markups have unexpectedly high dispersion.

TABLE 2  
PRICE DISPERSION AND PURCHASE FREQUENCY

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

NOTE.—GLS estimates allowing for correlation in the error terms across cities for each prescription ( $\hat{\rho}$  is the estimated correlation); standard errors are in parentheses. The number of observations is 428. The residual range (standard deviation) is the range (standard deviation) of the residuals from a regression of price on drug and pharmacy fixed effects, as described in the text. Estimated coefficients for a set of 20 drug class dummies are suppressed; a table listing the full set of coefficients is available from the author on request.

# Stango and Zinman, “... Price Dispersion and Shopping Behavior in the US Credit Card Market,” *RFS* 2016

Stango and Zinman are motivated more by their application.

Most Americans have some credit card debt. Many make large interest payments. Ausubel (*AER* 1991) noted that rates seem high despite large number of competing firms. Reported rates are fairly uniform across banks and insensitive to changes in interest rate.

Stango and Zinman get individual-level data from a panel of 4,312 consumers for 2006-2008. The data include transaction level activity, interest and fees paid, and consumer credit scores.

- There is tremendous raw heterogeneity in interest rates across consumers. The interquartile range in rates paid is 800 basis points. (This omits anyone on teaser rates and those who pay in full.)
- Default risk explains about 40% of the interest-rate variation. Other factors, e.g. offsetting rewards, demographics, explain little.
- There is substantial within-consumer variance in offers received. This could lead to substantial dispersion in rates paid, especially if search effort is heterogeneous.



# Stango and Zinman, “... Price Dispersion and Shopping Behavior in the US Credit Card Market,” *RFS* 2016

Table 1  
Cardholder-level summary statistics

	Revolving balance quartile				
	1	2	3	4	All
Quartiles [revolving balances, \$]	[0, 499]	[499, 1534]	[1534, 4586]	[4586, 62515]	[0, 62515]
Cards held	2.02	1.92	2.24	2.94	2.28
Average purchases per month, \$	730	393	499	740	591
Average revolving balances, \$	31	570	2199	11223	3505
Annualized interest costs, \$	6	113	412	1998	632
Interest costs/total borrowing costs	0.48	0.66	0.81	0.92	0.75
Annualized interest costs/annual income	0.00	0.00	0.01	0.03	0.01
Credit score	737	643	669	697	687
Income:					
Under \$45k	0.42	0.40	0.33	0.26	0.36
\$45k–\$125k	0.51	0.54	0.57	0.63	0.56
\$125k+	0.07	0.06	0.10	0.11	0.08
Education:					
HS or less	0.08	0.12	0.10	0.08	0.10
Some college	0.23	0.34	0.31	0.28	0.29
College degree +	0.69	0.53	0.59	0.64	0.61
Age:					
Under 30	0.27	0.27	0.26	0.21	0.25
30–49	0.46	0.49	0.50	0.54	0.49
50+	0.27	0.24	0.24	0.26	0.24
Cardholders	1,078	1,078	1,078	1,078	4,312
Accounts	2,079	1,987	2,247	2,994	9,307
Cardholder-months	18,561	19,761	21,030	21,960	81,312
Account-months	29,438	29,681	35,117	47,851	142,087

There is a lot of heterogeneity in credit card use.

Many people make large interest payments.

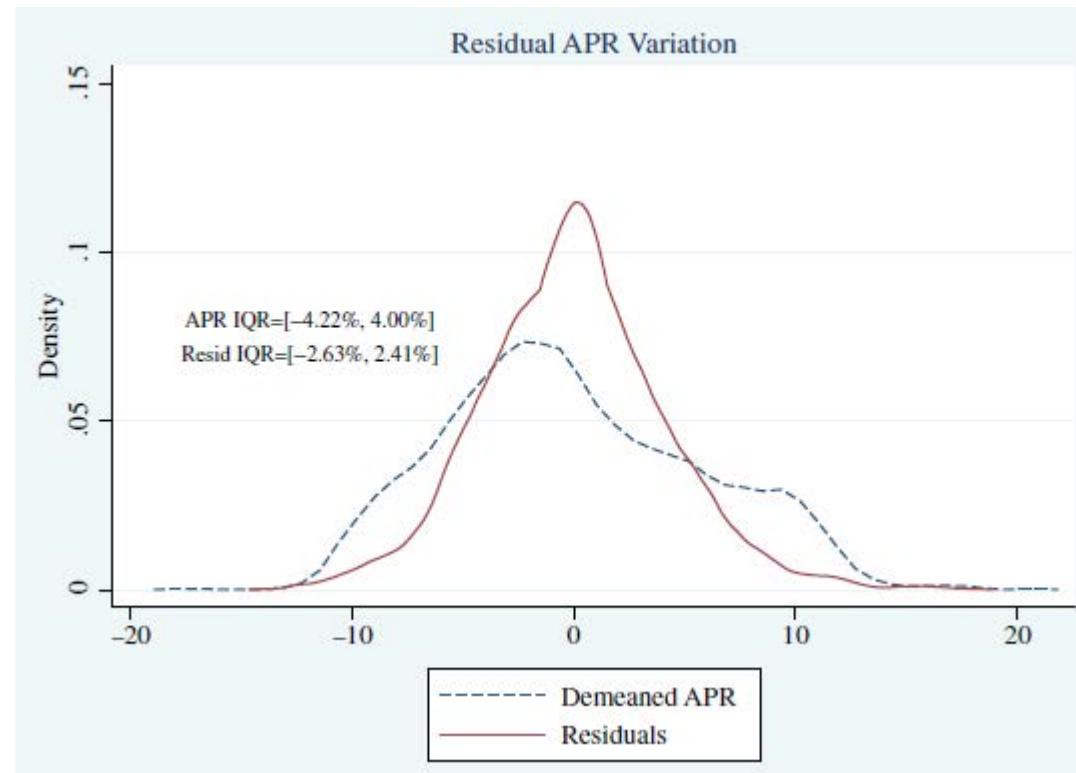
# Stango and Zinman, “... Price Dispersion and Shopping Behavior in the US Credit Card Market,” *RFS* 2016

**Table 2**  
Borrowing costs in the cross-section of cardholders

	Revolving balance quartile				Total
	1	2	3	4	
Quartile cutoffs (revolving balances)	[0, 499]	[499, 1534]	[1534, 4586]	[4586, 62515]	[0, 62515]
Cardholder-level weighted actual APR, all balances, all panelists ( $N = 4312$ )					
10th	0.00	3.04	6.38	8.80	0.00
25th	0.00	8.21	11.21	11.91	3.45
50th	0.00	15.96	16.18	16.13	13.17
75th	1.08	21.11	21.68	20.77	19.53
90th	7.57	25.14	25.90	25.42	24.38
Cardholder-level weighted actual APR, revolving balances, no teaser rates ( $N = 3629$ )					
10th	12.24	12.90	11.90	11.51	11.96
25th	14.99	15.74	15.24	14.01	14.99
50th	17.80	19.46	18.90	17.78	18.36
75th	21.07	24.03	23.78	22.31	23.21
90th	26.32	28.29	28.15	26.83	27.84
Cardholder-level weighted “best” APR, revolving balances, no teaser rates ( $N = 3629$ )					
10th	9.90	10.89	9.87	9.17	9.90
25th	13.38	14.66	13.50	12.12	13.42
50th	16.99	18.66	17.97	16.55	17.59
75th	19.80	23.53	23.04	21.17	22.49
90th	24.24	28.09	27.85	26.02	27.19
<i>R</i> -sq.: Monthly borrowing costs on panelist FEs	0.78	0.76	0.78	0.76	0.77

There is a lot of heterogeneity in interest rates,

# Stango and Zinman, "... Price Dispersion and Shopping Behavior in the US Credit Card Market," *RFS* 2016



Differences in credit scores and other observables account for less than half of the observed variation.

# Stango and Zinman, "... Price Dispersion and Shopping Behavior in the US Credit Card Market," *RFS* 2016

	Dependent variable: Weighted best APR (mean = 16.35)	
	OLS	IV
Coefficient: Self-reported search intensity (10-point scale)	-0.083 (0.078)	-1.146** (0.490)
<i>N</i>	497	476
<i>R</i> -squared	0.59	0.42

Regressions have many unreported RHS variables.

The OLS-IV gap seems large.

They also try to directly tie dispersion to search intensity.

The data also include a survey question asking consumers about how likely they are to look at credit card offers they receive in the mail.

In an IV regression (using gender and marital status as instruments for search intensity) they find that self-reported search intensity is a strong predictor of the lowest APR a consumer could pay given the cards they hold.



## Ellison and Ellison: “Search, Obfuscation, and Price Elasticities on the Internet,” *Econometrica* 2009

How will search costs change in the Internet era? What effects might this have on retail and other markets?

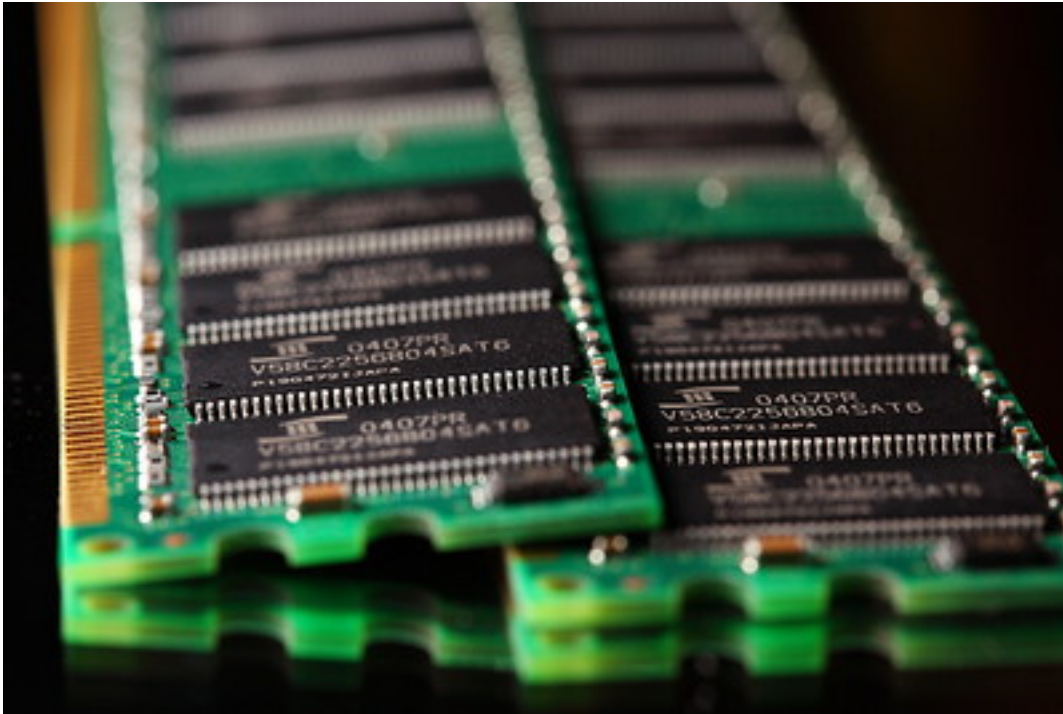
Price search engines have taken hold in a few markets, e.g. flights, hotels, rental cars. If search becomes very efficient and prices drop toward marginal cost, it is unclear how firms in many markets would cover their fixed costs.

To explore these issues, we examine an unusual corner of the Internet where an early price search engine achieved a dominant position.

# The Pricewatch Universe

Pricewatch was a simple database-based search engine that became popular among hobbyists and IT professionals interested in purchasing computers and computer parts.

← This is what we studied.



Courtesy of [Jonathan Cohen](#) on flickr. License: CC-BY-NC.

# The Pricewatch Universe

**PRICEWATCH**® est. 1995  
*Who has the lowest price?*

Search

My Saved Ads

## Technology

### Computers

PC - With OS  
PC - No OS  
PC - Barebones  
Servers

### Motherboards & CPUs

CPUs  
Motherboards  
Mother/CPU Combos  
Mother Combos w/Mem

Video Cards  
Sound Cards  
Controller

### Cases, P.S., Cooling

Cases and  
Racks  
Power Supply  
Fans / Cooling

### Cameras

Cameras  
WebCams  
Surveillance  
Binoculars

### Audio

MP3 players  
Audio  
Equipment

### Notebooks

Notebooks  
Accessories

### Storage

DVD and CD Drives  
Hard Drives  
Tape Drives

### Input / Output

Barcode  
Keyboards  
Mice  
Monitors  
Projectors  
Printers  
Scanners  
WebCams

### Software

Business  
Operating  
System / IT  
Security  
Other

### Video

TV  
Camcorders  
DVD Players  
DVD Burners  
Projectors  
Video  
Accessories

### Other

Point Of Sale /  
RFID  
Backup  
Supplies  
Cables  
Game  
Hardware  
GPS

# The Pricewatch Universe

**PRICEWATCH**® est. 1995  
Who has the lowest price?

Home > System Memory

All  System Memory

## Pricewatch Categories

- MBoard / CPUs**
  - Motherboards
  - CPUs
  - CPU Combos
  - Combos w/Mem
- Cards**
  - Video Cards
  - Sound Cards
  - Controller
- Cases, Cooling**
  - Cases, Racks
  - Power Supply
  - Fans / Cooling
- Storage**
  - DVD / CD Drives
  - Hard Drives
  - Tape Drives
- Memory**
  - RAM
  - Flash
- Networking**
  - Networking

## System Memory (Prices incl. shipping)

DDR		Notebook Memory DDR2
\$ 13.49	- ddr2-667 pc2-5300 1gb kit	\$ 32.99 - so-dimm ddr2 pc2-6400 2gb
\$ 80.00	- ddr pc4000 512mb	\$ 17.99 - so-dimm ddr2 pc2-6400 1gb
\$ 60.00	- ddr pc3500 512mb	\$ 26.99 - so-dimm ddr2 pc2-6400 1gb kit
\$ 68.92	- ddr pc3200 4gb	\$ 18.99 - so-dimm ddr2 pc2-6400 512mb
\$ 64.00	- ddr pc3200 2gb	\$ 176.98 - so-dimm ddr2 pc2-5300 4gb
\$ 33.70	- ddr pc3200 2gb kit	\$ 58.99 - so-dimm ddr2 pc2-5300 4gb kit
\$ 30.00	- ddr pc3200 1gb registered	\$ 29.46 - so-dimm ddr2 pc2-5300 2gb
\$ 16.98	- ddr pc3200 1gb	\$ 16.00 - so-dimm ddr2 pc2-5300 1gb
\$ 10.98	- ddr pc3200 512mb	\$ 9.22 - so-dimm ddr2 pc2-5300 512mb
\$ 7.75	- ddr pc3200 256mb	\$ 8.50 - so-dimm ddr2 pc2-5300 256mb
\$ 68.92	- ddr pc2700 4gb	\$ 29.50 - so-dimm ddr2 pc2-4200 2gb
\$ 33.74	- ddr pc2700 2gb	\$ 16.00 - so-dimm ddr2 pc2-4200 1gb
\$ 16.98	- ddr pc2700 1gb	\$ 9.22 - so-dimm ddr2 pc2-4200 512mb
\$ 10.98	- ddr pc2700 512mb	\$ 8.00 - so-dimm ddr2 pc2-4200 256mb
\$ 7.75	- ddr pc2700 256mb	\$ 69.00 - so-dimm ddr2 pc2-3200 2gb
\$ 68.92	- ddr pc2100 4gb	\$ 23.95 - so-dimm ddr2 pc2-3200 1gb
\$ 33.76	- ddr pc2100 2gb	\$ 12.94 - so-dimm ddr2 pc2-3200 512mb
\$ 16.98	- ddr pc2100 1gb	\$ 6.24 - ddr2
\$ 13.49	- ddr2-667 pc2-5300 1gb kit	
\$ 6.75	- ddr2-667 pc2-5300 512mb	
\$ 104.99	- ddr2-533 pc2-4200 8gb	
\$ 47.74	- ddr2-533 pc2-4200 4gb	
\$ 20.12	- ddr2-533 pc2-4200 2gb	
\$ 24.29	- ddr2-533 pc2-4200 2gb kit	
\$ 12.43	- ddr2-533 pc2-4200 1gb	
\$ 12.49	- ddr2-533 pc2-4200 1gb kit	
\$ 6.24	- ddr2-533 pc2-4200 512mb	
\$ 1250.00	- ddr2-400 pc2-3200 8gb	
\$ 179.99	- ddr2-400 pc2-3200 4gb	
\$ 72.99	- ddr2-400 pc2-3200 4gb kit	
\$ 39.99	- ddr2-400 pc2-3200 2gb	
\$ 36.99	- ddr2-400 pc2-3200 2gb kit	
\$ 17.59	- ddr2-400 pc2-3200 1gb	
\$ 28.99	- ddr2-400 pc2-3200 1gb kit	
\$ 12.00	- ddr2-400 pc2-3200 512mb	
\$ 6.24	- ddr2	



# The Pricewatch Universe

screenshot from  
1999---price-sorted  
list of 128MB  
PC100 memory  
modules for sale

(This is actually  
our data, as well.  
We have these  
hourly for a year.)

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	pcbeest.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 LIFETIME 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	-

# The Pricewatch Universe

There was a great deal of competition on Pricewatch, and prices were low, but it was clearly not the frictionless ideal.

Two experiences were common:

- Websites with complicated, annoying pages that made it time-consuming to determine what the price really was
- Websites that pushed add-ons or upgrades

Note also that the Bertrand paradox had not arisen. Markups were low, but firms were apparently doing well enough so that there were a large number of competitors in many of the product categories.

# The Pricewatch Universe

For instance, you might have to manually choose which of these upgrades to accept or reject.

**Tufshop Price: \$53.81**  
**Price (with Selected Options): \$90.36**



## Super Buys

Make processor upto 30% faster or your motherboard to run with maximum efficiency. You must have this awesome value package. **(Highly Recommended)**

- Memory Upgrade - Certified intel Approved specs Memory [+\$23.11]
- Memory Upgrade - Certified AMD Approved specs Memory [+\$17.35]



## Bonus Buys

Consider taking advantage of these special offers. Compare and save. Purchase everything from one location and save on shipping

- Cable Upgrades - Rounded IDE and Floppy Cables (Complete Set) [+\$11.91]
- Essential Equipment - Sony Floppy Disk Drive [+\$16.84]
- Bonus Buy - 10 pack of hand thumbscrews for Case [+\$4.95]
- Bonus Buy - 12-Pc Computer Tool Kit [+\$16.98]
- Bonus Buy - RatPadzGS Ultimate Mousepad/Gaming Surface [+\$11.97]
- Bonus Buy - CD-DVD Media Cleaning Kit [+\$4.93]
- Thermal Management - Dynatron 80mm Case Fan [+\$12.87]



## Related Options

Please take advantage of these special offers.

- Memory Upgrade - CAS 2 Upgrade (Offers Performance Increase & Helps in Overclocking) [+\$18.25]
- Memory Upgrade - CAS 2.5 Upgrade (Improves Performance over Cas3 & Helps with Applications and Games) [+\$6.35]



## Pretest

Have us test your merchandise before we ship to avoid costly RMAs in the future and Maximize your time

- No Pretesting
- Pretest - Standard Pretest (Avoid costly RMAs) [+\$6.97]



## Memory Performance

Options to make your hardware & applications fly

- No Memory Performance Enhancements
- Memory Upgrade - 6 Layer PCB For Stability of Memory - more layer - More = Better Design [+\$8.37]



## Enhancers

Options to make your hardware & applications fly

- No System Performance Enhancers
- Memory Upgrade - Thermaltake Memory Cooling Kit (Active) [+\$19.99]
- Memory Cooling - Copper Passive Memory Cooling Kit [+\$11.15]
- Memory Cooling - Aluminium Passive Memory Cooling Kit [+\$9.91]
- Memory Upgrade - Thermaltake Memory Cooling Kit (Passive) [+\$14.99]

# The Pricewatch Universe

## Memory Spec. Chart - PC3200 DDR 512MB (Select Your Memory Module)

Samsung/Micron or Major 512MB PC 3200 [ADD \$25]

- 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%

Industry Standard 512MB PC 3200 [ADD \$15]

- 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%

OEM 512MB PC 3200

- 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

And here is website seemingly designed to encourage consumers to upgrade, without helping one assess if improvements were worthwhile.

CAS 2.5 or 3.0 latency? 4 layer versus 6 layer?



# Obfuscation

We will argue that a potential explanation for what we are observing is that the price reductions that might otherwise occur are being partially offset by increases in obfuscation.

Obfuscation could increase prices via multiple channels:

- It could be similar to raising the per-visit search cost  $s$  in a standard search model.
- It could involve changing the form of competition from a standard single-good Bertrand-like environment to an environment with add-on pricing.

# “Search and Obfuscation,” Ellison and Ellison

We focus on four categories of memory modules: 128MB PC100, 128MB PC133, 256MB PC100, and 256MB PC133.

Within each category modules can differ in quality. Quality is many dimensional and hard to align across retailers. Our retailer sells three products in each category. We call them Low, Medium, and High quality.

The lowest 12-24 prices in each category were downloaded from Pricewatch at hourly frequency from May 2000 – May 2001. (All prices are presumably for low-quality modules.)

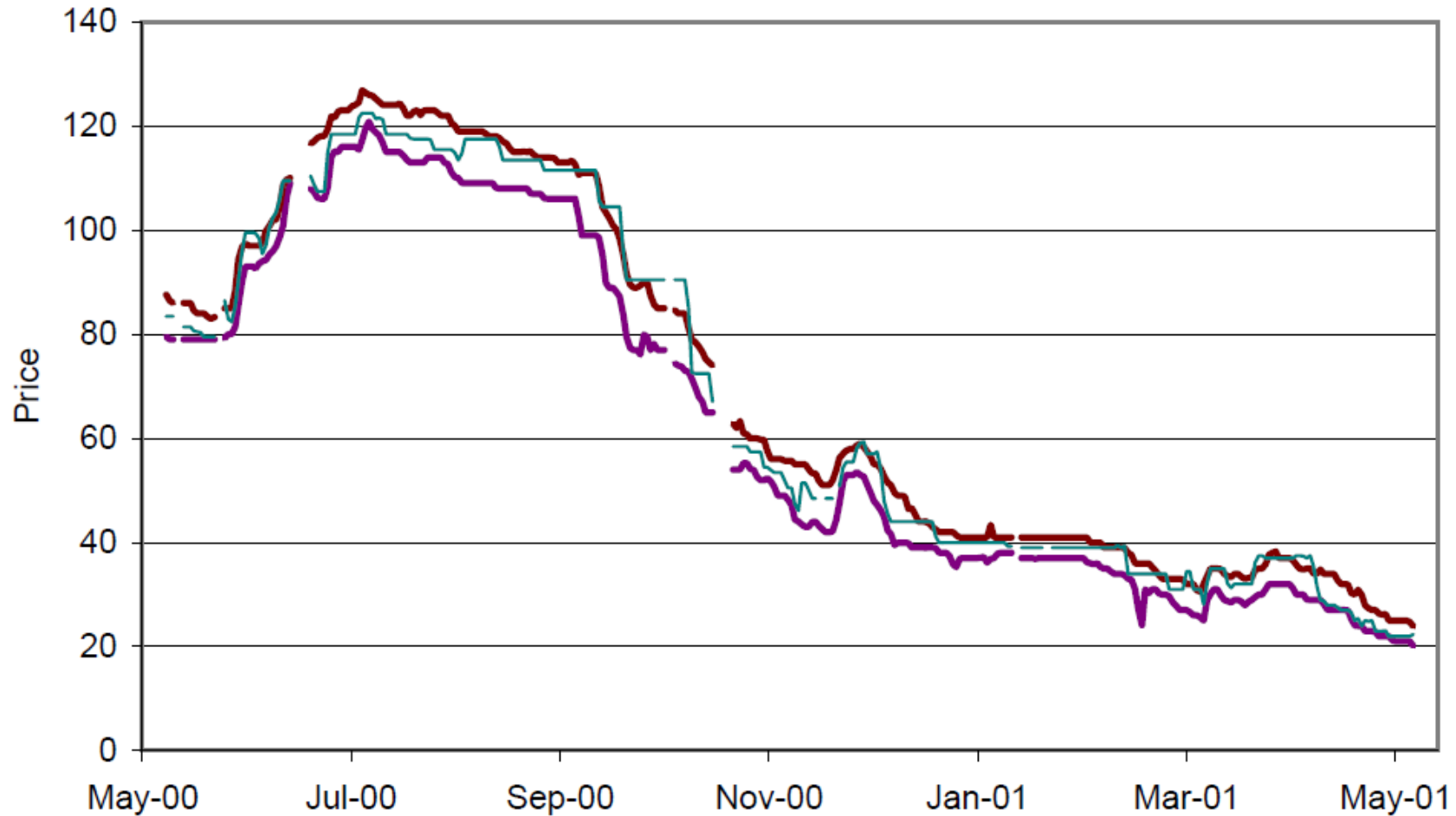
Quantity and additional price data were obtained from one retailer that owns websites A and B.

Cost data were obtained from the same retailer.

*We have used these data now on several projects.*

# “Search and Obfuscation,” Ellison and Ellison

Prices for 128MB PC100 Memory Modules



Prices volatile,  
but dropping  
throughout most  
of this period.

# “Search and Obfuscation,” Ellison and Ellison

TABLE I  
SUMMARY STATISTICS FOR MEMORY MODULE DATA (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
<i>P</i> Low	66.88	34.51	21.00	123.49
<i>P</i> Mid	90.71	40.10	35.49	149.49
<i>P</i> Hi	115.19	46.37	48.50	185.50
$\log(1 + P_{\text{LowRank}})$	1.86	0.53	0.69	3.26
<i>Q</i> Low	12.80	17.03	0	163
<i>Q</i> Mid	2.44	3.33	0	25
<i>Q</i> Hi	2.02	3.46	0	47

Mostly sold low-quality modules, but some upgrades. And, as we will see, those upgrades were crucial to profits because the low-quality modules were being sold at such thin margins.

# “Search and Obfuscation,” Ellison and Ellison

We 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

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

and  $E(u_{wcqt}|X_{wct}) = 1$ .

We estimate the model separately for each category-quality level. The base estimates are from GMM estimation using the moment conditions

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

We also present estimates from two IV strategies: one instruments 128MB PC100 prices with 128MB PC 100 costs; the other instruments 128MB PC100 prices with 128MB PC133 prices.



# “Search and Obfuscation,” Ellison and Ellison

Very elastic demand for low quality---as high as -33!!

TABLE II  
DEMAND FOR 128MB PC100 MEMORY MODULES<sup>a</sup>

Independent Variables	Dep. Var.: Quantities of Each Quality Level		
	Low $q$	Mid $q$	High $q$
$\log(1 + P_{\text{LowRank}})$	-1.29*	-0.77*	-0.51*
	(10.9)	(4.6)	(2.9)
$\log(P_{\text{Low}})$	-3.03	-0.59	1.49
	(2.3)	(0.4)	(0.9)
$\log(P_{\text{Mid}})$	0.68	-6.74*	2.38
	(0.8)	(5.9)	(1.7)
$\log(P_{\text{Hi}})$	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)
$\log(\text{LowestPrice})$	1.20	0.83	-0.14
	(1.1)	(0.6)	(0.1)
Number of obs.	683	683	683

<sup>a</sup>Absolute value of  $t$ -statistics in parentheses. Asterisks (\*) denote significance at the 5% level.

# “Search and Obfuscation,” Ellison and Ellison

TABLE II  
DEMAND FOR 128MB PC100 MEMORY MODULES<sup>a</sup>

Independent Variables	Dep. Var.: Quantities of Each Quality Level		
	Low $q$	Mid $q$	High $q$
$\log(1 + P_{\text{LowRank}})$	-1.29* (10.9)	-0.77* (4.6)	-0.51* (2.9)
$\log(P_{\text{Low}})$	-3.03 (2.3)	-0.59 (0.4)	1.49 (0.9)
$\log(P_{\text{Mid}})$	0.68 (0.8)	-6.74* (5.9)	2.38 (1.7)
$\log(P_{\text{Hi}})$	0.17 (0.2)	2.72 (1.8)	-4.76* (3.3)
SiteB	-0.25* (3.5)	-0.31* (2.9)	-0.59* (5.6)
Weekend	-0.49* (8.4)	-0.94* (8.3)	-0.72* (5.8)
$\log(\text{LowestPrice})$	1.20 (1.1)	0.83 (0.6)	-0.14 (0.1)
Number of obs.	683	683	683

Low ranks (from low prices for low-quality) also lead to higher demand for medium- and high-quality---evidence of loss-leader effect.

<sup>a</sup>Absolute value of  $t$ -statistics in parentheses. Asterisks (\*) denote significance at the 5% level.

# “Search and Obfuscation,” Ellison and Ellison

TABLE II  
DEMAND FOR 128MB PC100 MEMORY MODULES<sup>a</sup>

Independent Variables	Dep. Var.: Quantities of Each Quality Level		
	Low $q$	Mid $q$	High $q$
$\log(1 + P_{\text{LowRank}})$	-1.29*	-0.77*	-0.51*
	(10.9)	(4.6)	(2.9)
$\log(P_{\text{Low}})$	-3.03	-0.59	1.49
	(2.3)	(0.4)	(0.9)
$\log(P_{\text{Mid}})$	0.68	-6.74*	2.38
	(0.8)	(5.9)	(1.7)
$\log(P_{\text{Hi}})$	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)
$\log(\text{LowestPrice})$	1.20	0.83	-0.14
	(1.1)	(0.6)	(0.1)
Number of obs.	683	683	683

<sup>a</sup>Absolute value of  $t$ -statistics in parentheses. Asterisks (\*) denote significance at the 5% level.

But the effects are not as strong as for the low-quality---evidence of adverse selection

# “Search and Obfuscation,” Ellison and Ellison

TABLE II  
DEMAND FOR 128MB PC100 MEMORY MODULES<sup>a</sup>

Independent Variables	Dep. Var.: Quantities of Each Quality Level		
	Low $q$	Mid $q$	High $q$
$\log(1 + P_{\text{LowRank}})$	-1.29* (10.9)	-0.77* (4.6)	-0.51* (2.9)
$\log(P_{\text{Low}})$	-3.03 (2.3)	-0.59 (0.4)	1.49 (0.9)
$\log(P_{\text{Mid}})$	0.68 (0.8)	-6.74* (5.9)	2.38 (1.7)
$\log(P_{\text{Hi}})$	0.17 (0.2)	2.72 (1.8)	-4.76* (3.3)
SiteB	-0.25* (3.5)	-0.31* (2.9)	-0.59* (5.6)
Weekend	-0.49* (8.4)	-0.94* (8.3)	-0.72* (5.8)
$\log(\text{LowestPrice})$	1.20 (1.1)	0.83 (0.6)	-0.14 (0.1)
Number of obs.	683	683	683

Overall strong price effects

<sup>a</sup>Absolute value of  $t$ -statistics in parentheses. Asterisks (\*) denote significance at the 5% level.

# “Search and Obfuscation,” Ellison and Ellison

With these demand estimates, we can compute elasticity matrices---let's focus on the 128MB PC100 modules.

TABLE III  
PRICE ELASTICITIES FOR MEMORY MODULES: THREE QUALITIES IN EACH OF FOUR PRODUCT CLASSES<sup>a</sup>

	128MB PC100 Modules			128MB PC133 Modules		
	Low	Mid	Hi	Low	Mid	Hi
<i>P</i> Low	-24.9*	-12.5*	-7.2*	-33.1*	-11.2*	-4.9*
<i>P</i> Mid	0.7	-6.7*	2.4	0.8	-3.6*	0.5
<i>P</i> Hi	0.2	2.7	-4.8*	0.2	-4.8*	-4.8*
	256MB PC100 Modules			256MB PC133 Modules		
	Low	Mid	Hi	Low	Mid	Hi
<i>P</i> Low	-17.4*	-8.1*	-4.1	-24.8*	-12.5	-6.6
<i>P</i> Mid	5.7	-7.8	-4.1	0.3	3.3	3.9*
<i>P</i> Hi	0.7	6.4	-3.8	-0.9	-7.2	-0.8

<sup>a</sup>Asterisks (\*) denote significance at the 5% level.



# “Search and Obfuscation,” Ellison and Ellison

You get this unusual pattern of cross-price elasticities of very similar goods---negatives on diagonal, mostly positives on off-diagonal, except these two spots. This is the loss-leader effect working.

TABLE III  
PRICE ELASTICITIES FOR MEMORY MODULES: THREE QUALITIES IN EACH OF FOUR PRODUCT CLASSES<sup>a</sup>

	128MB PC100 Modules			128MB PC133 Modules		
	Low	Mid	Hi	Low	Mid	Hi
<i>P</i> Low	-24.9*	-12.5*	-7.2*	-33.1*	-11.2*	-4.9*
<i>P</i> Mid	0.7	-6.7*	2.4	0.8	-3.6*	0.5
<i>P</i> Hi	0.2	2.7	-4.8*	0.2	-4.8*	-4.8*
	256MB PC100 Modules			256MB PC133 Modules		
	Low	Mid	Hi	Low	Mid	Hi
<i>P</i> Low	-17.4*	-8.1*	-4.1	-24.8*	-12.5	-6.6
<i>P</i> Mid	5.7	-7.8	-4.1	0.3	3.3	3.9*
<i>P</i> Hi	0.7	6.4	-3.8	-0.9	-7.2	-0.8

<sup>a</sup>Asterisks (\*) denote significance at the 5% level.

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You get this unusual pattern of cross-price elasticities of very similar goods---negatives on diagonal, mostly positives on off-diagonal, except these two spots. This is the loss-leader effect working.

TABLE III  
PRICE ELASTICITIES FOR MEMORY MODULES: THREE QUALITIES IN EACH OF FOUR PRODUCT CLASSES<sup>a</sup>

	128MB PC100 Modules			128MB PC133 Modules		
	Low	Mid	Hi	Low	Mid	Hi
<i>P</i> Low	-24.9*	-12.5*	-7.2*	-33.1*	-11.2*	-4.9*
<i>P</i> Mid	0.7	-6.7*	2.4	0.8	-3.6*	0.5
<i>P</i> Hi	0.2	2.7	-4.8*	0.2	-4.8*	-4.8*
	256MB PC100 Modules			256MB PC133 Modules		
	Low	Mid	Hi	Low	Mid	Hi
<i>P</i> Low	-17.4*	-8.1*	-4.1	-24.8*	-12.5	-6.6
<i>P</i> Mid	5.7	-7.8	-4.1	0.3	3.3	3.9*
<i>P</i> Hi	0.7	6.4	-3.8	-0.9	-7.2	-0.8

<sup>a</sup>Asterisks (\*) denote significance at the 5% level.

Adverse selection effect is evident from the fact that those two off-diagonals are smaller than the own-price for<sub>32</sub> low *q*.

# “Search and Obfuscation,” Ellison and Ellison

TABLE III  
PRICE ELASTICITIES FOR MEMORY MODULES: THREE QUALITIES IN EACH OF  
FOUR PRODUCT CLASSES<sup>a</sup>

	128MB PC100 Modules			128MB PC133 Modules		
	Low	Mid	Hi	Low	Mid	Hi
<i>P</i> Low	-24.9*	-12.5*	-7.2*	-33.1*	-11.2*	-4.9*
<i>P</i> Mid	0.7	-6.7*	2.4	0.8	-3.6*	0.5
<i>P</i> Hi	0.2	2.7	-4.8*	0.2	-4.8*	-4.8*
	256MB PC100 Modules			256MB PC133 Modules		
	Low	Mid	Hi	Low	Mid	Hi
<i>P</i> Low	-17.4*	-8.1*	-4.1	-24.8*	-12.5	-6.6
<i>P</i> Mid	5.7	-7.8	-4.1	0.3	3.3	3.9*
<i>P</i> Hi	0.7	6.4	-3.8	-0.9	-7.2	-0.8

<sup>a</sup>Asterisks (\*) denote significance at the 5% level.

Note also:  
super price-  
sensitive low-  
quality, and  
medium- and  
high-quality less  
price-sensitive.

## “Search and Obfuscation,” Ellison and Ellison

We also explore whether the add-on pricing effect from Ellison (2005) can account for observed markups quantitatively. A generalization of the linear model there is that **average** markups will be

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

where  $p_L$  is the price of the base good,  $p_U$  is the price of the upgrade,  $x$  is the fraction of consumers who choose to upgrade and  $\epsilon = \frac{\partial D_1}{\partial p_{1L}} \frac{p_{1L}^* + x^*(p_{1L}^*, p_{2L}^*)p_{1U}^m}{D_1(p_{1L}^*, p_{2L}^*)}$  is an elasticity-like measure.

We can think of  $\epsilon$  as similar to the elasticity of demand w.r.t. the low-quality price, and the second term as a multiplier that captures effect on equilibrium prices of the presence of a cheapskate effect in demand (via the  $(p_{1U}^m - c_U) \frac{\partial x^*}{\partial p_{1L}}$  term).

# “Search and Obfuscation,” Ellison and Ellison

Using daily invoices for the wholesale cost of these memory modules (unusual), we could compute markups. Again we focus on the 128MB PC100.

TABLE VI  
MEAN PERCENTAGE MARKUP IN SIX PRODUCT CLASSES<sup>a</sup>

	Product Category			
	128MB Memory		256MB 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%
Overall elasticity $\epsilon$	-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%

<sup>a</sup>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.



# “Search and Obfuscation,” Ellison and Ellison

We found the low-quality markup to be slightly negative, on average. Others were substantial.

TABLE VI  
MEAN PERCENTAGE MARKUP IN SIX PRODUCT CLASSES<sup>a</sup>

	Product Category			
	128MB Memory		256MB 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%
Overall elasticity $\epsilon$	-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%

<sup>a</sup>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.

# “Search and Obfuscation,” Ellison and Ellison

How does the overall markup compare with what we would expect if 1) we computed markups based on overall  $\epsilon$  and 2) we took into account the adverse selection effect?

TABLE VI  
MEAN PERCENTAGE MARKUP IN SIX PRODUCT CLASSES<sup>a</sup>

	Product Category			
	128MB Memory		256MB 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%
Overall elasticity $\epsilon$	-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%

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# “Search and Obfuscation,” Ellison and Ellison

TABLE VI  
MEAN PERCENTAGE MARKUP IN SIX PRODUCT CLASSES<sup>a</sup>

	Product Category			
	128MB Memory		256MB 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%
Overall elasticity $\epsilon$	-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%

<sup>a</sup>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.

The overall markup is 7.7%, higher than you'd naively expect given the elasticity, and close to what we would expect with adverse selection.

# “Search and Obfuscation,” Ellison and Ellison

We estimated demand without making any use of supply-side first order conditions.

A comparison of actual and predicted markups is consistent with the demand estimation having worked well and the add-on pricing model capturing the equilibrium effect of unobserved add-ons.

1. Observed average markups are very close to the markups that one would predict given the demand estimates.
2. The model calculations indicate that the adverse selection effect in demand is roughly doubling average markups.
3. Markups for low-quality products are very low.

# Galenianos and Gavazza, “Regulatory Intervention in Consumer Search Markets: The Case of Credit Cards,” 2020

G & G use a macro-style calibration to investigate the degree to which the price dispersion in the Stango-Zinman data appears to be due to limited consumer search versus heterogeneity in costs, tastes, etc.

Buyers are assumed to have values  $z \sim M$  on  $[\underline{z}, \bar{z}]$ .

Lenders of mass  $L$  have costs  $k \sim G$  on  $[\underline{k}, \bar{k}]$ .

Buyers who exert effort  $s$  receive a Poisson( $sL$ ) random number of quotes.

Buyer  $i$ 's payoff from card  $j$  is  $v_{ij} = z_i - (R_j + \varepsilon_{ij})$  with  $R_j$  the interest rate. Define  $c_{ij} = R_j + \varepsilon_{ij}$ . Write  $F_c$  for the CDF of a random draw of  $c$  given the equilibrium interest rate distribution. (This reflects equilibrium price dispersion and shocks  $\varepsilon_{ij} \sim F_e$ .)

A seller's payoff is  $\pi(R_i) = P(R_i) (R_i(1-\rho(R_i)) - k)$ , where  $P(R)$  is the probability that each consumer chooses the card and  $\rho$  is the repayment probability.



# Galenianos and Gavazza, “Regulatory Intervention in Consumer Search Markets: The Case of Credit Cards,” 2020

The Poisson search model is surprisingly tractable. Search effort can be a continuous variable rather than the discrete choice that prevents one from taking FOCs in other models.

There are closed forms for the probability that a customer of type  $z$  accepts an offer with cost  $c$ :

$$\begin{aligned} P_c(c, z) &= \sum_{n=0}^{\infty} \frac{e^{-\alpha_z} \alpha_z^n}{n!} (1 - F_c(c))^n \\ &= e^{-\alpha_z F_c(c)} \\ &= e^{-\alpha_z \int_{\underline{R}}^{\bar{R}} F_e(c-x) dF_R(x)}, \quad \text{if } c \leq z \\ P_c(c, z) &= 0, \quad \text{if } c > z \end{aligned}$$

Integrating over the possible  $c$  and  $z$  they derive expressions for the probability that an offer at an interest rate of  $R$  will be accepted.

This lets them characterize a pure-strategy dispersed price equilibrium in which buyers of type  $z$  choose search effort  $s(z)$  and sellers with cost  $k$  choose interest rate  $R(k)$ .

# Galenianos and Gavazza, “Regulatory Intervention in Consumer Search Markets: The Case of Credit Cards,” 2020

G & G assume parametric forms for the various primitives, e.g. they assume that the buyers value distribution is lognormal with parameters to be estimated.

The ability to quickly find the equilibrium lets them calibrate the 11 model parameters to match 15 moments as closely as possible.

	DATA	MODEL
10TH PERCENTILE ACCEPTED OFFER DISTRIBUTION	12.68	12.87
25TH PERCENTILE ACCEPTED OFFER DISTRIBUTION	15.84	15.53
50TH PERCENTILE ACCEPTED OFFER DISTRIBUTION	19.31	19.09
75TH PERCENTILE ACCEPTED OFFER DISTRIBUTION	23.82	23.65
90TH PERCENTILE ACCEPTED OFFER DISTRIBUTION	28.60	28.54
FRACTION RECEIVING 2+ OFFERS (%)	75.00	74.22
MEDIAN NUMBER OF OFFERS RECEIVED, CONDITIONAL ON 2+ OFFERS	3.00	3.00
AVERAGE NUMBER OF OFFERS RECEIVED, CONDITIONAL ON 2+ OFFERS	4.00	3.32
10TH PERCENTILE DISTRIBUTION OF DIFFERENCES IN OFFERED RATES	0.00	1.38
30TH PERCENTILE DISTRIBUTION OF DIFFERENCES IN OFFERED RATES	2.25	3.48
50TH PERCENTILE DISTRIBUTION OF DIFFERENCES IN OFFERED RATES	4.34	5.31
70TH PERCENTILE DISTRIBUTION OF DIFFERENCES IN OFFERED RATES	7.25	7.02
90TH PERCENTILE DISTRIBUTION OF DIFFERENCES IN OFFERED RATES	9.25	9.13
FRACTION WITH CREDIT CARD DEBT	36.70	36.35
CHARGE-OFF RATE	4.01	4.14

# Galenianos and Gavazza, “Regulatory Intervention in Consumer Search Markets: The Case of Credit Cards,” 2020

The calibration suggests that buyers have high (and dispersed) valuations, that they exert minimal search effort, leading to inelastic demand and substantial markups.

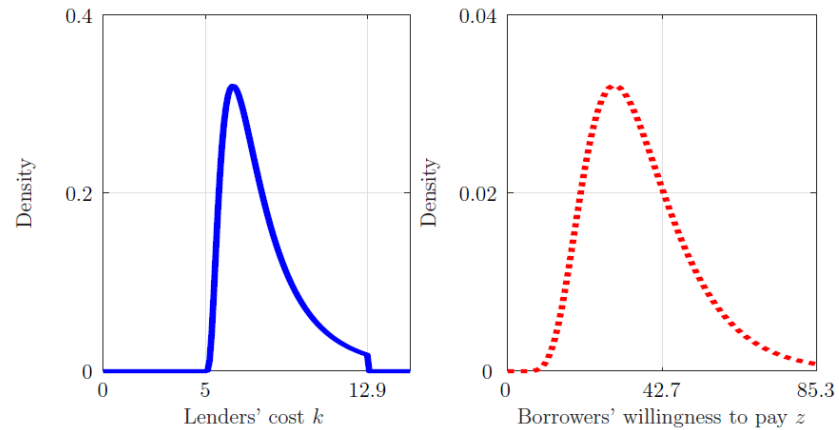


Figure 1: Distribution of lenders' costs (left panel) and borrowers' willingness to pay (right panel).

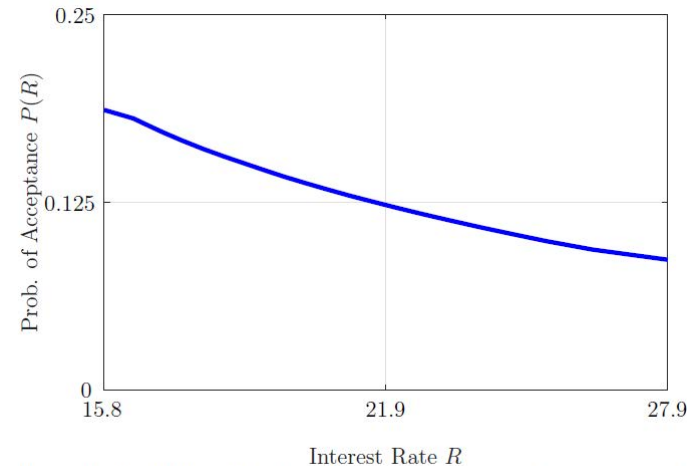


Figure 3: Probability  $P(R)$  that borrowers accept an offer with interest  $R$ .

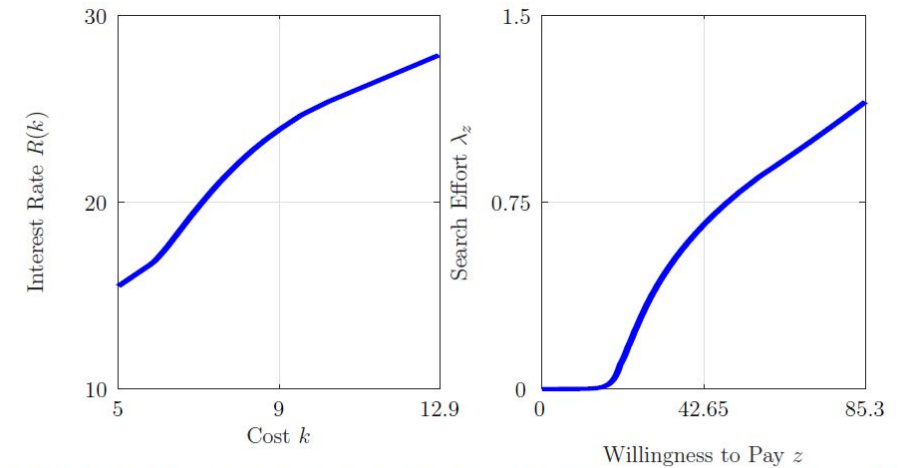


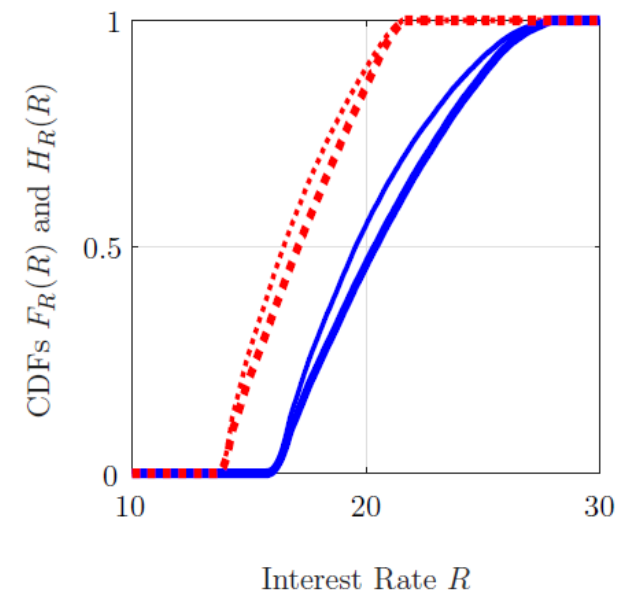
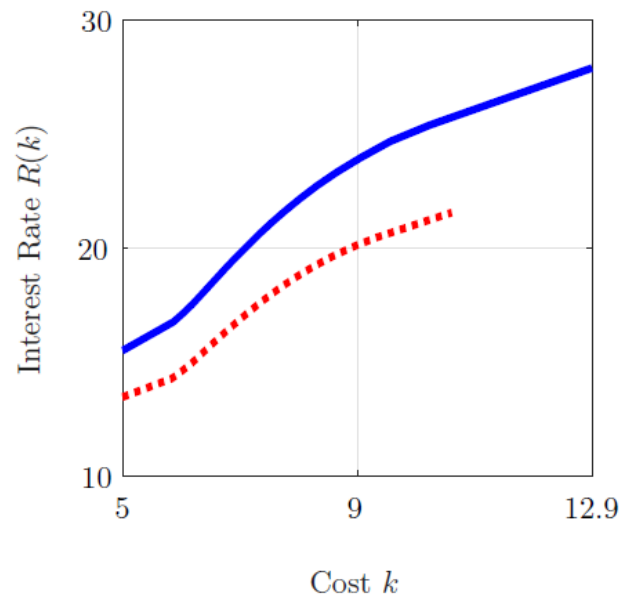
Figure 2: The left panel displays lenders' optimal interest rate  $R(k)$  as a function of their cost  $k$ , and the right panel displays borrowers' optimal search effort  $\lambda_z$  as a function of their willingness to pay  $z$ .

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They use the estimated parameters to discuss a pair of counterfactuals.

One considers the effect of a regulation capping interest rates at 22.5%. Theorists have noted that the effect of such a policy is ambiguous. It can reduce interest rates. But it could also raise equilibrium rates as the price cap reduces dispersion, reducing the incentive to search, leading to higher prices.

At the estimated parameters some credit card issues do drop out of the market, but we are in the more intuitive situation where interest rates are substantially reduced.



Next week Jean Tirole will be giving a pair of theory-focused guest lectures on platform competition.

Tobias returns on the following Monday. He'll talk more about search empirics, including structural work on the topic.

See you then!

Reminder: The midterm exam will be in class on Wed. Oct. 26

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